Nature's Premium: Impact of Biodiversity Regulatory Risk on House Prices*

Maxwell Sacher† Shikhar Singla‡

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Abstract

Biodiversity loss has potentially catastrophic consequences, prompting ambitious conservation efforts. In this paper, we exploit the increased regulatory risk resulting from the adoption of "30 by 30" in the United States, which seeks to protect 30 percent of land by 2030, alongside a novel geographic biodiversity risk measure, constructed by combining observational data on endangered species with machine learning, to study the impact of biodiversity regulatory risk on house prices. We validate our measure, showing that it predicts future government action to protect biodiversity. Using a difference-in-difference design, we find that a one standard deviation increase in biodiversity risk at the county level leads to an increase in house prices by 0.7 percent. Our analysis shows that the price effect is driven by counties with the lowest supply constraints and the highest demand for nature-related amenities. Evidence from loan applications and land value data further support a demand channel. Our results highlight that land protection for biodiversity may be less costly than anticipated, as it provides amenity benefits to surrounding communities.

Keywords: Biodiversity, Endangered Species, Regulatory Risk, House Prices

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†McCombs School of Business, University of Texas at Austin. Email: mnsacher@utexas.edu.

‡McCombs School of Business, University of Texas at Austin. Email: shikhar.singla@utexas.edu.

1 Introduction

We currently live in an age of rapidly increasing threats to biodiversity. Human activities are pushing more species toward global extinction than at any other point in history (Sandra Myrna Díaz, Josef Settele, Eduardo Brondízio, Hien Ngo, Maximilien Guèze, John Agard, Almut Arneth, Patricia Balvanera, Kate Brauman, Stuart Butchart et al. (2019))[1]. This profound loss of biodiversity is likely to impact billions of people as the degradation of natural systems presents a significant risk to quality of life and economies (Kendall R Jones, Oscar Venter, Richard A Fuller, James R Allan, Sean L Maxwell, Pablo Jose Negret and James EM Watson (2018), Henrique M Pereira, Inês S Martins, Isabel MD Rosa, HyeJin Kim, Paul Leadley, Alexander Popp, Detlef P van Vuuren, George Hurtt, Luise Quoss, Almut Arneth et al. (2024), James R Allan, Hugh P Possingham, Scott C Atkinson, Anthony Waldron, Moreno Di Marco, Stuart HM Butchart, Vanessa M Adams, W Daniel Kissling, Thomas Worsdell, Chris Sandbrook et al. (2022),Rebecca A Senior, Ruby Bagwyn, Danyan Leng, Alexander K Killion, Walter Jetz and David S Wilcove (2024), Benoit Paul Blarel, Giovanni Ruta, Olga Gavryliuk, Pauline Elodie Poisson, Fiona Elizabeth Stewart, Samantha Elizabeth Power, Benjamin Marie Camille Guillon, Irina Likhachova and Lisa Michelle Choux (2023), PwC WEF (2020))[2]. In this paper, we investigate how the increasing pressure placed on ecosystems, and the corresponding policy responses, affects key financial assets. In particular, we focus on housing, as land preservation has been the main tool to preserve biodiversity and protect ecosystems (Carlos Carroll and Reed F Noss (2022), Katherine Pulido-Chadid, Elina Virtanen and Jonas Geldmann (2023), Allan et al. (2022) and Penny F Langhammer, Joseph W Bull, Jake E Bicknell, Joseph L Oakley, Mary H Brown, Michael W Bruford, Stuart HM Butchart, Jamie A Carr, Don Church, Rosie Cooney et al. (2024)).

Yet, even as this risk becomes more prevalent, measuring and testing its effect on the housing market is difficult. We use novel data from NatureServe to measure the exposure of counties to areas that are critical for preserving biodiversity. NatureServe is a nonprofit organization whose experts hand collect precise occurrence data of endangered species. They combine the hand-collected data with machine learning models to predict which areas are critical habitat for each endangered species. This area is weighted by the current degree of protection each species already has and then added across all species at a 990m level to create a measure called “protection weighted range size rarity". This measure could capture several risks related to biodiversity. For example, there are physical risks from ecosystem collapse that could harm the economy (Eyal G Frank (2024) and Eyal Frank and Anant Sudarshan (2024)) or regulatory risks from government intervention to protect species. This measure can be applied broadly across asset classes and, to the best of our knowledge, is the first to have such granularity and coverage in terms of geography and species to

[1]Extinction rates are now estimated to be 10 to 100 times higher than the historical average over the past 10 million years Alexandra Marques, Inês S Martins, Thomas Kastner, Christoph Plutzar, Michaela C Theurl, Nina Eisenmenger, Mark AJ Huijbregts, Richard Wood, Konstantin Stadler, Martin Bruckner 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 (World Wide Fund (2020))

[2]For example, Justin Andrew Johnson, Giovanni Ruta, Uris Baldos, Raffaello Cervigni, Shun Chonabayashi, Erwin Corong, Olga Gavryliuk, James Gerber, Thomas Hertel, Christopher Nootenboom 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.

capture biodiversity risk.

Our primary contribution is in estimating the effect of biodiversity risk on house prices. Seven days into his administration, Biden signed Executive Order 14008 on 27th January 2021, the most ambitious land conservation program in United States history, aiming to conserve 30 percent of the United State's land and water by 2030[3]. Later, this executive order was followed by further pushes for conservation contained in the Inflation Reduction Act and Bipartisan Infrastructure Law. The executive order, combined with legislation, meant that the likelihood of government action increased, as well as magnifying the possible direction of realized shocks through both upside and downside risks[4]. Our study leverages this policy shock to assess impacts on housing markets—a question that has been largely unexplored.

Theoretically, the ex-ante direction of the effect of increased risk on house prices is ambiguous. An increase in risk may not be incorporated into house prices due to frictions in housing markets. If the risk is incorporated, the existence of both beneficial and harmful aspects to biodiversity regulatory risk creates ambiguity as to the overall direction of the effect. Our first analysis tests whether we can reject the null hypothesis that biodiversity-related risk has no impact on house prices. This null is plausible given that housing markets are often not highly forward-looking or sophisticated, as suggested by prior research (Karl E Case and Robert J Shiller (1988) and Monika Piazzesi and Martin Schneider (2016)). Unlike financial markets, housing markets face frictions such as high transaction costs, illiquidity, and barriers to arbitrage, making it difficult for buyers and sellers to fully price in future risk. Another possibility is that even if housing markets properly incorporate risk, there may be significant heterogeneity in the effect of biodiversity risk as there are both forces that increase and decrease prices. These forces may cancel each other out. As a result, even if housing markets properly incorporate risks, there may still be no measurable effect.

Even if we reject the null of no effect, there is further tension in the hypothesized direction of the effect. The directional effect of biodiversity risk is heterogeneous. There are both positive and negative effects on the price of housing. Houses more exposed to risk may have their price decrease through increased visibility of potential physical risk. For example, Frank and Sudarshan (2024) find that the loss of vultures in India leads to a significant increase in mortality due to worse sanitation and Frank (2024) finds that the death of bats from white nose syndrome and the

[3]Biden implemented other biodiversity actions during his administration. This includes executive 14072 which made it "the policy of my [Biden's] Administration ... to pursue science-based, sustainable forest and land management; conserve America's mature and old-growth forests on Federal lands; invest in forest health and restoration; support indigenous traditional ecological knowledge and cultural and subsistence practices; honor Tribal treaty rights; and deploy climate-smart forestry practices and other nature-based solutions to improve the resilience of our lands, waters, wildlife, and communities in the face of increasing disturbances and chronic stress arising from climate impacts. It is also the policy of my Administration, as outlined in Conserving and Restoring America the Beautiful, to support collaborative, locally led conservation solutions." (Federal Register, 2022)

[4]Biden also reversed several ESA policies that had been rescinded under the previous administration. This includes regulations that revised Fish and Wildlife Service's (FWS') process for considering exclusions from critical habitat designations and rules that created a regulatory definition of habitat. They also revised several rules, reinstating prior language affirming that listing determinations are made "without reference to possible economic or other impacts of such determination," revised the definition of "effects of the action" and associated provisions to that portion of the rule, with other potential revisions also under discussion, and reinstate its "blanket 4(d) rule," which was withdrawn by the previous administration. The blanket 4(d) rule establishes the default of automatically extending protections provided to endangered species to those listed as threatened. U.S. Fish and Wildlife Service (2021)

corresponding increase in pesticide use lead to higher infant mortality in effected regions. Decreases in biodiversity also risks damaging the local economy as firms may face regulatory risk in operating in these areas and hence might not expand operations or even shift away operations leading to worse economic conditions and house prices. Furthermore, homeowners could face difficulties in modifying or expanding their current homes or face higher costs in maintaining housing, leading to lower demand and decreasing prices. On the other hand, the price of housing could increase driven by several counterpoising effects. For example, house prices may increase as in working to protect biodiversity, Government may also provide natural amenities that households value such as parks, scenic walkways and improved nature recreation facilities. On the other hand, Government may also increase prices by restricting the supply of housing and decreasing the amount of land available for building.

To empirically test this hypothesis, we utilize the signing of executive order 14008 as an exogenous shock to risk allowing us to implement a difference-in-differences design measuring the average effect of biodiversity risk on house prices. We study the impact of house prices at the county level. Our measure of endangered species is at a much more granular level but land conservation or projects might happen nearby to area of unprotected biodiversity importance rather than at the area itself. The county level is also dispersed an area to still be able to study the impact on house prices. We therefore aggregate the NatureServe measure to the county level, creating a cross-sectional measure of exposure to biodiversity risk.

Before beginning our analysis, we validate our measure by demonstrating that our measure predicts regulatory risk captured by government intervention. We show that our measure of exposure to biodiversity risk strongly predicts future environmental government projects under the Inflation Reduction Act and the Bipartisan Infrastructure Act. Counties in the top tercile of exposure to unprotected biodiversity are 7.5 percentage points more likely to receive a biodiversity related project and also receive around $2,000,000 more in funding for projects. Additionally, our measure predicts the establishment of new conservation easements, which restrict land use to achieve conservation goals without requiring outright purchase. We find that treated counties having nearly double the relative probability of having a conservation easement after the signing of executive order 14008. Thus, our measure properly captures the realization of biodiversity risk. Unfortunately, the projects do not provide enough microdata, including exact timing or specific geographic extent to perform a precise analysis with the projects, nor is the realization of a specific type of risk the focus of our paper.

We implement a difference-in-difference approach using both a discrete and continuous measure of treatment. In order to form treatment using our continuous measure, we split counties by tercile based on exposure. Counties in the top tercile are treated while those in the bottom tercile are considered untreated. We also run a specification using the continuous measure without splitting the sample. We use the signing of executive order 14008 on 27th Jan 2021 as our event that shocked risk. We include a number of controls as well as county, month, and state $\times$ year-month fixed effects. For our preferred specification, we find that, on average, moving from the bottom tercile of exposure to the

top tercile of exposure leads to a 2.2% increase in house prices, or for a one standard deviation increase in exposure, a 0.7% increase in house prices. We also test the assumption of parallel trends by implementing a dynamic difference in differences. We hold fixed our definition of treatment, but estimate our coefficient for each month. Dynamics are presented in Figure 6. We find that while there are no significant pre-trends, after the signing of the act, there is a steady increase in the difference of value between treated and untreated counties. Our effect also builds up slowly, showing momentum consistent with literature on frictions in the housing market (Case and Shiller (1988), Piazzesi and Schneider (2016)). We find that at the end of the sample there is around a 3.7% difference in price between treated and untreated counties.

This result is robust to alternative definitions of treatment, varying control sets, and fixed effects specifications. In particular, one potential concern is that our measure is correlated with areas that experienced increased prices due to COVID-19. We address this issue in several ways. First, when we examine dynamics, our largest price increase occurs after 2021 and continue through 2024 while COVID-19's largest effects were in 2020 and major effects on house prices had dispersed by the second quarter of 2020 (Arpit Gupta, Vrinda Mittal, Jonas Peeters and Stijn Van Nieuwerburgh, 2022). Similarly, there was a reversal in house prices heavily affected by COVID in 2024, but our effect remains persistent across 2024. Second, we include several controls to deal with potential COVID related measures such as the total park area in a county (Kathleen K. L. Yap, Malcolm C. K. Soh, Angelia Sia, Wei Jun Chin, Sophianne Araib, Wei Ping Ang, Puay Yok Tan and Kenneth B. H. Er, 2022) and the prevalence of working from home which have been shown to capture the effect of COVID-19 on house prices (Gupta et al., 2022). Third, when we examine rent prices we find no effect of biodiversity risk, whereas COVID had a large impact on rent prices Gupta et al. (2022). A second potential concern is that areas at risk for biodiversity loss could also be more impacted by physical climate change or other environmental impacts. In order to address this issue, we include in our regressions several further controls for climate change exposure. These measures are also constructed by NatureServe and quantify 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. Adding these controls to our regression has little impact on the magnitude or significance of our estimates indicating that biodiversity risk is distinct from other climate related risks .

Having confirmed that biodiversity risk has a positive impact on house prices, our final contribution is disentangling whether the increase in prices is driven by an expected reduction in supply, or an expected increase in value, or some mix of both. For example, the supply of housing could be reduced as land previously available for construction is made unavailable or future projects are now limited in the kind or use of construction allowed (John A List, Michael Margolis and Daniel E Osgood (2006), Keith R. Ihlanfeldt (2007),Maximilian Auffhammer, Maya Duru, Edward Rubin and David L. Sunding (2020), Golnaz Bahrami, Matthew Gustafson and Eva Steiner (2024)). On the other hand, demand could increase, driven by upside risk from an expected increase in value from new nature amenities

such as improved trails, the creation of new parks, and a cleaner environment (Patrick Bayer, Robert McMillan, Alvin Murphy and Christopher Timmins (2016), Randy Walsh (2007),Virginia McConnell and Margaret Walls (2005), Tyler Reeves, Bin Mei, Pete Bettinger and Jacek Siry (2018)). Disentangling the channels is highly relevant to policymakers. The welfare impact of our average effect is ambiguous and therefore the correct policy implementation is ambiguous as well. To see why, imagine a policymaker who believes that our observed effect is only driven by an increase in demand. The policymaker would then believe that our effect has a low cost to implement. Yet, if the observed price increase is largely driven by a reduction in supply, our estimates would overstate the benefits of biodiversity protections and the price increase would not reflect greater desirability but rather an artificial scarcity of housing. If one had assumed that the price increase was driven only by a reduction in supply but instead the observed price increase is driven by an increase in demand, our average effect would understate the benefits of biodiversity protection. In this case, our estimate would not capture the full benefit of an increase in amenities and policymakers may under-provide biodiversity protection.

In order to disentangle the channels we use a measure of land unavailability to capture supply constraints and amenity demand. This measure, developed by Chandler Lutz and Ben Sand (2023) removes areas where housing cannot be expanded into, namely wetlands, water areas, and very high slope land. We utilize this measure due to its expansive coverage and construction. Ex-ante we expect the supply shock to be the smallest in areas high in land availability, as there is not much change in total area at the margin. Furthermore, since the measure is constructed by removing wetland, water bodies, and slopes, counties high in land availability are also lacking in nature amenities, which means that the demand effect is stronger as land unavailability decreases. We also note that a large part of Biden's agenda was to focus on nature deprived areas, as while these areas lack nature amenities, they do not lack possible improvements to their land, and this focus also created greater risk in higher marginal demand areas. We confirm this later hypothesis is true, showing that the land available measure has a negative relationship with park area, AUBI exposure, and with the White Houses' environmental advisory body, the Council of Environmental Qualities, nature-deprived community measure. Therefore, our measure captures two opposing supply and demand forces. As land availability increases the supply channel is weakened, while at the same time the demand channel, driven by upside risk is strengthened. We divide counties into four quartiles based on the land availability measure and run our original specification within each quartile. We find that the increase in house prices is concentrated in the counties with the most land available and that are most nature deprived. For example, using our original outcome variable we find that a one standard deviation increase in exposure in the first quartile leads to a 0.5% increase in house prices whereas for the fourth quartile we find that a one standard deviation increase in house prices leads to 2.1% increase in house prices, an effect four times as large. This lends evidence that the price increase is driven by increased expected amenity value or increased uncertainty with housing being a potential call option, as these areas are least supply constrained and would not experience a large impact due to biodiversity-related restrictions so face mainly upside

risk. To further support this conclusion, we examine other independent sources using HMDA loan application data as well as Morris A. Davis, William D. Larson, Stephen D. Oliner and Jessica Shui (2021) land values data. We find a significant increase in the value of loans applied for and originated in high-exposure nature deprived counties. Comparing again the first and fourth quartiles, a one standard deviation in exposure leads to 0.2% increase in loan amount applied in the first quartile while leading instead to a 1.5% increase in the fourth quartile. We also split loans by purpose, either residential or investment. We find a significant effect for residential loans, showing that it is the current residents valuing the amenities more and not speculation driving the price increase. We also find an increase in land values only in high-exposure nature deprived counties. We also show that the demand channel is salient to homeowners. We measure media response mentioning amenities and the *30 by 30* initiative and find a large increase post 2021. We also test using a direct measure of demand, utilizing google mobility reports on park visits. We find that there is a significant increase in visits post 2021 in only the fourth quartile of land availability. This further supports the idea that our effect is driven by increased demand for housing, rather than a reduction in supply. The land values data is especially pertinent as it is based on appraisals showing an underlying shift in value.

Finally, while regulatory constraints could theoretically restrict new construction, we confirm that there is no significant change in building permits following the policy shift. We also show that most AUBI areas fall outside of urban core areas and that regressions controlling for the intersection of urban and AUBI areas do not reduce or significantly alter our results, further providing evidence against a supply channel and for a demand channel. This provides additional evidence that biodiversity-related risk does not directly affect supply but instead enhances the desirability of certain areas, increasing demand and leading to higher house prices.

We show that our result is robust. Recently continuous difference and differences has been critiqued by Brantly Callaway, Andrew Goodman-Bacon and Pedro HC Sant'Anna (2024). In order to address these recent methodological issues we perform two robustness tests. First, we take the log of our treatment variable in order to make the weights of our fixed effects estimator and distribution of our treatment variable similar. Under this transformation we see no significant change in our estimates for our main result or our decomposition. Second, we form binary treatments within each of our quartiles. Using these estimators we again show that our main results still hold.

We conclude by highlighting the relevance of our results for policymakers as well as researchers. Most recently with the 2024 election of Trump, the political landscape of conservation has changed again. On his first day in office, Trump canceled the original executive order by Biden to conserve 30 percent of land and marine ecosystems. This provides another shock to biodiversity regulatory risk. While the data is sparse, we do find suggestive evidence that the effect has begun to reverse in our treated counties, although we cannot confirm this fully due to the slow moving nature of our outcome variable. Furthermore, even though the particular executive order was canceled by Trump, the IRA and BIL have been built into legislation and thus would require a further legislative action to undo the effects we find. Finally, with decreasing biodiversity, action will still be taken mechanically as the ESA will continue

to cover more species. In this context we see our results as informative about global awareness and actions like the Kunmig declaration about biodiversity, actions which we expect to only increase in the future. Our results indicate that biodiversity protection policies, such as conservation initiatives or government investment in natural amenities, can lead to significant increases in house prices. Yet policymakers should not despair. In areas with little land availability there is already plenty of areas for biodiversity improvement that our effect should not be a major constraint. Similarly, areas with high land availability will also not be constrained in future housing to the nature of their geography. Thus, while there is a price increase as a result of demand for nature preservation, it also highlights that the costs to preserving biodiversity are lower than previously expected.

The paper proceeds as follows: Section 2 reviews the literature. Section 3 discusses our institutional details. Section 4 introduces our biodiversity risk measure and other data used. Section 5 presents our empirical approach and main results. Section 6 decomposes the supply and demand channels. Section 7 concludes.

2 Literature Review

Biodiversity loss is rapidly becoming a crisis with severe consequences. Efforts are needed to stop biodiversity loss, yet these efforts may conflict with other goals such as economic growth or housing affordability. We show that efforts to protect biodiversity are less costly than policymakers may think since it creates an amenity that people value. We unmask heterogeneity and show that those who are most nature-deprived value it the most. We also show the impact of biodiversity regulatory risk on house prices. These results are novel and policy-relevant. It is difficult to study these research questions as regulatory risk around land and housing regulation needs geographic variation as well as time-series variation to study. This result does fit within previous literature trying to show the value of amenities in terms of open space and how it impacts house prices. McConnell and Walls (2005) provides a review of 60 studies that measure the value of open space in and around urban areas. They find that the value of nature amenities varies widely by type of open space, by the services provided, and by study methodology. Relevant to this paper, as we use conservation easements as a measure of regulatory risk, Reeves et al. (2018) reviews the literature on the effect of conservation easements on property value. Similar to McConnell and Walls (2005), the authors find widely varying estimates dependent on development potential, proximity, and the effect of forest composition and characteristics.

We are closely related to papers which investigate the impact of land conservation on land values. Eyal G Frank, Maximilian Auffhammer, David McLaughlin, Elisheba Spiller and David L Sunding (2025) shows that 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 of land supply being constrained due to ESA actions. Tristan Grupp, Prakash Mishra, Mathias Reynaert and Arthur A van Benthem (2023) do not find any effect of land protection on vegetation and nightlights. Bahrami, Gustafson and Steiner (2024) implement a regression discontinuity near areas

that are and are not currently protected and find a large discount in prices for those in protected areas. We differ in several ways to these papers. We first focus on uncertainty of regulatory actions. Second, we focus on most ambitious land conservation plan and finally, our measure captures the possibility of getting land conserved or ESA action.

Our results also show that house prices move slowly and exhibit momentum. We relate to the literature that shows that house prices react slowly to information due to several reasons such as illiquidity, high transaction costs, decentralized markets, indivisibility, nontradability of dividends (Case and Shiller (1988) and Piazzesi and Schneider (2016)). Another nascent literature we relate to is biodiversity in finance which focuses on biodiversity risk and stock returns and how biodiversity projects are financed (Stefano Giglio, Theresa Kuchler, Johannes Stroebel and Xuran Zeng (2023) and Alexandre Garel, Arthur Romec, Zacharias Sautner and Alexander F Wagner (2024) Caroline Flammer, Thomas Giroux and Geoffrey M Heal (2025) G Andrew Karolyi and John Tobin-de la Puente (2023)). Lastly, we speak to the broader literature of how policy uncertainty affects asset prices which focuses on equity and corporate bonds (Lubos Pastor and Pietro Veronesi (2012), L'uboš Pástor and Pietro Veronesi (2013) Lee H Seltzer, Laura Starks and Qifei Zhu (2022)).

3 Institutional Details

Modern federal interest in species protection can be traced back to the environmental movement of the 1960's. A groundswell of concern about biodiversity and environmental protection led to the establishment of the Land and Water Conservation Fund which began to purchase land for conservation. Also passed in the 60's was a series of Endangered Species Acts. These acts established the first list of endangered and threatened species as well as directed Government agencies to take into account their impact on the environment (B. 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 governments 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 by 30 initiative. At the 74th United Nations General Assembly, Costa Rica led a group of countries in forming a coalition for nature policy, calling themselves the High Ambition Coalition for Nature and People (High Ambition Coalition 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 Sec 216 committed America to preserving 30% of US land and water by

2030, dubbed the *America the Beautiful Initiative* (Federal Register, 2021).[5]

Following the signing of this initiative two major legislative actions were taken which had major provisions providing funding for biodiversity protection and that we focus on to validate our measure of biodiversity risk. The first piece of legislation passed was the Infrastructure Investment and Jobs Act also known as the Bipartisan Infrastructure Law (BIL). While primarily an omnibus bill to fund a wide variety of infrastructure projects, one of the major categories of infrastructure funded by the bill was "Restoration and Resilience" projects (DeFazio, Peter A., 2021). These projects were focused on restoring ecosystems and protecting biodiversity and increasing natural amenity value. For example, one project in Kittitas County's

> "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, several sections were directed towards conservation and resilience specifically, Title II subtitle B, and Title V, Part 2. Around $2.6 billion and 814 projects were allocated directly to conservation projects and included as part of the *America the Beautiful Initiative*.

Most recently with the 2024 election of Trump, the political landscape of conservation has changed again. On his first day in office, Trump canceled the original executive order by Biden to conserve 30 percent of land and marine ecosystems. This provides another shock for future research to address. We do not address this action in the paper due to the slow moving nature of our outcome variable, namely house prices. Furthermore, even though the particular executive order was canceled by Trump, the IRA and BIL have been built into legislation and thus would require a further legislative action to undo the effects we find. Finally, with decreasing biodiversity, action will still be taken mechanically as the ESA will continue to cover more species. In this context we see our results as informative about global awareness and actions like the Kunmig declaration about biodiversity, actions which we expect to only increase in the future.

On the ground, the form of conservation projects and conservation styles varies considerably. Government has several tools at its disposal to protect biodiversity which span Federal, State, and Local government actors as well as a number of private individuals and firms as well. In this section and paper we focus on land purchases and easements, but there are several other strategies employed including legislative, scientific, and outreach and education

[5]There were 6 areas of improvement listed as part of the America the Beautiful Initiative. Creating more parks and safe outdoor opportunities in nature-deprived communities. Supporting Tribally led conservation and restoration priorities. Expanding collaborative conservation of fish and wildlife habitats and corridors. Increasing access for outdoor recreation. Incentivizing and rewarding the voluntary conservation efforts of fishers, ranchers, farmers, and forest owners. Creating jobs by investing in restoration and resilience projects and initiatives, including the Civilian Climate Corps. More details can be found here: https://www.doi.gov/pressreleases/biden-harris-administration-outlines-america-beautiful-initiative

programs (U.S. Department of State, 2022). One major tool is to simply purchase land outright, also known as fee simple. A government or partner buys land and manages that for the purpose of conservation. This management can itself take many varied forms ranging from “process conservation" where the land is left to evolve naturally without intervention, to “species conservation" with active management to protect certain species for biodiversity (Janneke Westermann and Goddert von Oheimb, 2021). Furthermore, the allowed human interaction with this land can vary, from being used for only limited amounts and requiring “leave no trace" eco tourism and other kinds of recreation to allowing limited resource extraction within protected areas(J. Michael Scott, Frank Davis, Blair Csuti, Reed Noss, Bart Butterfield, Craig Groves, Hal Anderson, Steve Caicco, Frank D’Erchia, Thomas C. Edwards, Joe Ulliman and R. Gerald Wright, 1993)[6]. To get a sense of the diversity and range of protection, as well as how it overlaps with out measure of biodiversity risk we plot current GAP status 1 and 2 areas by ownership type in Panel A of Figure 3 and how it overlaps with our measure of biodiversity risk in Panel B of figure 3. In the Inflation Reduction Act, Title II, Sec. 23003 directly allocated funding for fee simple styles of conservation. Another method of protection is known as easements. In this case, instead of purchasing and managing land outright, the Government or a partner such as a nonprofit or local or state government purchase just certain property rights allowed in the land. The rights given away, sold, or otherwise transferred to the easement holder may include, for example, the right to construct buildings, to subdivide the land, to restrict access, or to harvest timber. By selling or donating a conservation easement, a landowner retains some rights and gives up others by deeding them to a qualified holder (J. Diehl, T.S. Barrett, Trust For Public Land and Land Trust Exchange, 1988).

4 Data

4.1 Biodiversity Measure

As the central question of our paper is to address the conflict between land preservation, conservation, and house prices, previous measures of biodiversity risk, such as 10k’s or aggregate media mentions, are inadequate to answer our question. Biodiversity is directly tied to ecosystems and the land area these ecosystems inhabit, and housing is also a highly geographic dependent outcome, therefore a proper measure of risk should take into account this geospatial component of biodiversity. We also desire a proper measure of risk, areas that are already conserved are no longer at risk and would not adequately provide a measure of exposure. This distinguishes our measure and research question from previous papers which have been concerned with how housing prices react when building is constrained within already protected areas. Taking these two facets together, our paper desires a measure that is both geographic and

[6]We simplify heavily here. Just at the Federal level there are a wide variety and type of protected areas, for example there are National Parks and Preserves, National Wildlife Refuges, National Conservation Areas, National Monuments, Wilderness Areas, National Historic Sites, National Memorials, National Battlefields, National Recreation Areas, Wild and Scenic Rivers, National Seashores, National Lakeshores, and National Trails, each with their own goals and regulations. Each state may also have it’s own system of nature conservation and preservation. In this paper we treat most of these areas the same.

uncertain. In this section, we describe the data we use and how our approach addresses these concerns in order to measure geographical exposure to biodiversity risk.

4.2 NatureServe

We use data on endangered species from NatureServe a nonprofit organization dedicated to advancing biodiversity conservation by providing high-quality, science-based 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. By offering detailed biodiversity data, NatureServe supports conservation planning and policy, assisting researchers, policymakers, and businesses in identifying high priority areas for biodiversity protection. Our paper leverages biodiversity importance measures developed by NatureServe scientists, as outlined in Healy Hamilton, Regan L. Smyth, Bruce E. Young, Timothy G. Howard, Christopher Tracey, Sean Breyer, D. Richard Cameron, Anne Chazal, Amy K. Conley, Charlie Frye and Carrie Schloss (2022). This study applies Habitat Suitability Models (HSMs) and machine learning 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. Using 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 m resolution for spatial aggregation.

From these modeled habitat areas (A_i), conservation priority is measured using Protection-Weighted Range-Size Rarity, which integrates Range-Size Rarity (RSR) with a measure of protection status. RSR is defined as:

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

where A_i is the total habitat extent of species i. Therefore, species with less potential habitat area are given greater weight in the measure. Yet, some species may already be fully protected and thus not need further regulatory action. Therefore, RSR alone may not provide an accurate measure of regulatory risk. RSR is augmented with the current amount of protection to create a more accurate measure.

Protection-Weighted Range-Size Rarity (PWRSR) integrates into RSR the degree to which the modeled habitat area already falls within a protected area, defined as Gap-1 or Gap-2 designated area. 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 proper measure of priority of conservation need.

Finally, to construct Areas of Unprotected Biodiversity Importance (AUBI) PWRSR values were summed across all species i within each 990-m grid cell, creating a continuous measure of biodiversity importance:

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

If a grid's PWRSR value is greater than 0.0005 then it is designated as an AUBI area. These areas represent concentrations of rare, but unprotected, species creating a measure of where regulators would want to focus if trying to protect biodiversity. We graph our measures of PWRSR as well as AUBI in Figure 1.

While PWRSR and AUBI are fine grained measures at the 1km grid level, this level of granularity is useful mostly for ecological studies, species conservation planning, and habitat assessments, where small differences in habitat availability and protection status matter. However, while this level of detail is useful for biologists and conservation planners, it is not necessarily 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. In order to address this concern, we aggregate the PWRSR measure as well as the AUBI measure to the county level for our main analysis. We take the area weighted mean for each measure. Letting A_g denote the total area of grid g within county C we define the PWRSR and AUBI for county C as:

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

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

We use both the continuous PWRSR and AUBI measures, as well as a binary treatment variable for our analysis, defined as being within the top tercile of AUBI or PWRSR. We show our county level measures of PWRSR as well as AUBI in Figure 2. We show in section 5.1 that this measure accurately captures future government action to protect biodiversity. This measure can be used by future finance researchers to address biodiversity risk that could not be captured by previous measures such as those that rely on a geographic exposure.

4.3 Other Data

House Price Data For our main outcome variable, we use the Zillow Home Value Index (ZHVI). The Zillow Home Value Index attempts to provide the value of a typical property within a certain geographic boundary. The index is seasonally adjusted and smoothed using a three-month moving average. We use county-level ZHVI data for single-

family residences, condos, as well as rental prices. 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. Summary statistics for the Zillow Home Value Index are in Table 1.

Inflation Reduction Act and Bipartisan Infrastructure Law In order to confirm the validity of our biodiversity measure, we use information released on conservation projects initiated by the government in response to 30 by 30 as part of 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 remove projects unrelated to the protection of biodiversity as well as projects where the location is coded as the lead department building as opposed to the area of management. To further validate our measure, we examine whether the spatial distribution of these projects aligns with expectations based on existing protected areas and ecological priorities. This allows us to confirm that our biodiversity exposure variable is capturing meaningful conservation efforts rather than noise in the data left from administrative artifacts.

National Conservation Easement Database We add to our collection of projects initiated by the government the National Conservation Easement Database (NECD). A conservation easement is an agreement to restrict certain types of land usage in order to protect conservation goals. 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. This can be a cheaper method to achieve conservation than outright purchases of land. NECD works with both private and public agencies to collect information on the established date, purpose, and area where conservation easements have been made.

Controls An important issue is that areas with higher bio diversity risk may be exposed to other climatic or geographic risks as well that could confound our measure. In order to control for this possibility we again utilize NatureServe. We utilize two geographical datasets from NatureServe: the Climate Change Exposure Score and the Habitat Climate Change Vulnerability Index (HCCVI) score. 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. We plot the geographic distribution of climate change exposure in Figure 4.

The Habitat Climate Change Vulnerability Index (HCCVI) score quantifies the vulnerability of various habitats within a 7-square-mile hexagonal spatial unit. The Exposure Score serves as a critical input into the HCCVI framework, which calculates average scores for 99 distinct habitat types. Higher HCCVI scores indicate lower vulnerability—reflecting greater resilience or diminished exposure—whereas lower scores suggest higher vulnerability. Both datasets offer temporal assessments for near-term and mid-to-late century projections, providing nuanced insights into

the evolving impacts of climate change on natural habitats. We aggregate both measures to the county level in the same manner we use for PWRSR and AUBI. We plot the geographic distribution of Habitat Climate Change Vulnerability Index in Figure 5.

Another issue is that our measure might be correlated with areas that experienced increased prices due to COVID-19. As stated in the introduction we approach this issue in several ways. On the data side, we include several controls to deal with potential COVID related measures. First, we include in all regressions the total park area in a county. This should control for the increased benefits of already existing nature amenities shown to lead to a price increase during COVID-19 (Gupta et al., 2022). As a second control we control for the prevalence of working from home which has also been shown to capture the effect of COVID-19 on house prices (Gupta et al. (2022), John A Mondragon and Johannes Wieland (2022)). Furthermore, while in COVID-19 current nature amenities drove house price increases, we show in a later section that our effect comes from nature deprived areas that instead anticipate an increase in amenities.

We also test that our measure of biodiversity exposure is randomly assigned and broadly uncorrelated with other county level variables. We regress our measures of exposure on several control variables; Habitat Climate Change Vulnerability Index, Climate Exposure both Mid and Near Century, prevalence of work from home, log of employment, total park area, total percent urban area, log of total land area, log of total water area, and log of local GDP. We also include in one specification state fixed effects. Results are presented in Table 3. In the first two columns the only highly significant variables are park area which we include in our regressions and total land area. We also note that the R^2 of these regressions are very low, around 8%. Therefore, little of the variation is explained by county level characteristics, suggesting the random assignment of our measure. One may also be worried that individuals were aware of counties high AUBI or PWRSR and selectively chose where to live before the anticipated shock by Biden, but the data from NatureServe used in our measure was only made public in 2020, thus obviating this concern.

Land Availability In order to disentangle supply and demand we focus on areas where supply is unconstrained and demand is high. We do this by utilizing Lutz and Sand (2023) land unavailability measure. This measure is constructed by taking the total area of counties once parks, wetlands, and high slope areas have been removed and dividing that area by the total area in a county. This then provides a measure of how sensitive an area is to supply shocks with areas with very little land availability very sensitive to shocks and these with high land availability insensitive to supply shocks. At the same time, since the measure is constructed by removing nature amenities like parks, areas low in land unavailability are also low in nature amenities, and therefore should have a higher marginal demand for improved natural amenities. Two other measures are also available. Both Nathaniel Baum-Snow and Lu Han (2024) and Joseph Gyourko, Albert Saiz and Anita Summers (2008) construct elasticity measures for a number metropolitan areas. These measures are not comprehensive enough for our purpose to use. Furthermore, the construction of the measures do not provide the counteracting effect of increasing nature demand paired with decreasing supply effects that we exploit in our empirical analysis.

Measures of Supply and Demand We also confirm our results on supply and demand by using more direct measures of supply and demand. On the demand side we utilize HMDA loan applications, in particular the number of loan origination and the value of the mortgagees. We also split this data by applications that are primarily for residing in from those that are for investment. We also utilize google mobility reports as a measure of amenity use. For supply, we use the census housing permits data. This data is a monthly survey collecting the new number of permits issued and has the number of new units, buildings and the building value.

5 Results

5.1 Validation of AUBI Measure and Government Conservation Projects

In this section, we demonstrate that our measurement of biodiversity serves as a valid instrument for regulatory risk. In response to the *30 by 30* and *America the Beautiful* initiatives, as well as President Biden's broader environmental platform, numerous regulatory actions were launched to preserve and protect biodiversity. In particular, sections of the Inflation Reduction Act and the Bipartisan Infrastructure Law, along with associated funding provisions, were dedicated to advancing the goals outlined in the *America the Beautiful* initiative. As part of these efforts, many new projects were initiated. We collect data on these projects, including their geographic centroids, funding amounts, and project categories.

We begin by summarizing the projects in Table 2. The first column presents aggregate statistics for the government programs. A total of 2,112 projects were launched under the Inflation Reduction Act (IRA) and Bipartisan Infrastructure Law (BIL), with approximately $6 billion in funding. We define conservation projects as those with the Atlas category "Resilience and Ecosystem Restoration," "America the Beautiful Challenge Grants," or those with "Conservation" in the program name. These conservation projects account for roughly 33% of the total number of projects and about 20% of the total funding. We also provide summary statistics disaggregated by the originating program, either the IRA or the BIL.

We then show which proportion of the centroid of these projects falls within AUBI areas. In the column titled "$<$ 2km" the size of the AUBI grids is expanded around each edge by 1km. We then calculate both the number and proportion of project centroids that fall within an AUBI area. In the first two rows we show that 18.7% of projects and 20% of funding is in grids that are designated as AUBI. We perform the same exercise in the next two columns, increasing the grid size by 4km and 9km respectively. Increasing the grid to 5km we find that 37% of all projects occur in AUBI grids and 41% of all funding. Increasing the grid to 10km we find that 46.6% of all projects occur in AUBI grids and 50.2% of all funding. These results provide strong non-parametric evidence that our ex ante AUBI measure predicts ex post regulatory action on conservation projects.

We further support this non-parametric evidence with regression analyses at the county level. We begin by aggregating the number of projects and total funding to the county level. We then construct four outcome variables to assess a county's realization of biodiversity-related regulatory risk under the IRA and BIL. The first outcome variable is a binary variable equal to 1 if a county receives at least one project and 0 otherwise. The second 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 is a binary indicator equal to 1 if a county receives a project that eventually receives funding, and 0 otherwise. The fourth is a continuous variable representing 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 use binary indicators equal to 1 if a county is in the top tercile of either AUBI or PWRSR exposure and 0 if it is in the bottom tercile. We also employ a normalized version of our continuous measures of AUBI and PWRSR exposure using the full sample of counties. Specifically we implement the following 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 outcome variables. Results are presented in Table 4.

In the first column exploring the probability of receiving a project, 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. Counties in the top tercile of PWRSR exposure are also 1.3 times more likely to receive a project. Similarly, for a one standard deviation in AUBI (PWRSR) exposure, counties are 3.89 (5.17) percentage points more likely to receive a project. In the next column we look at the intensity of regulatory intervention using the count of projects counties receive. Again, we find that all of our measures of biodiversity exposure are significant at the one percent level. Counties in the top tercile of AUBI and PWRSR exposure receive on average 1.8 times more projects relative to counties in the bottom tercile. In the third column of the table we do not find any significance when predicting if a project once announced will receive funding, but in the fourth column we find that conditional on receiving funding, biodiversity exposure does significantly predict a higher intensity of funding. Counties in the top tercile of AUBI exposure receive over $1.9 million more than those in the bottom tercile and counties in the top tercile of PWRSR exposure receive $2.4 million more. Similarly, for a one standard deviation in AUBI (PWRSR) exposure, counties receive $1.2 million ($1.4 million) more in funding.

Taken together, this evidence shows that our ex ante measure of biodiversity risk is capturing what we intend. AUBI areas are a good measurement of future regulatory and government risk. Our analysis demonstrates that these areas are significantly more likely to receive conservation projects and funding under major federal initiatives, confirming

that biodiversity risk translates into actual government intervention. The results validate our biodiversity risk measure as a predictor of regulatory action, reinforcing its relevance for understanding policy induced regulatory risk.

We further confirm our measure by looking at conservation easements started 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 utilize data from the national conservation easement database and collect information on the geographic boundaries of easements, as well as their purpose they are set aside for, such as scenic or wetlands preservation. We create four outcome variables to test whether biodiversity exposure predicts regulatory intervention. First, we create a binary variable equal to one if a county intersects with a conservation easement. We then create an intensity measure using the count of unique conservation easements that intersect with a county. We also create a binary variable equal to one if a county has a conservation easement that intersects its geography. An easement is defined as conservation if its purpose is labeled as environmental, recreation, or scenic. Finally, we create an outcome variable using the count of conservation easements that intersect a county. We then regress these four outcomes on our four measures of biodiversity exposure. Our first two measures are both binary variables equal to one if a county is in the top tercile of AUBI or PWRSR exposure. Our second two measures use the full sample and our continuous measure of AUBI and PWRSR exposure. Results are reported in Table 5.

In the first column exploring the probability of receiving an easement, 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 10.6 percentage points more likely to receive a project, while counties in the top tercile of PWRSR exposure see an even larger increase of 10.35 percentage points. Similarly, for a one standard deviation in AUBI (PWRSR) exposure, counties are 0.66 (0.17) percentage points more likely to receive a project. In the next column, we look at the intensity of regulatory intervention using count of easements counties receive. Again, we find that all of our measures of biodiversity exposure are significant at the one percent 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 are even more pronounced. Counties in the top tercile of AUBI exposure counties experience a 4.3 percentage point increase in the probability of receiving a conservation project, while counties in the top tercile of PWRSR exposure see an increase of 4.9 percentage points. This is nearly double the relative probability of having a conservation project. Looking at the final column measuring the intensity of treatment for conservation easements we find that the number of conservation projects 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 risk measures are strongly associated with actual government action, validating their use as an instrument for regulatory risk 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 testing our hypothesis that biodiversity risk has an impact on house prices. Specifically, we examine whether counties with higher exposure to 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 test this using a difference-in-difference design. We designate as out post event the signing of Executive Order 14008 by President Biden in January 2021, which heightened risk about Government led response to biodiversity. The outcome variable (Y) is the log of county-level home prices, using Zillow's Home Value Index (ZHVI). On the right hand side of the equation we include our measure for treatment using NatureServe data, equal to one for counties in the top tercile of AUBI or PWRSR exposure, and zero for those in the bottom tercile. We interact treatment with a post variable indicator equal to one after January 2021.

We implement the above design by first implementing the following specification:

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

where $ln(price)_{it}$ is the natural logarithm of the Zillow Home Value Index of county i in month t and $Treat \times Post$ is our treatment variable interacted with a our post period indicator. 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-by-year-month fixed effects (γ_{st}) to absorb state-level time-varying shocks. Our vector of controls (X_{it}) includes: (i) log 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 6. Columns (1) and (2) show raw estimates without fixed effects or controls. Columns (3) and (4) add county and month fixed effects. Columns (5) and (6) present our preferred specification with full controls and state-by-year-month fixed effects. Our coefficient of interest is β_1. Across all columns, β_1 is positive and statistically significant in eleven of twelve cases. 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 policy shock. Given a median county home value of \$167,000, this corresponds to a \$3,841 increase in home value. We have therefore shown that biodiversity risk has a positive impact on house prices.

In Table 7, we test the same hypothesis as in Table 6, that biodiversity-related regulatory risk affects house prices. However, instead of using a binary treatment definition, we use the continuous measure of biodiversity risk, as one may be concerned that a large share of county AUBI values are 0. For these specifications we are also able to include the full sample. Specifically, we use the Protection-Weighted Range-Size Rarity (PWRSR) and AUBI scores directly.

We also include a specification using the log of our exposure variables.

The policy shock remains the same: the signing of Executive Order 14008 in January 2021. This announcement introduced heightened risk around future regulatory interventions in high-biodiversity areas and serves as the event in our difference-in-difference specification. As before, we use monthly county-level Zillow Home Value Index (ZHVI) data from 2017 through 2024 to capture changes in house prices. On the right hand side of the equation we include our measure for treatment using the continuous measure of AUBI or PWRSR exposure and include the full sample. We interact exposure with a post variable indicator equal to one after January 2021.

We implement the above design by first implementing the following specification:

$$ln(price)_{it} = \beta_0 + \beta_1(ExposureMeasure \times Post)_{it} + \beta_2' X_{it} + \alpha_i + \delta_t + \gamma_{st} + \varepsilon_{it} \tag{3}$$

Where *Exposure* is either the continuous AUBI score or PWRSR score and either the raw or log version is used. As in Table 6, we include county fixed effects (α_i), month fixed effects (δ_t), and state-by-year-month fixed effects (γ_{st}). Controls include: (i) log employment, (ii) county-level park area $\times$ post, (iii) work-from-home suitability $\times$ post, (iv) two measures of climate change exposure from NatureServe $\times$ post, and (v) habitat climate change vulnerability from NatureServe $\times$ post.

Table 7 reports the results using the continuous measure. Columns (1) and (2) report raw estimates without fixed effects or controls. Columns (3) and (4) introduce county and month fixed effects. Columns (5) and (6) add the full set of controls and state-by-year-month fixed effects. Columns (7) and (8) include the full set of controls and fixed effects but replace our main exposure measures with the log of their measure. Across both AUBI and PWRSR specifications, the coefficient on the interaction term remains positive and statistically significant in seven of eight regressions. In our preferred specification (column 6), we estimate that a one standard deviation increase in exposure (0.13) leads to a 0.6 percent increase in exposure. Given a median county home value of $167,000, this corresponds to a $1,020 increase in home value. We have therefore shown that our result is robust across different measures of biodiversity risk.

Figure 6 presents our dynamic difference-in-difference analysis, which tests the parallel trends assumption and shows how the effect of biodiversity risk on house prices evolves over time. The figure plots monthly treatment coefficients from an event-study specification, allowing us to visualize both pre-trends and the timing of the price response after the policy shock. The goal of this figure is to test whether price trends between high- and low-exposure counties were similar prior to the announcement of the *30 by 30* initiative. In order to show that this assumption holds in the pre-period we implement a dynamic difference-in-difference using the following specification:

$$ln(price)_{it} = \beta_0 + \sum_{t}^{T} \beta_{1t}(Treat_i \times month_t) + \beta_2' X_{it} + \alpha_i + \delta_t + \gamma_{jt} + \varepsilon_{it} \tag{4}$$

Here, $Treat_i$ is a binary indicator equal to 1 for counties in the top tercile of AUBI or PWRSR exposure. Each coefficient β_{1t} captures the differential house price change for treated counties relative to untreated counties in month t. We use both one month and one year before the policy shock omitted as the reference period. As in our baseline specification, we include a full set of fixed effects: county, month, and state-by-year-month. Controls include employment, park area, work-from-home suitability, climate risk measures, and habitat vulnerability measure.

In all four panels of figure 6 there are no significant differences in house price trends between treated and untreated counties before January 2021, supporting 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 near the end of the sample, consistent with delayed price responses in housing markets, which often feature search frictions and slow-moving adjustments (Case and Shiller (1988), Piazzesi and Schneider (2016)). Near the end of our sample the coefficient on β_{1t} is 0.037. By the end of the sample period we would expect for a house in a particular county going from bottom to top tercile to have a 3.7% increase in house value or a $7,363 increase in value based on the median house value. We also implement our regressions at the MSA level. We implement Equation 3 but instead use MSA level zhvi index. Results are reported in Table IA.6. We also implement a dynamic difference in difference implementing equation 4. Results are reported in figure IA.1. Across both the regular and dynamic difference and difference we find similar results to our county level measure, suggesting our results are not an artifact of our level of aggregation. We find that at the end of the sample prices at the MSA level for treated counties are around 4% higher compared to a non-treated county.

Together, Figures 6 and IA.1 provide strong visual and statistical evidence that biodiversity-related regulatory risk is priced into housing markets, and that the effect persists and grows 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 an artifact of short-run shocks or local idiosyncrasies.

Two particular concerns remain. First, one may worry that since the timing of our shock overlaps with COVID and there is a possibility that areas high in COVID are correlated with our biodiversity measure, that our our results are driven by COVID effects as opposed to an increase in regulatory risk. Second, one may worry that areas that are high in exposure to biodiversity are also high in climate related risk and that the election of Biden also coincided with an increase in regulatory for climate risks.

We address the first concern in several ways. First, in figure 6 we observe that the dynamics of our price behavior differ significantly from observed COVID effects. In particular, our largest price increase occurs after 2021 and continues through 2024 while COVID's largest effects were in 2020 and effects of COVID on house prices had largely subsided by the second quarter of 2020 (Gupta et al., 2022). We also include several controls to directly address the possibility of correlation between our measure of biodiversity exposure and COVID effects. First, the prevalence of working from home has been shown to capture the effect of COVID-19 on house prices (Gupta et al., 2022). We

include this measure in our regressions and find it has little effect on our coefficients. Second, nature amenities have also been shown to capture COVID effects on house prices (Yap et al., 2022). We construct and include our own measure of total park area in a county and include this measure in our regressions. Including this control has little effect on significance or magnitude of our results. Given that our effect does not follow trends similar to COVID effects, and that we construct controls that take account of possible corelation between our measure and COVID's effects on house prices this implies that our previous regressions are distinct from COVID's effect.

We address the concern with climate risk in a similar manner. We include in our regression several controls for climate exposure. We include three controls for climate risk. First we include in our regressions a climate exposure score for both near century and mid to late century. The climate exposure score is constructed by NatureServe and assesses the stress induced by climate change and its potential 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 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 Patrick J. Comer, Jon C. Hak, Marion S. Reid, Stephanie L. Auer, Keith A. Schulz, Healy H. Hamilton, Regan L. Smyth and Matthew M. Kling (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 4 and Figure 5. Including these measures does not affect the significance or magnitude of our coefficient estimates implying that climate risk is distinct from our measures of biodiversity risk. Next we turn to investigating the channel of our effect.

We also perform several robustness checks. First, we show that our result is not sensitive to our choice of treatment. Figure IA.2 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-by-year-month fixed effects. Standard errors are clustered at the county level. Across both panels, the estimated effect size remains significant and positive across a wide range of definitions, suggesting that our primary results are not driven by an arbitrary percentile cutoff but instead reflect a dose–response relationship between biodiversity exposure and project activity. We also perform a similar exercise but include the full sample in each regressions. Figure IA.3 examines the robustness of our main

results to alternative treatment thresholds while holding the sample constant. For each threshold from the 50th to the 99th percentile of biodiversity exposure, counties above the threshold are classified as treated and those below as untreated, but the regression is run on the full sample of counties. All regressions include the full set of controls as well as state-by-year-month and county fixed effects. Standard errors are clustered at the county level. Panel A uses the AUBI measure of biodiversity exposure, while Panel B uses the PWRSR measure. Each point in the plots represents the estimated treatment effect on log housing prices, with 95% confidence intervals. Across both panels, the estimated effect size remains significant and positive across a wide range of cutoffs for treatment. This pattern further supports the claim that biodiversity exposure is associated with housing market responses and that our results are not are not driven by an arbitrary percentile cutoff.

6 Channels: Demand vs Supply

In this section we test several hypothesis about what is driving our average price effect. Given that we observe an increase in price there are two possibilities. There is either an increase in demand or a decrease in supply or some mix of both. On the supply side, increased biodiversity risk may lead to an expected reduction in future housing supply, as developers and contractors anticipate stricter land-use regulations in high-risk areas. On the demand side, biodiversity risk may increase housing prices by increasing expectations of receiving nature-related amenities.

In order to disentangle the channel we focus on the heterogeneity within our sample. Some areas will have a lower sensitivity to supply shocks than others, while simultaneously having a higher sensitivity to demand shocks. We utilize Lutz and Sand (2023)'s land availability measure. This measure is constructed by taking land cover values within counties and removing wetlands, water and areas with a slope greater than 15%. We plot this measure in Figure 7. Areas low in land availability are very sensitive to supply shocks because they have very little room to expand. On the other hand, because they already have large amounts of nature they have little sensitivity to demand shocks. As land availability increases there should be a monotonic decrease in sensitivity to supply and a similar increase in sensitivity to demand. As mentioned in the data section, two other possible measures of supply elasticity are also available and commonly used. Both Baum-Snow and Han (2024) and Gyourko, Saiz and Summers (2008) construct elasticity measures for a number metropolitan areas. We choose not to use these measure and instead select Lutz and Sand (2023) as these measures are not comprehensive enough for our purpose to use, only having measures for a select number of urban areas whereas Lutz and Sand (2023) have data available for almost all counties in the continental United States. Furthermore, the construction of the measures do not provide the counteracting effect of increasing nature demand paired with decreasing supply effects that we exploit in our empirical analysis.

In order to confirm this hypothesis we create bin scatter plots of AUBI exposure, area covered by parks, area covered by wetlands, and nature deprivation. Nature deprivation is a measure constructed by the White Houses'

environmental advisory body, the Council of Environmental Qualities, and 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." Bin scatters are shown in Figure 8. Each of the figures confirm the monotonic relationship between land availability and nature amenities. Therefore, Lutz and Sand (2023)'s measure captures two opposing supply and demand forces. As land availability increases the supply channel is weakened, while at the same time the demand channel is strengthened. Lutz and Sand (2023)'s measure is also advantageous due to its expansive coverage construction as compared to other measures of elasticity. Once further concern is that our result is mechanical, as places with higher land availability might be more likely to be selected for projects due to the fact that they have the land available for it. We show that this is not true. In Figure IA.4, we create another bin scatter and show that land availability has an inverse relationship with projects, our measure of regulatory risk realization. Therefore, our results are not mechanical. We also present summary statistics for each land availability quartile in Table 8. Inspecting the table we can see that our quartile measures follow the same trends as the bin scatter. High land availability quartiles (4) have the fewest projects and low AUBI measures while low land availability quartiles have the most projects and high AUBI measures.

Our first test is whether our price effect is driven by supply or demand. We begin by dividing our land availability measure into four quartiles. We plot these four quartiles in panel b of Figure 7. Quartile 1 has the least amount of land available and the least nature deprivation while quartile 4 has the highest amount of land available and the most nature deprivation. We then implement the following specification in each of the land availability quartiles:

$$ln(price)_{it} = \beta_0 + \beta_1 (Treat \times Post)_{it} + \beta_2' X_{it} + \alpha_i + \delta_t + \gamma_{jt} + \varepsilon_{it} \tag{5}$$

where $ln(price)_{it}$ is the natural logarithm of the Zillow Home Value Index of county i in month t, $Treat \times Post$ is our treatment variable interacted with a our post period indicator, we include county fixed effects (α_i) to account for time-invariant differences across counties, year-month fixed effects (δ_t) to capture national housing market trends, and state $\times$ year-month fixed effects ($\gamma_s t$) to absorb state-level time-varying shocks. Our vector of controls ($X_i t$) includes: (i) log employment in county i in month t, (ii) work-from-home suitability $\times$ post, (iii) two measures of climate change exposure from NatureServe, and (iv) habitat climate change vulnerability from NatureServe.

Results are reported in Table 9. In columns (1)-(4) we implement our regression without any employment, work from home, climate exposure, or habitat vulnerability controls. In columns (5)-(8) we include all controls as well as county, month, and State$\times$Year-Month fixed effects. We find that results for the first and second quartile are borderline significant while results for the fourth quartile are significant at the 1% level. Economically, we find for a one standard deviation increase in exposure in the first quartile leads to an increase in house prices of 0.5%, while a one standard

deviation of exposure in the second quartile leads to an increase in house value of 0.4% and a one standard deviation increase in exposure in the third quartile is associated with an increase of 0.09% in house value. Compared to these results we find that a one standard deviation increase in exposure in the fourth quartile leads to an increase of 2.1% in house value. As a robustness check we also run our main regressions but use as our exposure measure the log of our AUBI measure. Results are reported in Table IA.7. Results are qualitatively similar to our main results. We also use an alternative measure of land availability from Lutz and Sand (2023), namely 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 is reported in Table IA.4. Again, results are qualitatively the same. As a final test of robustness we implement equation 5, but instead form treatment *within* each land availability quartile. Thus, we compare the most exposed homes in the fourth quartile to the least exposed homes in the fourth quartile. Results are reported in table IA.8. Again we find that our results are coming only from the fourth quartile of land availability. These regressions imply that the our overall effect is much stronger in areas with high demand for nature amenities and low sensitivity to supply shocks.

Figure 9 presents our dynamic difference-in-differences analysis within land availability quartiles, which tests the parallel trends assumption and shows how the effect of biodiversity risk on house prices evolves over time within our land availability quartiles. The figure plots monthly treatment coefficients from an event-study specification, allowing us to visualize both pre-trends and the timing of the price response after the policy shock. We implement a dynamic difference in difference using the following specification for each land availability quartile:

$$ln(price)_{it} = \beta_0 + \sum_{t}^{T} \beta_{1t}(Exposure_i \times month_t) + \beta_2' X_{it} + \alpha_i + \delta_t + \gamma_{jt} + \varepsilon_{it} \tag{6}$$

Here, $Exposure_i$ is our continuous AUBI treatment measure. We use one month before the policy shock as the reference period. As in our baseline specification, we include a full set of fixed effects: county, month, and state-by-month. Controls include employment, park area, work-from-home suitability, climate risk measures, and habitat vulnerability measure.

In all four panels of figure 9 there are no significant differences in house price trends between treated and untreated counties before January 2021, supporting the parallel trends assumption. Following the policy announcement, however, we observe a steady and statistically significant increase in house prices only in the fourth land availability quartile. Similar to our main effect, the effect in the fourth land availability quartile builds gradually over time and levels off near the end of the sample, consistent with delayed price responses in housing markets, which often feature search frictions and slow-moving adjustments (Case and Shiller (1988), Piazzesi and Schneider (2016)). Consequently, we do not see the same response in the other land availability quartiles. Near the end of our sample the coefficient on β_{1t} is 0.44. By the end of the sample period we would expect for a one standard deviation increase in exposure a house

in the fourth land availability quartile to have a 0.7% increase in house value or a $970 increase in value based on the median house value in the fourth land availability quartile.

An important aspect of the relationship between house prices and county AUBI exposure if the channel is demand is that the effect of AUBI and the expected increase in amenities is salient to homeowners. We measure media attention to projects and programs enacted by the 30 by 30 initiative by extracting the number of mentions in Factiva, as plotted in Figure 10. The number of articles referencing the initiative increases sharply following the announcement of the executive order. This trend suggests a rise in public attention to biodiversity conservation, and the resulting government action, reinforcing the potential for demand side reactions. We also provide excerpts from select articles showing the combination of how conservation and amenities were dually provided in table IA.5. Literature also shows that current homeowners are very watchful of effects that affect home values, and that "everything is capitalized" (William A Fischel, 2002).

We also test whether our main price effect is driven by supply or demand using loan data as our outcome. We continue with our previous difference and difference set up as well as our definition of land availability. We implement equation 5 but instead replace our outcome variable with either the log of the total amount of loans applied for in a county or the log of the total amount of loans originated in a county. For all outcomes we include county fixed effects, month fixed effects, and state-by-month fixed effects. Our vector of controls includes: (i) log employment in county i in month t, (ii) work-from-home suitability $\times$ post, (iii) two measures of climate change exposure from NatureServe, and (iv) habitat climate change vulnerability from NatureServe.

Panel A of Table 10 and Table 11 presents results from our regressions. In the first panel of Table 10 we look at the relationship between biodiversity risk and the amount of loans applied for. We find that the only significant and positive effect is found in the fourth quartile. We find that in column (1) for the first quartile of land availability a one standard deviation increase in exposure is associated with a decrease of 0.2% in the amount of loans applied for. In column (2) we find that a one standard deviation increase in exposure is associated with a 0.01% decrease in the amount of loans applied for in the second quartile of land availability and in column (3) we find a one standard deviation increase in exposure is associated with 0.02% decrease in loans applied for in the third quartile of land availability. However, for the fourth quartile we find a a 1.2% increase in the amount of loans applied for. These regressions further imply that the our overall effect is much stronger in areas with high demand for nature amenities and low sensitivity to demand shocks. Loan applications can also be thought of as a more direct measure of demand as well, further reinforcing the conclusion that our price effect is driven by demand. In the first panel of Table 11 we implement the same regression but look at the amount of loans originated in the county. We find similar results as before. The only significant coefficient is in the fourth land availability quartile. In column (8) we find a coefficient of 0.404 for our regression implemented in the fourth quartile. For a one standard deviation increase in biodiversity risk we find an increase in loan origination in these counties of 1.5%, a large and economically significant amount. The results suggest that

biodiversity's relationship with loan demand is significant in areas high in nature deprivation suggesting that our effect is driven by positive effects expected from being exposed to biodiversity risk such as expected nature amenities.

The expectation of increased nature amenities could be valued by different individuals. For example, people who are already living in the areas expected to receive a benefit may be the primary individuals driving the increase in demand. On the other hand, the increase in demand could also be driven by speculators anticipating the price increase. In order to test which individuals are driving the increase in demand we again use the HMDA data. The HMDA data classifies loans as to their purpose either for "primary residence", "secondary residence" or for "investment." We classify loans that are for "secondary residence" or for "investment" as "investment" loans following Zhenyu Gao, Michael Sockin and Wei Xiong (2020*a*). We implement equation 5, but split our sample by loan type as well as by land availability quartile. We use as our outcome variable the log sum of the loan amount applied for. Results for this regression are reported in 10. In Panel B results are reported for the subsample of loans whose purpose is labeled as "investment." We find a coefficient on our interaction term of 0.684. Thus, for a one standard deviation increase in exposure we find a 2.7% increase in the amount of investment loans applied for. Similarly, in Panel C we report results for our regression but limit our loans to the sample whose purpose is labeled as "primary residence." We find a positive and significant coefficient with a magnitude of 0.298, for a one standard deviation increase in exposure then, we would expect an increase of 1.2% in residential loans. We also implement our experiment but replace our outcome with the log sum of the amount of loans originated. Results for this regression are reported in 11. In Panel B results are reported for the subsample of loans whose purpose is labeled as "secondary residence" or for "investment." For all outcomes we do not find any significant relationship between biodiversity exposure and the amount of investment loans originated. In contrast, in Panel C we report results for our regression but limit our loans to the sample whose purpose is labeled as "primary residence." We find a positive and significant coefficient with a magnitude of 0.371, corresponding to an increase of 1.4% in residential loans for a one standard deviation increase in exposure. These results are ambiguous and while it does seem to appear that the demand effect is mostly driven by current residents, the speculation motive cannot be ruled out. The fact that residents are more savvy than investors may seem surprising, but literature shows that homeowners are "vigilant" watchers of home values (Fischel, 2002).

We next further confirm our demand result and also test the effects of uncertainty from value. We utilize data from Davis et al. (2021) on yearly land values from 2012 to 2022. Since housing is already built there is no option value from the increased uncertainty created by the singing of the executive order. On the other hand, lot value does have option value from building, thus using land values allows us to test if there is a further increase due to uncertainty as well. We run our main specification but replace our outcome variable with the log of land value for each county as reported by Davis et al. (2021). The results of this regression is reported in Table 12. In columns (1)-(4) we run our specification omitting our control variables for (i) log employment in county i in month t, (ii) work-from-home suitability $\times$ post, (iii) two measures of climate change exposure from NatureServe, and (iv) habitat climate change

vulnerability from NatureServe. Columns (5)-(8) include all controls as well as county and year $\times$ state fixed effects. We find a significant and positive effect on land values in the fourth quartile of land availability only. Column (8) reports this coefficient. We find a magnitude of 0.462. Thus, for a one standard deviation increase in exposure we would expect an increase in land values of 1.8%. This is slightly larger than our estimate using housing values alone. This suggest that part of our demand channel also may incorporate part of the option value from the expected increase in value. Davis et al. (2021) include four other measures of land values in their data. They include also their raw property estimates from appraisal values, as well as 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." We run our main regression but replace our outcome with each of these variables. Results for standardized land values are reported in Table IA.1. Results for property values are reported in Table IA.2. Results for standardized property values are reported in Table IA.3. For all outcomes, results are qualitatively similar to our reported main results.

We also test our result using more direct measures of demand. In particular, we look at whether usage of amenities does increase in areas with higher biodiversity risk in the post period. In order to measure usage of amenities we utilize google mobility reports. Google mobility reports creates aggregated, anonymized sets of data from users who have turned on the Location History setting and calculates the percent change in visits to particular categories of locations relative to a baseline period in 2019. We test our demand hypothesis by looking at the change in visits to park locations in the post period. We implement equation 5 but change the outcome to be the yearly average change in park visits for a county relative to 2019. Results are presented in Table 13. Across all the land availability quartiles we only find significant results for the fourth land availability quartile. This suggests that there was a direct increase in usage and demand of nature amenities in the fourth quartile related to biodiversity exposure in the post period, further confirming our hypothesized channel.

The results are also informative about the channel through which biodiversity regulatory risk affects house prices. In particular, the findings provide evidence that biodiversity regulatory risk relates to house prices through demand channels. We next turn to testing whether there is a supply channel at work.

We next show that we cannot reject the null of no decrease in housing supply for treated areas. Developers may reduce their planned construction of new buildings or be unable to construct new buildings due to an expectation of increased regulatory burden or the inability to fully develop the land in the desired way. In order to measure if there is a shift in supply we utilize building permit data from the Census Building Permit Survey data. We implement the specification from equation 5 but we change the outcome variable to be one of three separate measures of supply: total buildings, total units, and total value. Results are reported in Table 14. In the first panel we examine the relationship between biodiversity risk and the log of the number of buildings in a county within land availability quartiles. Across all regressions we do not find any significant results. In the next panel we examine the relationship between biodiversity risk and the log of the number of units in a county within land availability quartiles. Again, across all land availability

quartiles we find no significant relationship between biodiversity risk and construction. In the last panel of Table 14 we examine the relationship between biodiversity risk and the log value of construction. There is again no relationship between our measure of biodiversity risk and the supply measure. We also run all results using imputed values provided by census. Results are reported in Table IA.9. As can be seen, all results remain insignificant. These results imply that the shock to biodiversity risk had no impact through the supply channel and that individuals did not expect a reduction in supply due to increased biodiversity risk.

One potential concern is that, although we do not observe a reduction in permits, we might expect to see an increase in permits in areas with higher supply elasticity. However, there are several reasons why an increase in permits may not occur, even under a demand-driven channel. First, even in regions with high land availability, supply is not perfectly elastic—it is only more elastic relative to constrained areas. Nationwide trends in rising development restrictions may still result in highly inelastic supply, even in these more flexible markets. Second, recent research suggests that traditional measures of supply elasticity may not be strong predictors of house prices or construction activity (Schuyler Louie, John A Mondragon and Johannes Wieland, 2025). Third, as documented in Caitlin S Gorback and Benjamin J Keys (2020) and partially in Zhenyu Gao, Michael Sockin and Wei Xiong (2020*b*), our sample period (post-2008, with further declines after 2015) coincides with historically low rates of new home construction—even in high-elasticity areas. Additionally, this period was marked by rising interest rates and elevated inflation, both of which tend to suppress new residential development. Taken together, these factors help explain the absence of a positive permitting response in our results.

Another concern with supply is that even if permits did not fall, AUBI areas and thus the expected constraints, could still fall directly within urban areas restricting supply even if areas are high in land availability. In order to test this hypotheses we calculate the share of AUBI area falling within urban areas over all AUBI areas within counties. We begin with census tiger shapefiles which provide geometries of urban areas. To qualify as an urban area an area must encompass at least 2,000 housing units or have a population of at least 5,000. We then overlay the shapefile with our AUBI measure and calculate the intersection varying the buffer we draw around urban areas from 0-15 kilometers in 5 kilometer increments. We divide this intersection by total AUBI area within a county to create four different control variables. As an illustration, we plot our four highest AUBI and land available counties in Figure 11. As can be seen, most AUBI areas fall outside the urban area suggesting that AUBI does not restrict supply. To test this hypothesis parametrically, we implement equation 5 but add in an extra control for the share of AUBI that falls within urban area within the fourth quartile. Results are reported in Table 15. As can be seen, controlling for urban AUBI has marginal impacts on magnitude and significance. This suggest that the supply effect from AUBI falling within urban areas does not have a large impact or is a driver of our results.

Finally, we test the time frame over which individuals expect biodiversity risk to be implemented. We also test the hypothesis of whether the price impact is due to the realization of biodiversity risk. In order to test these hypothesis

we utilize zillow's observed rent index. We implement the specification from equation 5 but we change the outcome variable to be the log of observed rent as reported by zillow. Results are reported in Table 16. In columns (1)-(4) we implement our regression without any employment, work from home, climate exposure, or habitat vulnerability controls. In columns (5)-(8) we include all controls as well as county, month, and state$\times$ year-month fixed effects. As rent has less coverage we also run a regression using our main house price variable but for the restricted sample. Results for these regressions are reported in columns (9)-(12). Results in columns (5)-(8) show that there is no effect on rent prices. Turning to columns (9)-(12) we see that our main results hold. In column (12) there is a positive and significant coefficient for biodiversity risk in the post period. These results suggest that biodiversity risk operates over a long time period. These results also suggest that biodiversity risks impact on house price is driven bu long term expectations and not short term realizations of that risk.

With the 2024 election of Donald Trump, there has been another large shock to biodiversity regulatory risk. On his first day in office, Trump canceled executive order 14008. In order to test whether our hypothesis is correct and if there is a reversal we extend our data to March 2025 and run another dynamic difference-in-difference specification, namely equation 6, this time using as reference the month before the election of Donald Trump. Results of the dynamics are reported in Figure **??**. While the data is sparse, we do find suggestive evidence that the effect has begun to reverse in our treated counties, although we cannot confirm this fully due to the slow moving nature of our outcome variable. This provides suggestive evidence that households take into account biodiversity risk.

7 Conclusion

Our paper investigates the economic implications of biodiversity risk and regulatory intervention, focusing on its impact on housing markets. Using a novel measure of biodiversity risk constructed from NatureServe data, we provide a geographic measure that captures housing exposure to biodiversity risk. Leveraging the 30 by 30 initiative and America the Beautiful plan as a shock to biodiversity regulatory risk, we examine whether increased biodiversity risk influences home prices. Our analysis employs a difference-in-differences approach to measure the causal effect of biodiversity risk, while also exploring the underlying mechanisms driving this relationship. We further validate our measure by demonstrating that it strongly predicts actual government intervention, such as conservation projects and easements, reinforcing its utility for assessing regulatory risk. Finally, we disentangle whether house price changes are driven by constraints on housing supply or increased demand for nature-related amenities, shedding light on how biodiversity protection policies influence market dynamics.

Our findings indicate that biodiversity-related policy risk leads to a statistically and economically significant increase in house prices, with more exposed areas experiencing a 1.6% price increase post-policy and a cumulative 3.7% rise by the end of our sample period. This effect is distinct from other climate-related risks and remains robust across

various specifications and control sets. We further establish that this price increase is primarily driven by increased demand rather than supply constraints. First, we find no measurable impact on building permits, suggesting that biodiversity risk does not directly limit new housing construction. Second, when focusing on areas where additional supply constraints are unlikely,regions with little available buildable land, we observe the largest price effects, reinforcing the demand-driven nature of the increase. Finally, we confirm this pattern using mortgage loan data, which shows a significant rise in loan applications in high-exposure areas, further supporting the conclusion that increased demand for nature-related amenities is the primary mechanism behind the observed price appreciation.

Beyond its direct policy implications, our findings highlight the broader economic impact of biodiversity regulation, particularly on housing affordability. While conservation policies help protect ecosystems and provide long-term benefits, they can also drive up home prices, making it harder for lower-income households to afford housing in affected areas. This creates a challenge for policymakers who must balance environmental goals with the need for affordable housing. Without additional policies, such as zoning changes or housing affordability programs, conservation efforts may end up benefiting wealthier households while making housing less accessible for others. More broadly, our study shows the importance of considering economic trade-offs when designing environmental policies to ensure they do not unintentionally create financial burdens.

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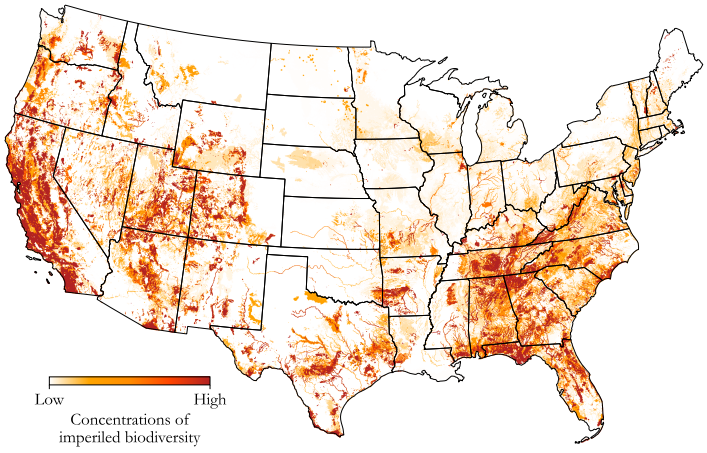
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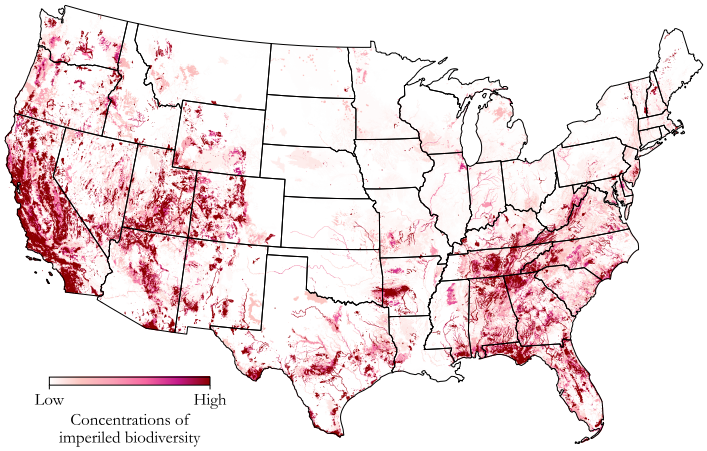
Figure 1: **Measures of Endangered Biodiversity**

This figure shows the primary measures of biodiversity 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 risk.

Panel A: Protected Weighted Range Size Rarity (PWRSR)



Panel B: Range Size Rarity (PSR)



Panel C: Areas of Unprotected Biodiversity Importance (AUBIs)

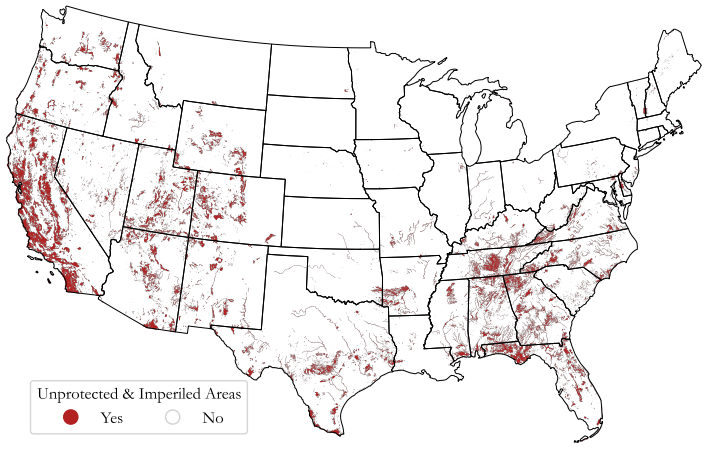
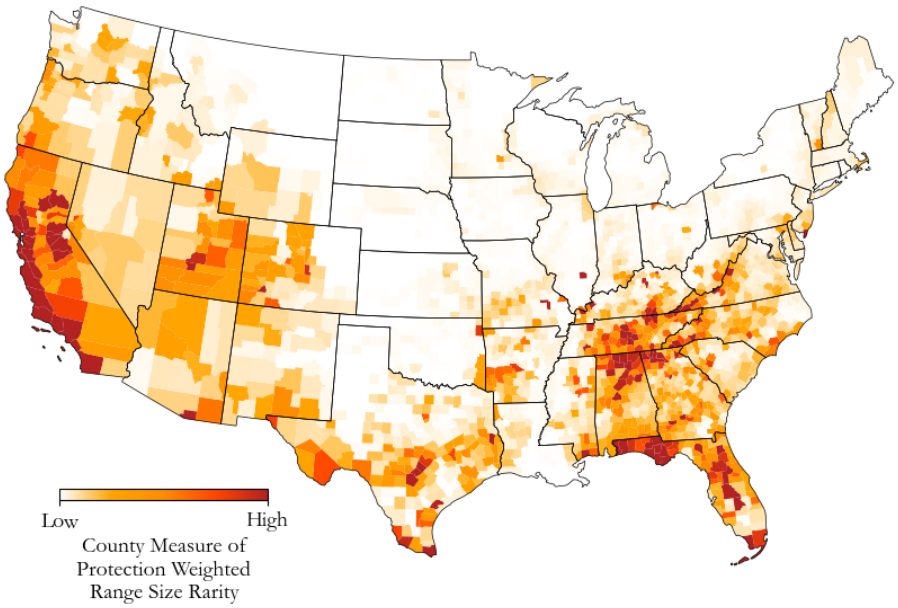


Figure 2: **County Level Biodiversity Regulatory Risk Exposure Measures**

This figure shows our measures of biodiversity 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 measures



Panel B: County Level AUBI measures

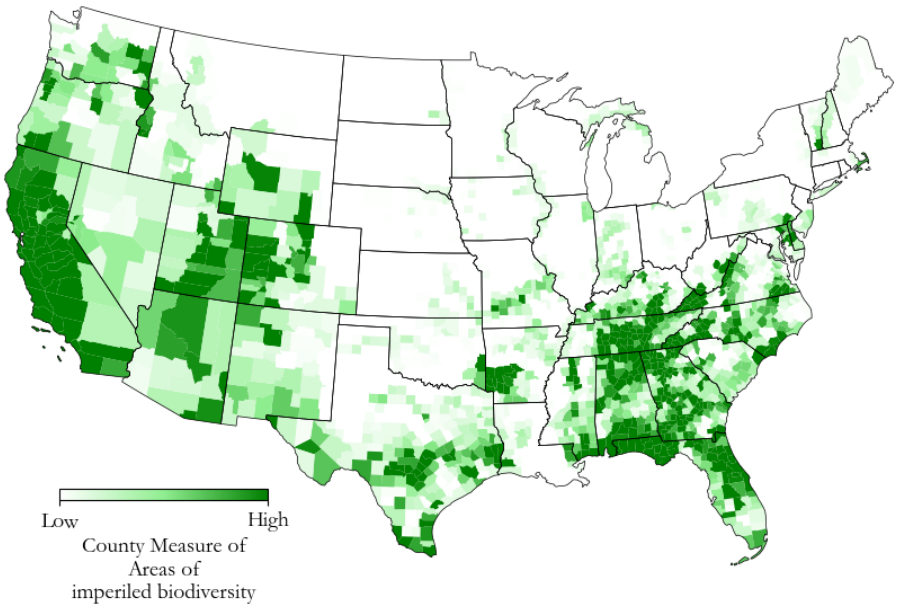
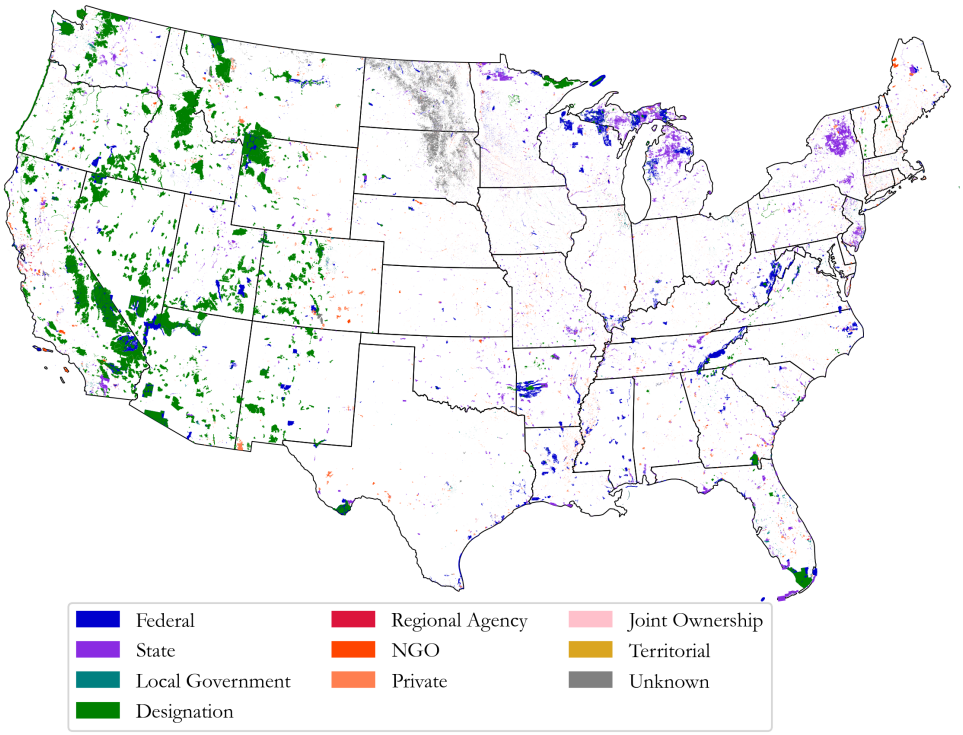


Figure 3: **Protected Areas**

This figure shows the areas that are permanently protected for biodiversity conservation. Panel A shows the protected areas. 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. The areas are colored by the type of agency that owns the land. Panel B shows both the protected areas and the main continuous measure of biodiversity risk, Protected Weighted Range Size Rarity (PWRSR).

Panel A: Protected Areas by Ownership Type



Panel B: Protected Areas and PWRSR

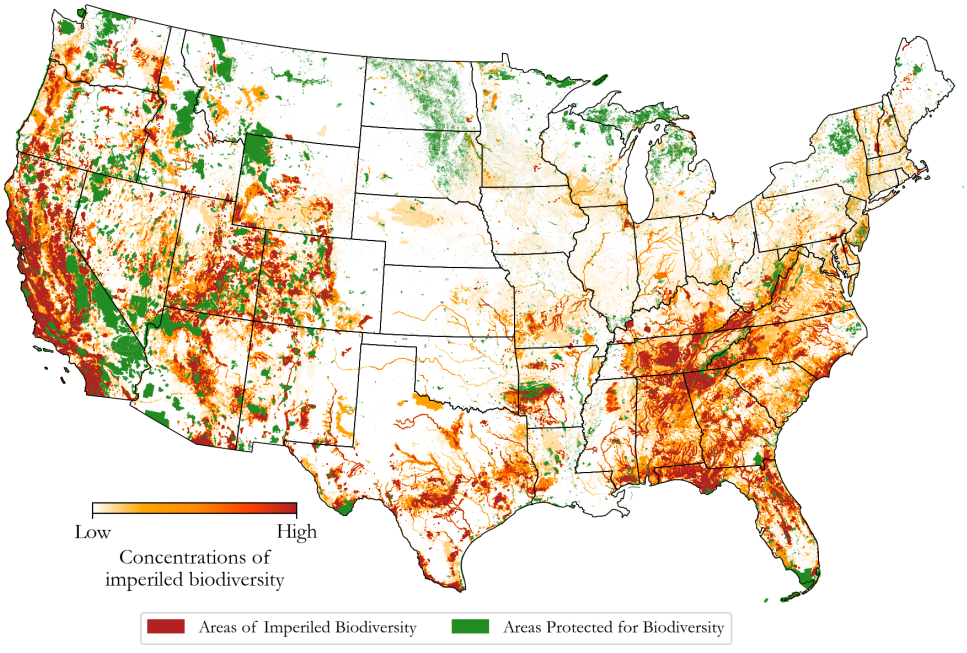
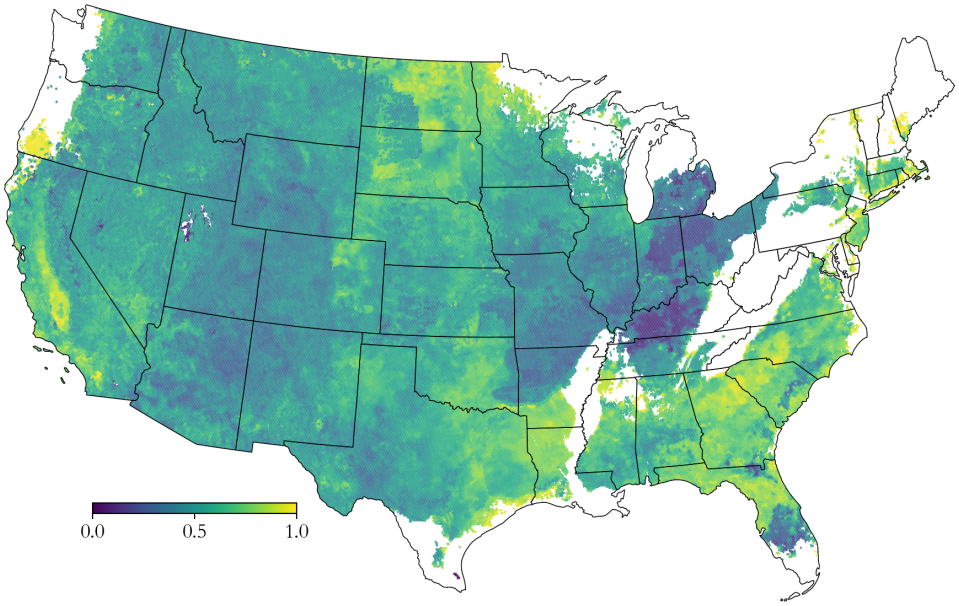


Figure 4: **Climate Change Exposure**

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

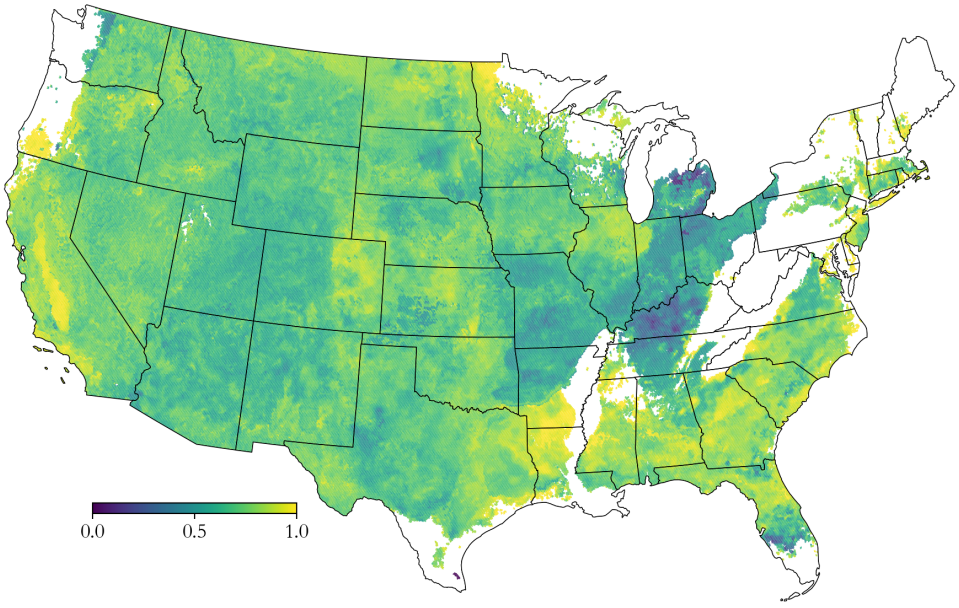
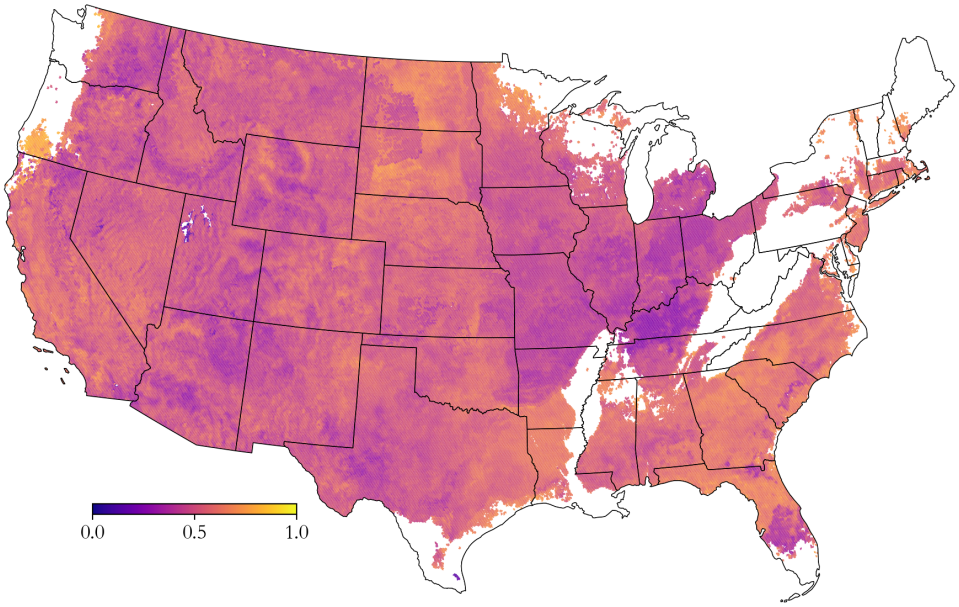


Figure 5: **Habitat Climate Change Vulnerability Index (HCCVI)**

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

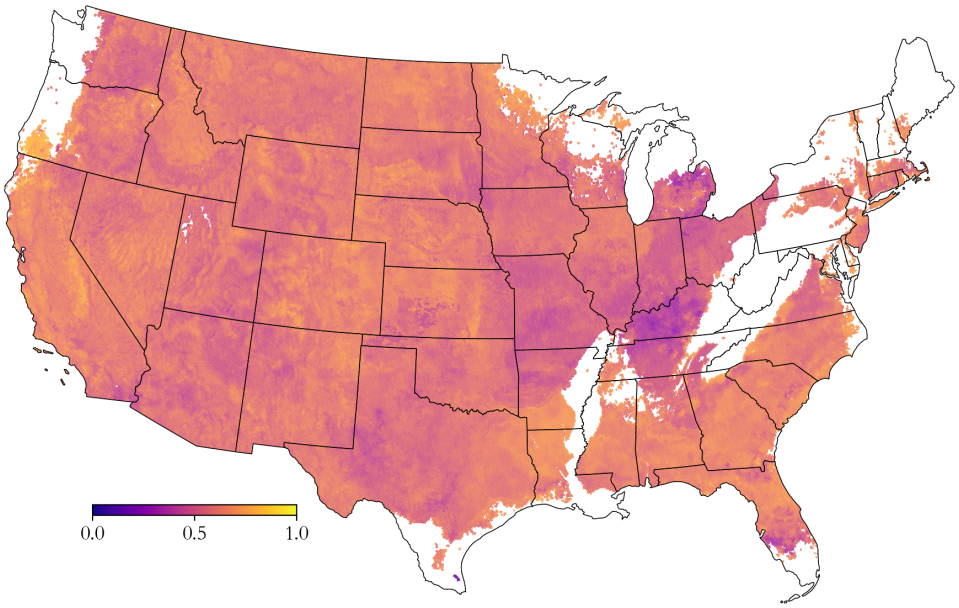
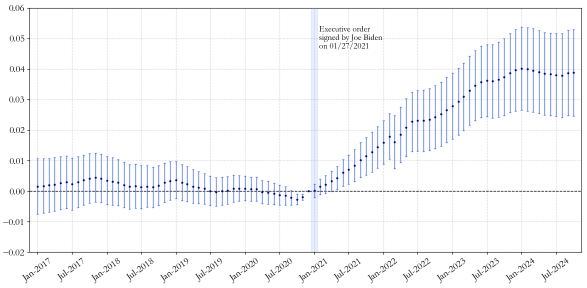
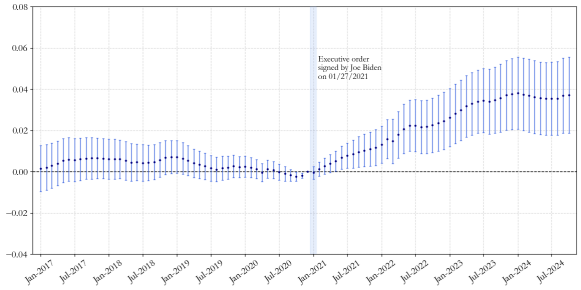


Figure 6: Impact of Biodiversity Regulatory Risk on House Prices: Dynamics

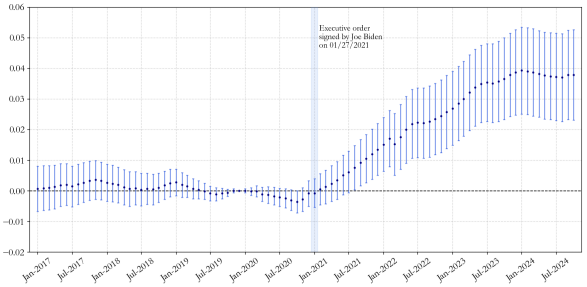
This figure tests the parallel trends assumption by plotting dynamic coefficients from a specification regressing the log Zillow Home Value Index on indicators for top-tercile AUBI exposure. We implement equation 3. We compare treated (top tercile) to control (bottom tercile) counties across two alternative biodiversity measures. 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), log employment, 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. Dots show point estimates; 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 2020 as the reference year. Panel B displays coefficients from the PWRSR biodiversity measure specification, also using December 2020 as the reference year. Panel C presents estimates based on the AUBI measure, but using December 2019 as the reference year for comparison. Panel D shows dynamic effects from the PWRSR measure specification with December 2019 as the reference year.



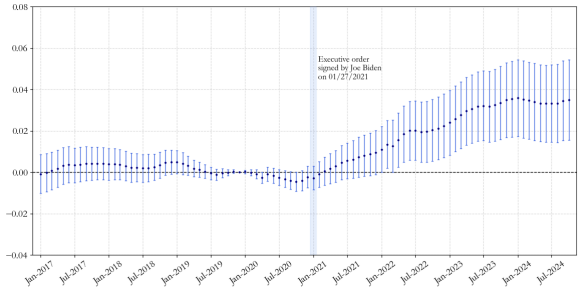
Panel A: AUBI Measure, 2020 Reference



Panel B: PWRSR Measure, 2020 Reference



Panel C: AUBI Measure, 2019 Reference

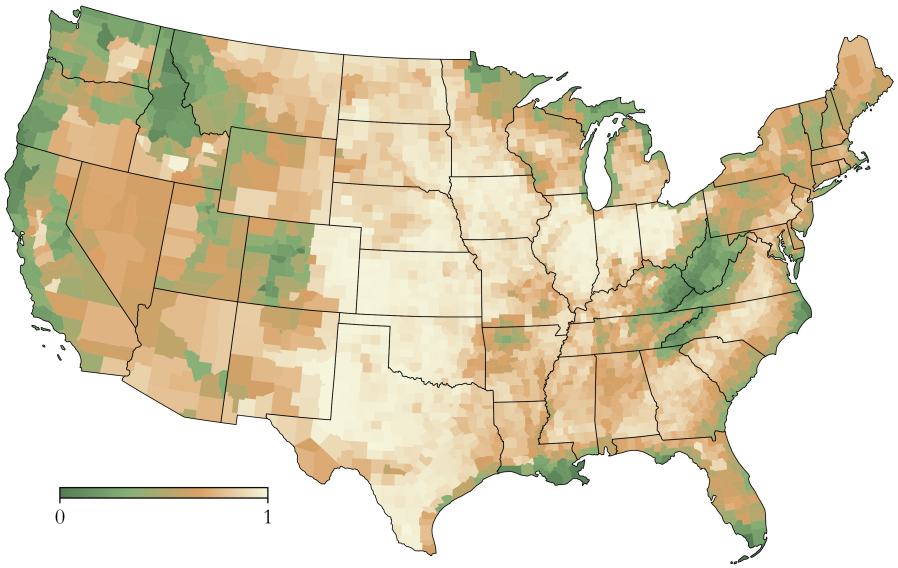


Panel D: PWRSR Measure, 2019 Reference

Figure 7: 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 nature amenities. 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

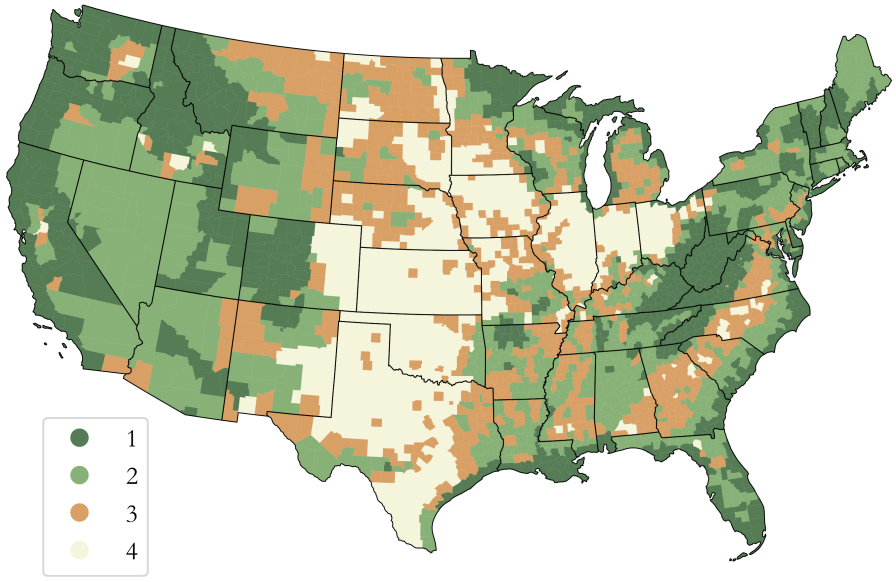
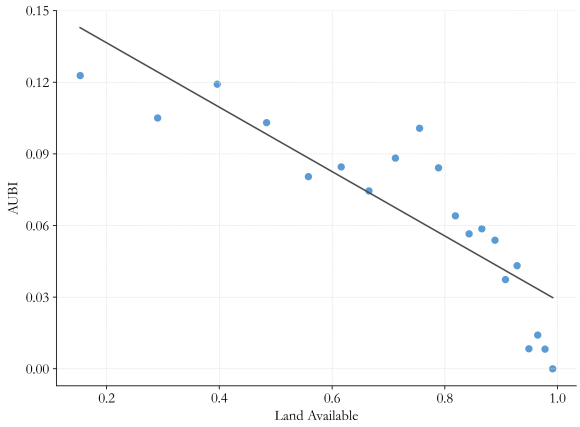
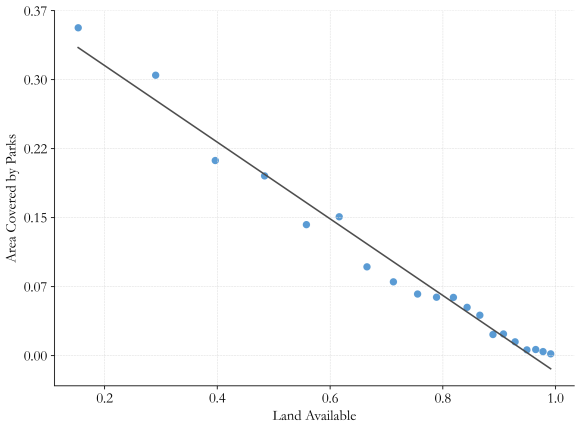


Figure 8: Relationships Between Land Availability and Nature Metrics

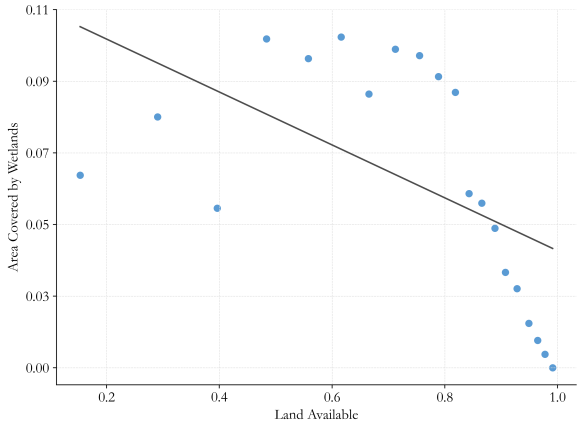
This figure shows the relationship between the Lutz and Sand (2023) measure of land availability and four key indicators of nature access and biodiversity. We bin the land availability measure and plot average values for each indicator within those bins. All panels display fitted linear trends. Panel (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) demonstrates examines the relationship between land availability and nature deprivation.



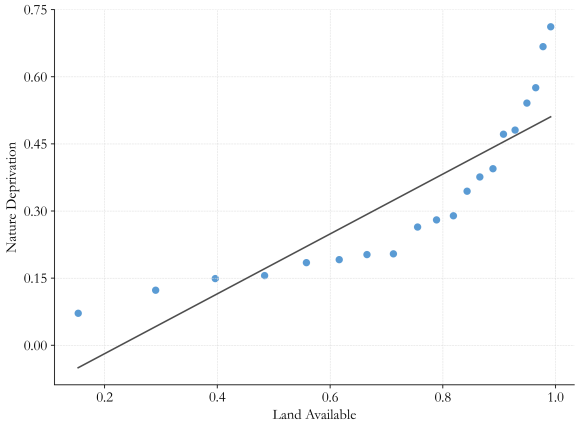
Panel A: AUBI



Panel B: Area Covered by Parks



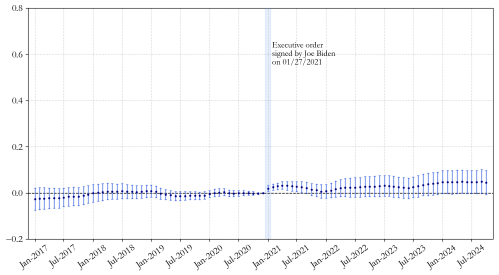
Panel C: Area Covered by Wetlands



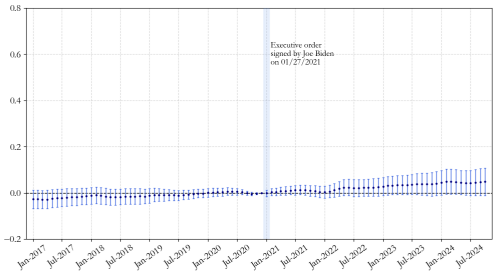
Panel D: Nature Deprivation

Figure 9: Impact of Biodiversity Regulatory Risk on House Value Within Land Availability Quartiles: Dynamics

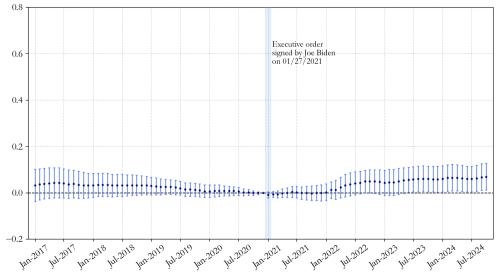
This figure tests the parallel trends assumption by plotting dynamic coefficients from a specification regressing the log Zillow Home Value Index on our AUBI continuous measure of biodiversity exposure within Lutz and Sand (2023) land availability quartiles. We implement equation 4. We include controls for Work From Home share, park area, climate risk (Habitat Climate Change Vulnerability Index, Climate Exposure Near Century, Climate Exposure Mid to Late Century), log 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 year. 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. All standard errors are clustered at the county level.



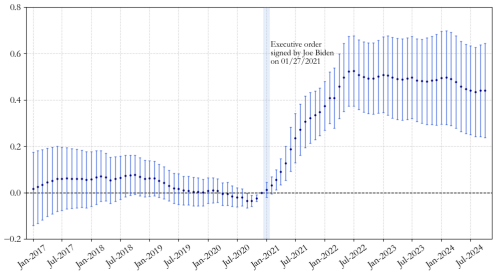
Panel A: Land Availability Quartile 1



Panel B: Land Availability Quartile 2



Panel C: Land Availability Quartile 3



Panel D: Land Availability Quartile 4

Figure 10: Media Attention of Projects Started Under America the Beautiful

This figure illustrates the media attention surrounding nature amenities 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.5.

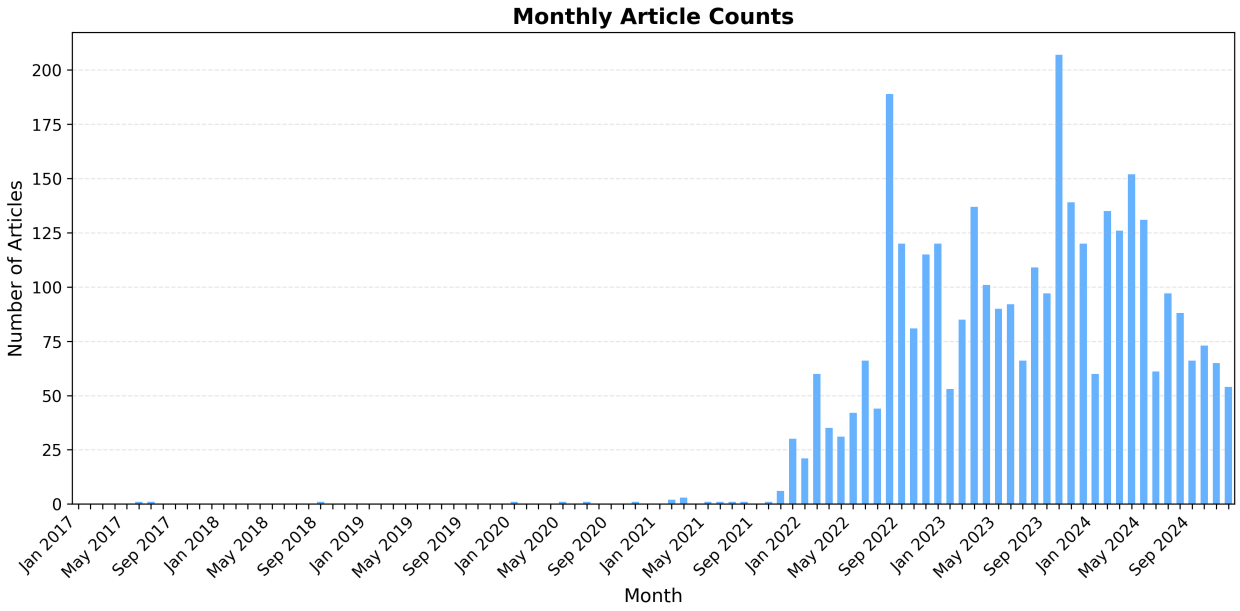
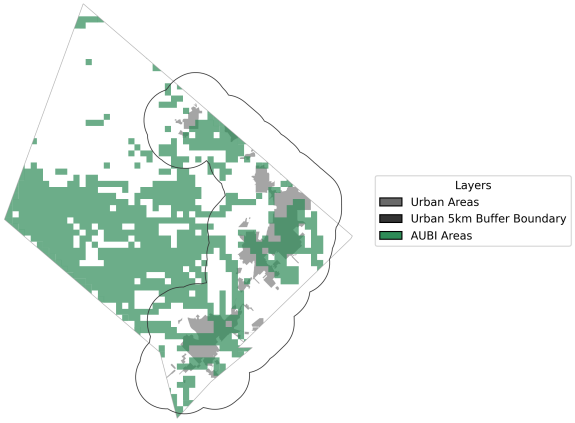
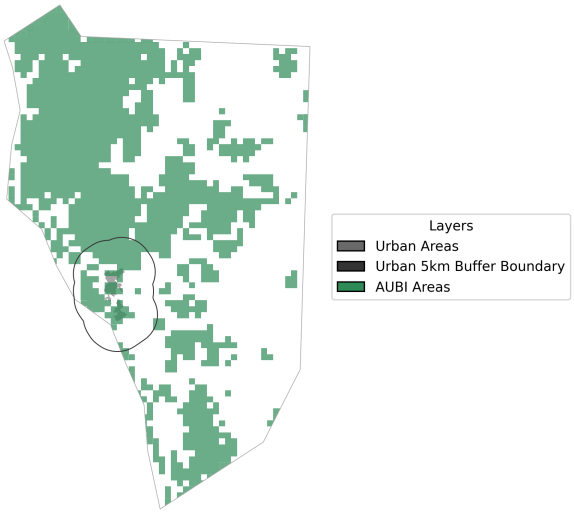


Figure 11: County AUBI and Urban Area oOverlap

This figure presents four examples of individual county urban areas and the AUBI areas within those counties. We select four counties from the top ten of AUBI exposure in the fourth build decile and plot the resulting Urban Area from Census TIGR and our AUBI measures from Nature Serve. Panel A plots urban and AUBI areas for Hays County. Panel B plots urban and AUBI areas for Zapata County. Panel C plots urban and AUBI areas for Suwannee County. Panel D plots urban and AUBI areas for Covington County.



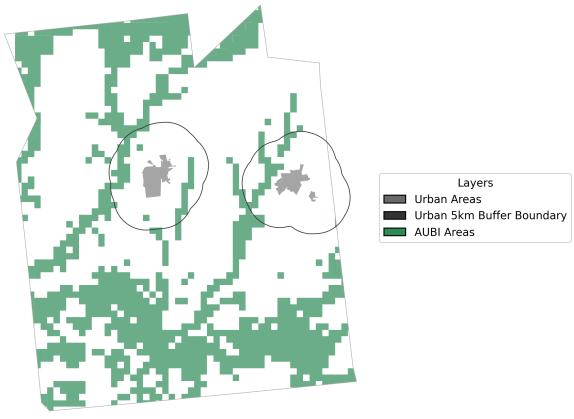
Panel A: Hays County, TX



Panel B: Zapata County, TX



Panel C: Suwannee County, FL



Panel D: Covington County, AL

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 Originated ('000)	County × Year	17,116	1,089,341	5,704,255	7,325	34,010	111,438	459,195	4,431,770
Value of Loans Applied For ('000)	County × Year	17,116	1,978,838	11,148,423	14,980	64,913	199,925	795,423	8,000,185
Value of Loans Originated for Residence ('000)	County × Year	17,116	1,022,995	5,239,490	6,850	32,295	105,945	435,208	4,193,665
Value of Loans Originated for Investment ('000)	County × Year	17,116	904,847	6,344,755	7,355	31,108	89,873	343,753	3,521,815
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: 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
Panel J: 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 K: 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 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 3: **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 (%)	6.241***	0.151***	3.275***	0.072***
	(0.914)	(0.022)	(0.834)	(0.019)
Land Area Urban (%)	-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	0.086	0.082	0.039	0.028
Obs	2,673	2,673	2,672	2,672

Table 4: **Biodiversity Risk and Government Projects**

This table examines the relationship between unprotected biodiversity and government conservation projects started by the IRA and BIL. 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. "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. Standard errors are clustered at the county level and are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.

	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)

Table 5: **Biodiversity Risk and Easements**

This table examines the relationship between unprotected biodiversity and easements created after 2021. Each column represents a different outcome. 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. 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 grid has an intersecting geometry with an easement. "# of projects" is a discrete measure of the number of easement geometries that intersect a grid. "Has conservation project" is a binary variable equal to 1 if a grid 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 grid. Standard errors are clustered at the county level and are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

	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 6: **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 risk to the home value in counties that are in the bottom tercile of exposure to biodiversity 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 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 and difference 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.

	Log(Zillow Home Value Index)					
	(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 Month FE					✓	✓

Table 7: **Impact of Biodiversity Regulatory Risk on House Value**

This table examines the relationship between counties exposure to biodiversity risk and home value (Equation 5). 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 risk. We use a continuous measure of biodiversity risk in all columns. Columns (1) and (2) focus solely on the difference-in-difference 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 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 Month FE					✓	✓	✓	✓

Table 8: **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
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
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
Panel C: 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

Table 9: **Impact of Biodiversity Regulatory Risk on House Value Within Land Availability Quartiles**

This table examines the relationship between our continuous measure of biodiversity 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 5). 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 10: **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 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 5). HMDA loans are at the county × year level. Residential loans are loans in which occupancy type is reported as residence. Investment loans are loans in which occupancy type is reported as secondary or investment. 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-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(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	0.005	-0.032	0.079	0.329**
	(0.048)	(0.044)	(0.069)	(0.148)
Post × Work From Home	-1.182***	-1.294***	-1.964***	-1.248***
	(0.218)	(0.204)	(0.190)	(0.212)
Post × Climate Exposure Near Century	0.061	0.357	-0.191	-0.155
	(0.172)	(0.228)	(0.306)	(0.276)
Post × Climate Exposure Mid to Late Century	-0.080	0.040	-0.173*	0.093
	(0.072)	(0.078)	(0.097)	(0.122)
Post × Habitat Climate Change Vulnerability Index	0.055	-0.536	0.721	0.358
	(0.233)	(0.423)	(0.564)	(0.499)
Log(Employment)	0.122	-0.077	-0.106	0.240***
	(0.144)	(0.081)	(0.096)	(0.090)
Adj. R-squared	0.995	0.995	0.993	0.991
Obs.	3,918	4,878	5,008	4,926
County FEs	✓	✓	✓	✓
State × Year-Month FEs	✓	✓	✓	✓
Panel B: Investment Loans				
Post × Areas of Unprotected Biodiversity Importance	-0.004	0.190*	0.215	0.656
	(0.086)	(0.115)	(0.157)	(0.412)
Post × Work From Home	0.205	-0.263	-0.882**	-0.369
	(0.340)	(0.405)	(0.448)	(0.508)
Post × Climate Exposure Near Century	0.119	0.253	-0.295	-0.542
	(0.304)	(0.569)	(0.645)	(0.725)
Post × Climate Exposure Mid to Late Century	-0.105	0.378*	0.009	0.562
	(0.133)	(0.200)	(0.219)	(0.347)
Post × Habitat Climate Change Vulnerability Index	-0.021	-1.374	0.679	-0.248
	(0.429)	(1.011)	(1.230)	(1.302)
Log(Employment)	0.318	-0.135	-0.361	-0.098
	(0.208)	(0.207)	(0.271)	(0.279)
Adj. R-squared	0.979	0.960	0.951	0.930
Obs.	3,918	4,878	5,008	4,926
County FEs	✓	✓	✓	✓
State × Year-Month FEs	✓	✓	✓	✓
Panel C: Residential Loans				
Post × Areas of Unprotected Biodiversity Importance	-0.014	-0.075	0.020	0.270
	(0.048)	(0.046)	(0.060)	(0.170)
Post × Work From Home	-1.413***	-1.453***	-2.099***	-1.367***
	(0.244)	(0.217)	(0.199)	(0.218)
Post × Climate Exposure Near Century	-0.060	0.374	-0.056	-0.243
	(0.177)	(0.234)	(0.281)	(0.293)
Post × Climate Exposure Mid to Late Century	-0.066	0.023	-0.152	0.094
	(0.076)	(0.081)	(0.099)	(0.125)
Post × Habitat Climate Change Vulnerability Index	0.226	-0.506	0.418	0.594
	(0.254)	(0.431)	(0.535)	(0.523)
Log(Employment)	0.107	-0.050	-0.002	0.269***
	(0.151)	(0.089)	(0.103)	(0.096)
Adj. R-squared	0.995	0.994	0.993	0.991
Obs.	3,918	4,878	5,008	4,926
County FEs	✓	✓	✓	✓
State × Year-Month FEs	✓	✓	✓	✓

Table 11: **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 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 5). HMDA loans are at the county × year level. Residential loans are loans in which occupancy type is reported as residence. Investment loans are loans in which occupancy type is reported as secondary or investment. 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-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(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	-0.001	-0.020	0.065	0.404***
	(0.052)	(0.047)	(0.076)	(0.153)
Post × Work From Home	-1.133***	-1.361***	-1.813***	-1.398***
	(0.228)	(0.198)	(0.198)	(0.218)
Post × Climate Exposure Near Century	0.080	-0.043	-0.200	-0.099
	(0.181)	(0.242)	(0.325)	(0.286)
Post × Climate Exposure Mid to Late Century	-0.087	0.150*	-0.169	-0.000
	(0.071)	(0.080)	(0.105)	(0.123)
Post × Habitat Climate Change Vulnerability Index	0.036	-0.064	0.634	0.443
	(0.247)	(0.459)	(0.589)	(0.526)
Log(Employment)	0.054	-0.011	-0.056	0.301***
	(0.137)	(0.091)	(0.100)	(0.093)
Adj. R-squared	0.995	0.995	0.994	0.990
Obs.	3,918	4,878	5,008	4,926
County FEs	✓	✓	✓	✓
State × Year-Month FEs	✓	✓	✓	✓
Panel B: Investment Loans				
Post × Areas of Unprotected Biodiversity Importance	0.019	0.213	0.199	0.595
	(0.085)	(0.130)	(0.166)	(0.412)
Post × Work From Home	0.278	-0.310	-0.909**	-0.504
	(0.359)	(0.434)	(0.456)	(0.520)
Post × Climate Exposure Near Century	0.042	0.040	-0.409	-0.449
	(0.292)	(0.627)	(0.677)	(0.724)
Post × Climate Exposure Mid to Late Century	-0.007	0.425**	0.079	0.451
	(0.131)	(0.214)	(0.235)	(0.349)
Post × Habitat Climate Change Vulnerability Index	-0.017	-1.031	0.731	-0.478
	(0.422)	(1.127)	(1.282)	(1.307)
Log(Employment)	0.291	-0.240	-0.368	-0.046
	(0.221)	(0.214)	(0.254)	(0.266)
Adj. R-squared	0.980	0.955	0.948	0.927
Obs.	3,918	4,878	5,008	4,926
County FEs	✓	✓	✓	✓
State × Year-Month FEs	✓	✓	✓	✓
Panel C: Residential Loans				
Post × Areas of Unprotected Biodiversity Importance	-0.029	-0.067	0.010	0.338*
	(0.055)	(0.050)	(0.067)	(0.182)
Post × Work From Home	-1.386***	-1.512***	-1.937***	-1.455***
	(0.276)	(0.213)	(0.200)	(0.236)
Post × Climate Exposure Near Century	-0.048	-0.001	-0.038	-0.229
	(0.200)	(0.241)	(0.290)	(0.307)
Post × Climate Exposure Mid to Late Century	-0.077	0.144*	-0.157	-0.007
	(0.079)	(0.084)	(0.105)	(0.125)
Post × Habitat Climate Change Vulnerability Index	0.236	-0.103	0.283	0.809
	(0.293)	(0.454)	(0.541)	(0.559)
Log(Employment)	0.024	0.023	0.063	0.329***
	(0.139)	(0.094)	(0.104)	(0.099)
Adj. R-squared	0.995	0.994	0.993	0.990
Obs.	3,918	4,878	5,008	4,926
County FEs	✓	✓	✓	✓
State × Year-Month FEs	✓	✓	✓	✓

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

This table examines the relationship between our continuous measure of biodiversity 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 5). 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-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(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 13: **Impact of Biodiversity Regulatory Risk on Park Visits Within Land Availability Quartiles**

This table examines the relationship between our continuous measure of biodiversity 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 5). 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-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.

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

This table examines the relationship between our continuous measure of biodiversity 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 5). 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 reported 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	0.213	-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 15: **Impact of Urban Biodiversity Regulatory Risk on House Prices Within Land Availability Quartile Four**

This table examines the relationship between our continuous measure of biodiversity risk using Areas of Unprotected Biodiversity and the log of Zillow Home Price Index while controlling for the share of Areas of Unprotected Biodiversity that fall in surrounding urban areas within the fourth build quartile as defined by Lutz and Sand (2023) land availability measure (Equation 5). 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. For this specification we restrict to Quartile 4. We calculate the share of AUBI that falls within urban areas as defined by Census Tiger using four different boundaries. In column (1) urban areas are not expanded. In column (2) Urban areas are expanded by 5km. In column (3) urban areas are expanded by 10km. In column (4) urban areas are expanded by 15km. Standard errors are clustered at the county level and are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

	Urban Buffer Area			
	(1) Log(Zillow Home Value Index)	(2) Log(Zillow Home Value Index)	(3) Log(Zillow Home Value Index)	(4) Log(Zillow Home Value Index)
Post × Areas of Unprotected Biodiversity Importance	0.321***	0.332***	0.243**	0.278**
	(0.098)	(0.109)	(0.118)	(0.108)
Post × Share of Areas of Unprotected Biodiversity Importance Within Urban Area	0.024			
	(0.038)			
Post × Share of Areas of Unprotected Biodiversity Importance Within 5km of Urban Area		0.013		
		(0.062)		
Post × Share of Areas of Unprotected Biodiversity Importance Within 10km of Urban Area			0.122	
			(0.087)	
Post × Share of Areas of Unprotected Biodiversity Importance Within 15km of Urban Area				0.074
				(0.061)
Log(Employment)	0.133*	0.133*	0.130*	0.131*
	(0.075)	(0.076)	(0.075)	(0.075)
Post × Work From Home	0.129	0.115	0.111	0.111
	(0.219)	(0.217)	(0.218)	(0.217)
Post × Climate Exposure Near Century	0.126	0.130	0.136	0.133
	(0.247)	(0.247)	(0.247)	(0.247)
Post × Climate Exposure Mid to Late Century	0.091	0.085	0.089	0.081
	(0.135)	(0.134)	(0.133)	(0.134)
Post × Habitat Climate Change Vulnerability Index	-0.308	-0.308	-0.332	-0.300
	(0.444)	(0.445)	(0.444)	(0.445)
Adj. R-squared	0.986	0.986	0.986	0.986
Obs.	22,692	22,692	22,692	22,692
County FEs	✓	✓	✓	✓
State × Year FEs	✓	✓	✓	✓

Table 16: **Impact of Biodiversity Risk on Observed Rent Within Land Availability Quartiles**

This table examines the relationship between our continuous measure of biodiversity 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 5). 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

Internet Appendix for:

"Nature's Premium: How Biodiversity Risk Impacts House Prices"

Maxwell Sacher and Shikhar Singla

A Additional Figures and Tables

Figure IA.1: 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.

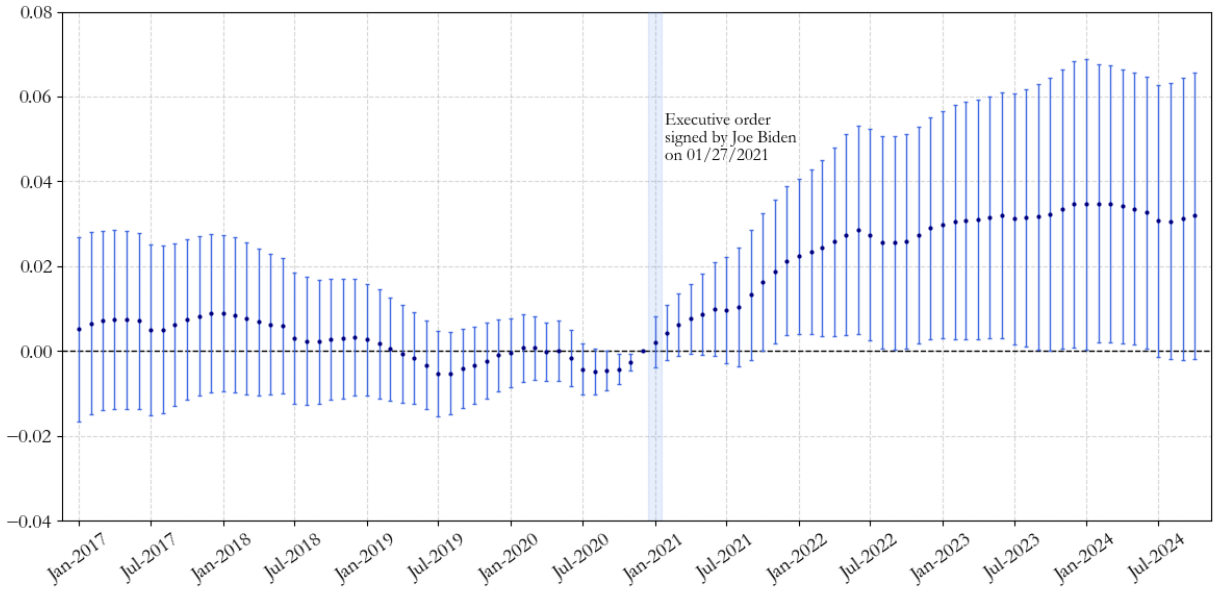
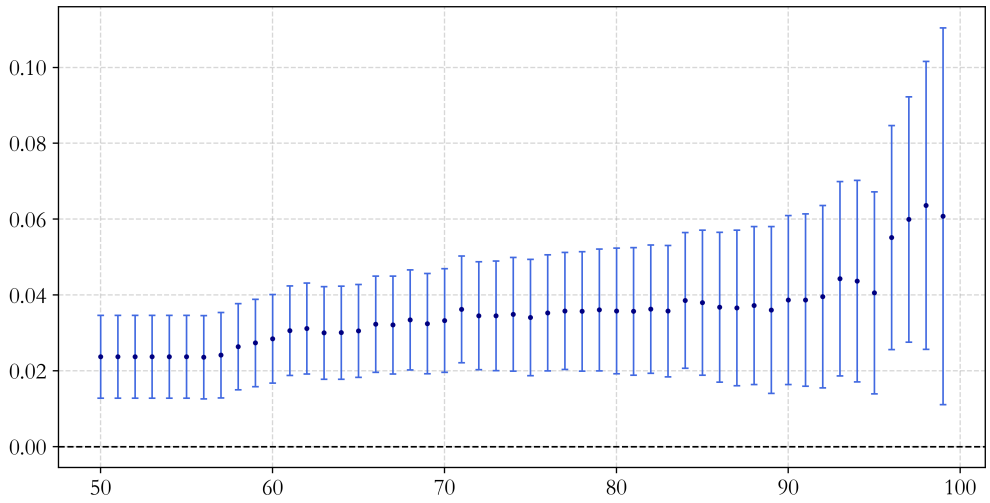


Figure IA.2: Robustness to Treatment Definition

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 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

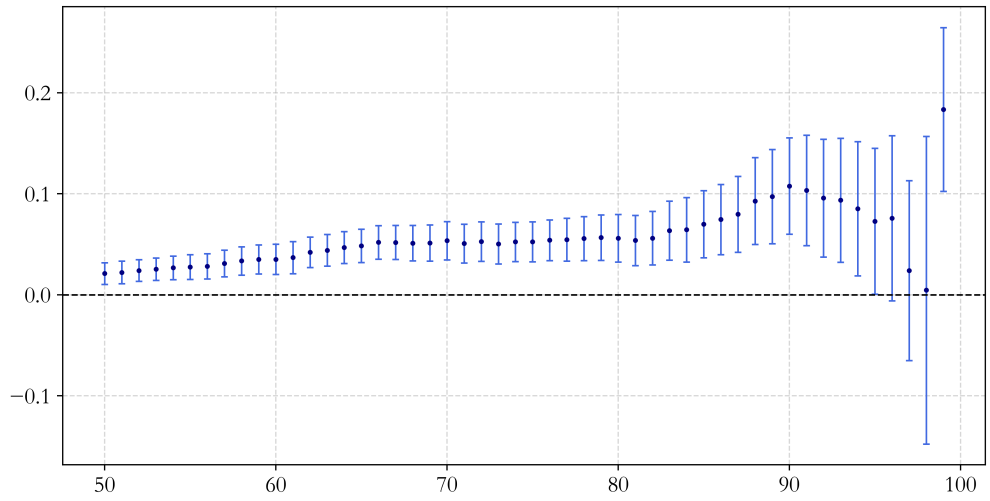
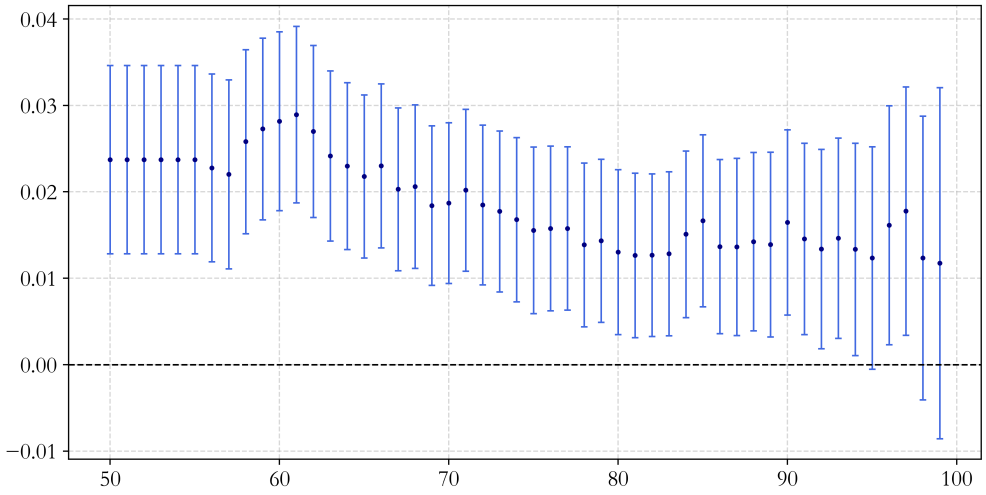


Figure IA.3: Robustness to Treatment Definition and Sample

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 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 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

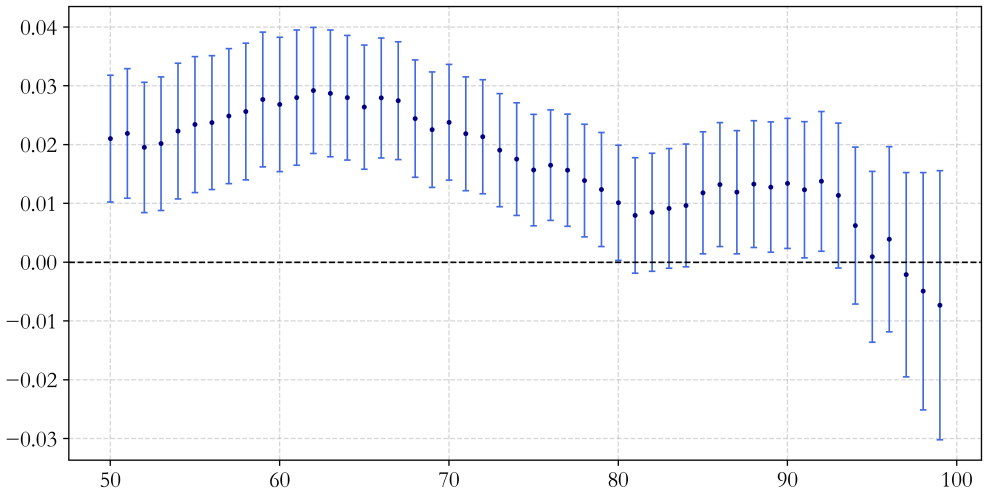


Figure IA.4: Land Availability and Projects

This figure shows the relationship between the Lutz and Sand (2023) measure of land availability and the total number of projects started in counties. We bin the land availability measure and plot average values for the number of projects started under the IRA and BIL in a county. We also fit a linear trends.

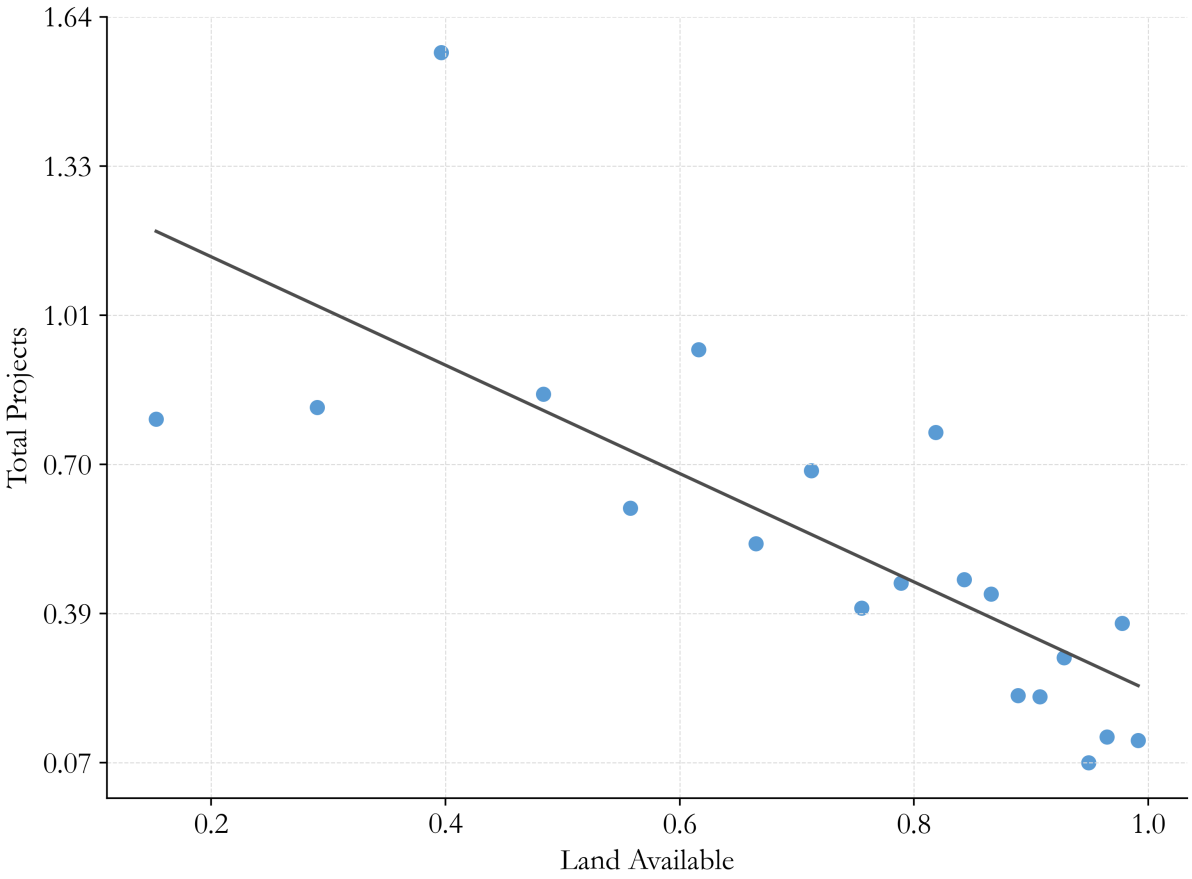


Figure IA.5: Factiva Search

This figure shows our search process in Factiva to retrieve relevant articles on the "America The Beatuiful" initiative. We present the search filters and the query we used in Factiva. The query is limited to U.S.-based sources and English-language articles with a subject around nature articles.

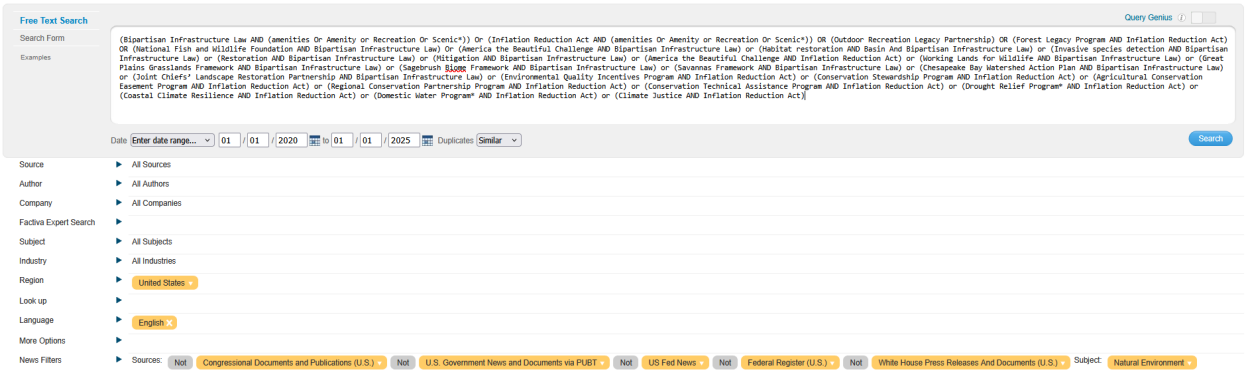
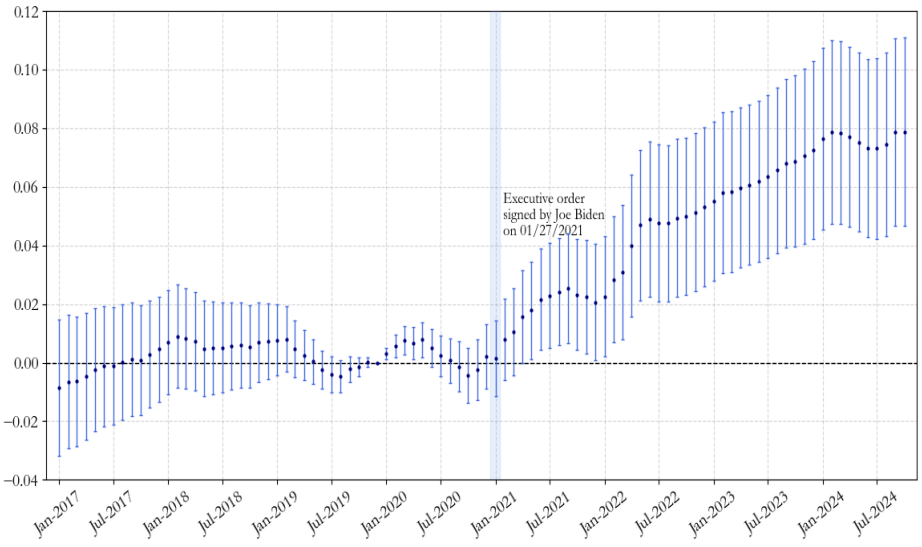
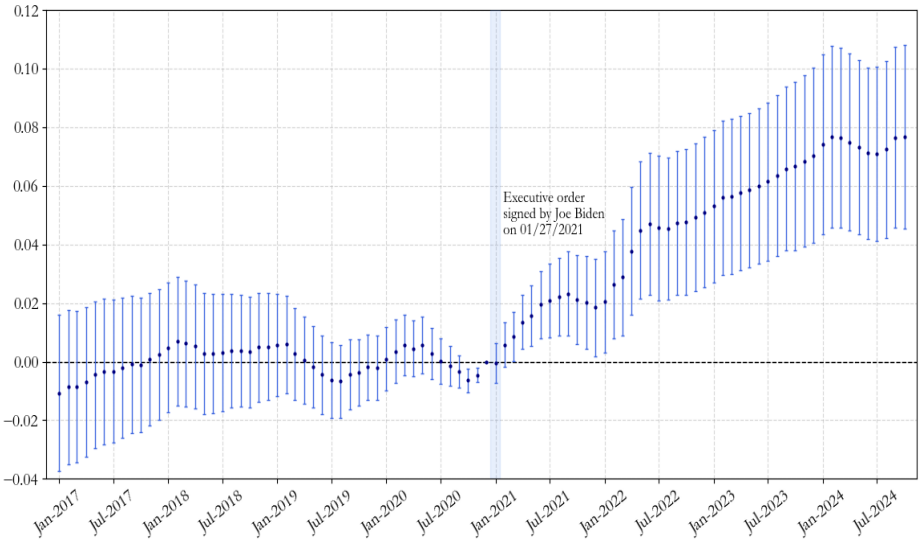


Figure IA.6: Effect of Continuous Biodiversity Risk on House Value: Dynamics

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 a 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, log employment, and fixed effects for county and state × 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 year for the time indicators in the regression. Panel (B) repeats the analysis with December 2020 as the reference year. Standard errors are clustered at the county level.



Panel (A): December 2019 Reference Month



Panel (B): December 2020 Reference Month

Table IA.1: **Impact of Continuous Biodiversity Regulatory Risk Exposure on Standardized Land Values Within Land Availability Quartiles**

This table examines the relationship between our continuous measure of biodiversity 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 5). 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 × 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 × 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(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 × 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 × Work From Home					-0.415*	-0.142	0.292*	0.218
					(0.239)	(0.225)	(0.177)	(0.297)
Post × Climate Exposure Near Century					-0.078	-0.023	0.111	1.240**
					(0.209)	(0.375)	(0.324)	(0.586)
Post × Climate Exposure Mid to Late Century					0.028	0.015	0.045	-0.148
					(0.084)	(0.111)	(0.124)	(0.169)
Post × 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 × Year-Month FEs	✓	✓	✓	✓	✓	✓	✓	✓

Table IA.2: **Impact of Biodiversity Regulatory Risk on Property Values Within Land Availability Quartiles**

This table examines the relationship between our continuous measure of biodiversity 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 5). 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 × 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 × 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(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 × 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 × Work From Home					-0.628***	-0.634***	-0.478***	0.048
					(0.137)	(0.118)	(0.112)	(0.128)
Post × Climate Exposure Near Century					-0.027	-0.101	0.042	0.484**
					(0.092)	(0.280)	(0.185)	(0.229)
Post × Climate Exposure Mid to Late Century					0.021	0.026	0.032	0.016
					(0.040)	(0.044)	(0.052)	(0.091)
Post × 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 × Year-Month FEs	✓	✓	✓	✓	✓	✓	✓	✓

Table IA.3: **Impact of Biodiversity Regulatory Risk on Standardized Property Values Within Land Availability Quartiles**

This table examines the relationship between our continuous measure of biodiversity 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 5). 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 × 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 × 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(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 × 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 × Work From Home					-0.680***	-0.497***	-0.428***	-0.022
					(0.129)	(0.108)	(0.099)	(0.111)
Post × Climate Exposure Near Century					-0.043	-0.130	0.022	0.471**
					(0.082)	(0.235)	(0.169)	(0.207)
Post × Climate Exposure Mid to Late Century					0.033	0.020	0.021	0.019
					(0.037)	(0.041)	(0.048)	(0.089)
Post × 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 × Year-Month FEs	✓	✓	✓	✓	✓	✓	✓	✓

Table IA.4: **Impact of Biodiversity Regulatory Risk on House Value Within Buildable Land Quartiles**

This table examines the relationship between our continuous measure of biodiversity 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 5). 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.5: Excerpts of Project News from Local Media

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.6: **Impact of Biodiversity Risk on House Value at the MSA Level**

This table examines the relationship between counties exposure to biodiversity 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 Zillow Home Value Index at the MSA level. 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 risk. We use a continuous measure of biodiversity risk in all columns. Columns (1) and (2) focus solely on the difference and 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 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.7: **Impact of Biodiversity Risk on House Value Within Land Availability Quartiles**

This table examines the relationship between the log of our continuous measure of biodiversity 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 5). 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.8: **Impact Within Land Availability Quartiles of Biodiversity Risk on House Value**

This table examines the relationship within Land Availability and our measure of biodiversity risk using Areas of Unprotected Biodiversity and the Log of Zillow Home Price Index (Equation 5). 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 × Land Availability Quartile 1 Top Tercile of Exposure	0.035			
	(0.031)			
Post × Land Availability Quartile 2 Top Tercile of Exposure		0.026		
		(0.016)		
Post × Land Availability Quartile 3 Top Tercile of Exposure			0.000	
			(0.019)	
Post × Land Availability Quartile 4 Top Tercile of Exposure				0.054***
				(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.9: **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 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 5). 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 × Yea FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓