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Working Paper

Employment responses to increased biodiversity transition risk

IWH Discussion Papers, No. 20/2025

Provided in Cooperation with:

Halle Institute for Economic Research (IWH) – Member of the Leibniz Association

Suggested Citation: Nguyen, Duc Duy; Nguyen, Huyen; Nguyen, Trang; Sila, Vathunyoo (2025) : Employment responses to increased biodiversity transition risk, IWH Discussion Papers, No. 20/2025, Halle Institute for Economic Research (IWH), Halle (Saale), <https://doi.org/10.18717/dp640x-nc05>

This Version is available at:

<https://hdl.handle.net/10419/331888.2>

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Discussion Papers

No. 20

November 2025



Employment Responses to Increased Biodiversity Transition Risk

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<https://doi.org/10.18717/dp640x-nc05>

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ISSN 2194-2188

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IWH Discussion Papers are indexed in RePEc-EconPapers and in ECONIS.

Employment Responses to Increased Biodiversity Transition Risk*

First version: 19.11.2025

This version: 03.12.2025

Abstract

This paper examines how firms adjust the *number* and *types* of workers they hire in response to increased biodiversity transition risk. Using the adoption of the Key Biodiversity Areas Standard of 2016 as a source of variation that increases the *risk* of future land-use restrictions, we find that firms reduce job postings in affected areas and reallocate labor to less exposed regions. This effect is concentrated among firms that make negative impacts on biodiversity. Cuts are stronger among production roles, while hiring in green and adaptive occupations increases. The effect is not driven by changes in capital investment or workers' labor supply decisions. Our findings contribute to the ongoing debate on the costs and benefits of biodiversity conservation policies and their implications for labor market outcomes.

Keywords: biodiversity risk, Key Biodiversity Areas; labor demand, labor supply

JEL classification: G30, J01, Q57

* We thank Yassine Bakkar, Maria Boutchkova, Jo Danbolt, Philip Fliers, Servanna Fu, Zhehao Jia, Winifred Huang, Renatas Kizys, Yangke Liu, Felix Noth, Sarmistha Pal, Vasileios Pappas, Eleonora Sfrappini, Hanwen Sun, Luca Taschini, Fanis Tsofigkas, Shuhui Wang, Shuo Wang, Jon Williams, Rafal Wojakowski, Xinyu Yu, Huacheng Zhang, Yupu Zhang, Yitao Zheng, and seminar participants at the Universities of Bath, Belfast, East Anglia, Edinburgh, Southampton, Surrey, and St Andrews for helpful comments and suggestions. Huyen Nguyen acknowledges the financial support from the IWH Seed Fund Project. Sanjeev Jha provided excellent research assistance.

1 Introduction

Over half of global GDP is dependent on nature and ecosystem services, leaving economic activities highly vulnerable to disruptions in natural systems (WEF, 2020). In response to accelerating biodiversity loss, governments worldwide are expanding protected areas that restrict land use and economic activities to prevent ecological harm and conserve biodiversity. The policy momentum is accelerating: protected land coverage has increased from less than 10% in 2000 to 15% in 2022, and further to 17% by 2025, as governments move toward the global target of conserving 30% of the Earth’s land and ocean areas to safeguard essential ecosystems.

This regulatory response to biodiversity decline creates biodiversity transition risk for firms (Giglio et al., 2025). Such risks arise not only where protection already exists, but also in areas where protection has become increasingly likely (Lueck and Michael, 2003; Melstrom, 2017). Specifically, firms operating in regions that could be designated protected in the near future face growing uncertainty about land-use restrictions, operational feasibility, compliance obligations, and potential legal and financial consequences. There is anecdotal evidence of firms adjusting their investment in anticipation of biodiversity-related regulations. For instance, Chevron has adjusted routing and deferred infrastructure expansions near California wetlands to mitigate potential Endangered Species Act exposure.¹ Disney has redesigned and delayed development around Walt Disney World where proposed wetland protections threaten permit feasibility.² These dynamics raise an important question: how do firms adjust their investment decisions as the likelihood of future biodiversity protection intensifies?

¹Chevron (n.d.). Protecting Wetlands and Forestlands. Available at: <https://pascagoula.chevron.com/sustainability/environment/protecting-wetlands-and-forestlands>.

²Orlando Weekly (2015). “Disney to preserve 3,000 acres of wetlands so they can destroy wetlands closer to park”. Available at: <https://www.orlandoweekly.com/arts/disney-to-preserve-3000-acres-of-wetlands-so-they-can-destroy-wetlands-closer-to-park-2445024>.

We explore this question by analyzing firms' labor investment decisions. Our main conceptual framework is based on the concept of investment irreversibility and the associated real option value (Bernanke, 1983; Bloom et al., 2007; Dixit, 1979). Under this framework, firms consider human capital investment as a largely irreversible decision due to substantial upfront recruitment costs, as well as potential compensation expenses if contracts are terminated early. Moreover, since firms cannot own or fully control workers' skills and effort, human capital is inherently characterized by contractual incompleteness (Hart and Moore, 1990). These features make human capital management more complex and sensitive to the uncertainty stemming from evolving biodiversity regulations than physical investment. As a result, firms may find it optimal to delay hiring until greater clarity emerges. We complement this perspective with the strategic growth option theory, which suggests that under uncertainty, firms retain or expand investment in capabilities that preserve future growth opportunities and competitiveness (Kulatilaka and Perotti, 1998). Since firms operate in unprotected areas could face greater future regulatory scrutiny, they may adapt by changing the *types* of workers they hire, investing in human capital that can enhance their ability to comply with emerging biodiversity protection frameworks.

To answer our research question, we exploit the establishment of the Key Biodiversity Areas (KBA) Standard in 2016, which for the first time provides a unified scientific benchmark for identifying ecologically significant sites. Before this standard, biodiversity assessments were highly fragmented, making it difficult to determine which areas warrant protection. By providing a clear and consistent framework, the KBA Standard allows governments to readily identify key biodiversity areas, thereby increasing the likelihood that these sites will be designated as protected areas in the future.³ To this end, we develop a novel, geography-based measure of biodiversity transition risk. Our measure focuses on exposed locations that are not yet protected but are considered valuable for biodiversity.

³Survey evidence across 11 countries documents a 164% increase in key biodiversity areas, with the proportion overlapping protected areas rising from 25% to 32% (Plumptre et al., 2025).

Following the KBA Standard, firms with operations in these unprotected key biodiversity areas face increased risk of future land-use restrictions and stricter environmental regulations.

Our analyses make use of big data on millions of job postings of public U.S. manufacturing firms from Lightcast. Each posting provides detailed information on the employer’s name, job title, location, as well as the level of education, experience, and skills required for the job. This setting offers several advantages. First, unlike capital investment data, job postings data are highly granular at the job-location level, enabling us to directly link county-level KBA exposures to firms’ hiring decisions in the same counties where those jobs are located. Second, the detailed information on each job posting allows us to provide new, labor-specific insights into how firms adjust not only the *number* but also the *types* of jobs in response to biodiversity transition risk. We complement the Lightcast database with data from Revelio Labs, allowing us to track the number of employee inflows and outflows at each firm in each job location county in each year. The employee flow data enable us to explore the possible role of changes in employees’ labor supply decisions on observed changes in corporate hiring.

We aggregate job postings data to a firm-county-year panel consisting of 897,939 observations from 1,717 unique manufacturing firms between 2010 and 2023. Our regression specifications include firm fixed effects, job location county fixed effects, as well as headquarters’ state \times year, job location state \times year, and industry (defined at the two-digit NAICS code) \times year fixed effects. This allows us to exploit *within-firm* variation in hiring activities, while accounting for time-invariant differences in job posting activity across counties. The fixed effects also control for time-varying industry and state-level factors (such as environmental or labor regulations) that might otherwise confound the estimated effects.

Consistent with the real options framework, we find that the establishment of the 2016 KBA standard has a negative impact on firms’ hiring activities in exposed counties, i.e., those with a greater share of land considered valuable for biodiversity but not yet protected. Specifically, a one standard deviation increase in the county’s exposure is associated with

a 0.8% reduction in annual job postings. This corresponds to a cumulative 4% reduction in hiring over a five-year period. Moreover, the reduction in hiring is concentrated among firms that make negative impacts on biodiversity.⁴ These firms are likely to face greater public scrutiny, stricter regulations, and a higher risk of sanctions and reputational loss for activities that violate biodiversity protection frameworks. Thus, the higher expected costs increase the anticipated risks on additional human capital investment, which discourages hiring.

We perform various tests to corroborate our results. First, we show that the significant treatment effects only materialize after, and not before, the establishment of the KBA Standard, indicating that there are no pre-trends in hiring activities in exposed counties. Second, we conduct a placebo test by shuffling each county’s KBA exposure levels while maintaining the original data structure. We do not observe any changes in hiring activities around these placebo events, further mitigating the concern that our results are driven by omitted variables. Third, we conduct a horserace test comparing our measure of unprotected but biodiversity-valuable areas with a measure of already protected areas. Ex ante, the 2016 KBA Standard should not affect already protected areas since economic activities there are already constrained. Consistent with this, we find no change in job postings in already protected areas, whereas at-risk areas exhibit a decline in job postings.

Finally, we validate that our results are not driven by concurrent changes in workers’ labor supply decisions by analyzing employee separation. Following Dambra et al. (2025), we classify an employee departure as voluntary if the gap between their job’s end date and the start date of their next job is less than six months, and as involuntary otherwise.⁵ We find no significant changes in either voluntary or involuntary employee departures from

⁴We measure firms’ biodiversity impact using data from the Exploring Natural Capital Opportunities, Risks and Exposure (ENCORE) platform. Impact reflects how much its activities harm biodiversity. Following Garel et al. (2025), we compute firm-year scores as the number of revenue-weighted “very high” impacts based on each firm’s industry composition.

⁵The intuition is that employees who resign voluntarily typically secure another job before leaving and therefore exhibit shorter gaps between consecutive employments, whereas terminated employees tend to experience longer gaps.

exposed counties after 2016, a finding at odds with the labor supply explanation. Overall, the evidence supports a labor demand interpretation, suggesting that firms respond to heightened biodiversity transition risk by reducing new hiring.

We then evaluate two non-mutually exclusive economic mechanisms that explains *how* firms reduce hiring in response to increased biodiversity transition risk. The first channel postulates that firms may adjust their workforce composition in response to increased biodiversity transition risk. Specifically, since firms that operate in unprotected areas could face future land use restrictions and greater regulatory risks, they can adapt by reducing demand for roles that are closely linked to local physical operations while retaining those that can support their compliance efforts. Consistent with this channel, we find that firms restructure their workforce by making greater cuts among roles that are closely tied to local physical operations. In contrast, the demand for occupations that can support firms' technical and administrative compliance efforts, such as green occupations, as defined by O*NET, and legal and office support increases relatively. These roles can enable firms to comply with emerging biodiversity protection frameworks and build the capacity to adapt their business models in key biodiversity areas.

The second channel postulates that firms adjust the type of roles they demand in response to increased biodiversity transition risk. Firms operating in unprotected areas can face future land-use restrictions and heightened regulatory scrutiny. To mitigate these risks, they may reduce demand for roles tied to local physical operations while increase demand for roles that support compliance efforts. Consistent with this mechanism, we find that the decline in hiring is greater for locally focused operational roles, whereas demand for those that facilitate technical and administrative compliance increases.

Our further findings suggest that firms' hiring adjustments remain primarily adaptive rather than transformative. Specifically, firms expand hiring for occupations that O*NET classifies as *Green Increased Demand*, roles for which the core tasks remain largely unchanged, yet demand increases as firms face greater environmental monitoring and compliance

requirements.⁶ In contrast, we find no evidence that firms create entirely new green occupations or that they increase the green skill requirements within existing roles. In other words, the observed shift reflects adaptation and compliance behavior rather than strategic transformation.

The third channel suggests that firms may respond by reallocating portions of their labor force to less exposed counties where regulatory risks are lower. We test this using a methodology developed by Giroud and Mueller (2019), finding that exposure to biodiversity transition risk in one county leads multi-location firms to increase labor demand in less affected counties. This indicates that firms do not merely cut employment in exposed areas but also actively reallocate labor across regions.

Our paper makes important contributions to various strands of the literature. We are first related to an active research area that examines how biodiversity loss and the prospect of stricter conservation policies influence corporate behavior. To the best of our knowledge, we are the first to examine how biodiversity transition risk shapes human capital investment decisions. Understanding this is important, given the roles of human capital in shaping long-term adaptation and productivity. In particular, we show that firms adjust not only the *number* but also the *types* of jobs in response to increased biodiversity transition risk. This contribution is made possible by the detailed data we use, which provide information on labor demand and worker flows at a granular level over time. Our firm-level evidence aligns with earlier findings on how the capital markets respond to biodiversity transition risk: Garel et al. (2024) show that firms with larger biodiversity footprints suffer significant valuation losses following key biodiversity events such as the Kunming Declaration, indicating that investors view these policy signals as reflecting growing biodiversity transition risk. Similarly, Giglio et al. (2025) document that although investors incorporate biodiversity exposure into asset prices, this pricing effect remains incomplete, reflecting persistent uncertainty about the scope and timing of future biodiversity-related regulation and litigation. These findings

⁶For example, environmental technicians perform largely the same tasks as before, but are in higher demand as firms face increased environmental monitoring and compliance requirements.

underscore the growing importance of biodiversity transition risk as a determinant of firm activities and value.

We further contribute by proposing a novel geography-based measure of biodiversity transition risk. Instead of focusing on areas already designated as protected, which reflect past policy decisions, we identify locations *at risk* of future protection under emerging conservation standards, capturing both their biodiversity value and current level of protection. Our measure exhibits substantial variation across the country, allowing us to study *within-firm* labor reallocation in response to heightened biodiversity transition risk. This way, we complement existing approaches in measuring biodiversity transition and impact risk, including the biodiversity news index (Giglio et al., 2025), the corporate biodiversity footprint (Garel et al., 2024), and firm-level nature dependence (Garel et al., 2025). Our work also complements Akbari et al. (2025), who show that the establishment of new protected areas leads to workforce contraction. In contrast to their focus on *realized* changes in protected areas, we examine locations *at risk* of being transformed into protected areas in the future and find that the effects on employment emerge not only after formal regulations are implemented, but also in anticipation of potential protection in regions with high biodiversity value and highlight how expected rather than realized policy actions can shape labor outcomes.

More broadly, our paper is related to the literature on climate and green finance (see, for example, Bolton and Kacperczyk (2023), Flammer (2021), Fuchs et al. (2023), Ilhan et al. (2021), Ilhan et al. (2023), Krueger et al. (2020), Mueller and Sfrappini (2025), Müller et al. (2025), Nguyen and Uzonwanne (2024), among others). A number of studies examine the roles of green human capital in the green transition. For example, Darendeli et al. (2022) find that firms that increase green hiring see better performance and are more innovative. Hagendorff et al. (2025) find that increases in firms' demand for green skills are associated with subsequent reductions in toxic chemical emissions. We contribute by offering new evidence on the extent to which biodiversity transition risk drives firms to “green” their

workforce, finding that firms' responses primarily reflect compliance-oriented adjustments in existing roles rather than transformative, structural shifts toward new or innovation-driven capabilities.

Finally, we speak to a growing strand of research on how labor demand and supply respond to uncertainty. Campello et al. (2024b) find that firms reduce their labor demand, particularly for high-skill jobs, in response to the uncertain business environment at the onset of the Covid-19 pandemic. Flodén (2006) suggests that uncertainty about future wages raises current labor supply while reducing future labor supply. Fontaine (2021) finds that increased uncertainty shocks can lead to a decline in labor force participation.

From a policy perspective, our research highlights the costs and benefits of mitigating biodiversity loss and managing the impact of stricter nature conservation policies on the labor markets. Understanding these trade-offs enables policymakers to anticipate and mitigate negative economic impacts on the affected communities, especially the disruptions in employment. This is especially relevant in light of recent policy efforts such as the European Green Deal and the Convention on Biological Diversity's post-Kunming Declaration, which emphasize integrating biodiversity conservation with economic development.

2 Conceptual framework and hypothesis development

2.1 The 2016 Key Biodiversity Areas Standard

The Key Biodiversity Areas (KBA) Standard, adopted in April 2016 by the International Union for Conservation of Nature (IUCN) following an extensive global consultation process, was designed to identify sites of global biodiversity importance and provide a scientific foundation for future designation of protected areas. It is the first globally consistent scientific framework for identifying sites of exceptional biodiversity importance, and represents a major step toward harmonizing previously fragmented approaches by replacing a patchwork of international and regional conservation schemes with a unified,

standardized methodology grounded in five quantitative criteria: (i) threatened biodiversity, (ii) geographically restricted biodiversity, (iii) ecological integrity, (iv) biological processes, and (v) irreplaceability.⁷ Its adoption has stimulated substantive debate on land-use governance, firms' rights to operate within ecologically sensitive areas, and corporate environmental accountability, especially since data from S&P Global 1200 index shows that 46% of firms worldwide maintain assets within designated key biodiversity areas.

By providing a unified scientific benchmark to identify key biodiversity areas for the first time, the 2016 KBA Standard leads to a substantial expansion in officially recognized biodiversity sites. Moreover, following its adoption, areas recognized as key biodiversity areas now face a higher *risk* of becoming focal points for future protected or conserved area designations as governments and international bodies expand coverage to conserve biodiversity.⁸ Surveys across 11 countries document a 164% increase in key biodiversity areas, with the proportion overlapping protected areas rising from 25% to 32% (Plumptre et al., 2025).

This creates substantial regulatory uncertainty for firms operating within or near KBAs. Once an area is granted protected status, companies may face stricter biodiversity regulations, mandatory impact assessments, or restrictions on land use and resource extraction. These regulatory measures may extend beyond firms directly operating inside key biodiversity areas and affect nearby or indirectly connected businesses as well. Such changes increase firms' exposure to legal risk, including fines, litigation, or the risk of losing operational permits if they fail to comply with evolving biodiversity protection frameworks. To mitigate these risks, firms operating near key biodiversity areas may need to adapt by strengthening their environmental strategies. In some cases, companies can be forced to adjust their business activities, scale back hiring, or even close down establishments.

⁷Internet Appendix IA1 provides examples of the pre-2016 schemes consolidated under the KBA framework.

⁸Protected areas are geographically defined spaces managed through legal or other effective means to conserve nature, ecosystems, and cultural values. Many areas of high biodiversity value remain unprotected for various reasons. Data gaps and delays in conservation planning often leave scientifically recognized sites outside formal legal frameworks. Protection may also be administratively challenging, particularly for sites on private land or those overlapping with resource extraction leases or existing infrastructure.

Moreover, the timing and likelihood of transitions to convert key biodiversity areas into protected areas is highly uncertain and the extent of these costs is also unclear. Local governments may adopt different timelines, enforcement mechanisms, and interpretations of the KBA criteria. Firms are therefore exposed to both spatial uncertainty over how much land will ultimately be granted protected status, and policy uncertainty over when and how new protections will be implemented. Taken together, the establishment of the KBA Standard in 2016 represents a form of biodiversity transition risk, generating regulatory uncertainty for business and production activities near key biodiversity areas that are at risk of being designated protected areas. The greater the share of a county’s land classified as valuable for biodiversity, the higher the risk faced by firms operating within that county.

2.2 The effect on labor demand

Overall, the adoption of the 2016 KBA Standard has introduced a new source of biodiversity transition risk. By identifying sites of high ecological importance without a clear timeline or mechanism for their legal protection, the Standard creates uncertainty over if, when, and how these areas will be reclassified as protected. Firms with operations or assets located within or near KBAs therefore face the prospect of future land-use restrictions, regulatory delays, or compliance costs that are difficult to anticipate or price.

On this basis, we develop our main prediction on how firms’ hiring decisions respond to increased biodiversity transition risks. The real options framework predicts that firms will *reduce* hiring in areas exposed to such risks. Hiring is a forward-looking investment: the decision to post a vacancy depends on expectations of future cash flows brought by this marginal human capital investment (see, e.g., Bernanke, 1983; Bloom et al., 2007; Dixit and Pindyck, 1994). Hiring today involves irreversible sunk costs, such as recruitment and training, whereas delaying the hire avoids these costs but also postpones the potential cash inflows from additional labor. Firms therefore have the option to delay hiring to see how business conditions evolve. Because the establishment of the 2016 KBA Standard generates

greater uncertainty over which areas that will ultimately be granted protected status and uncertainty other biodiversity-related regulation, firms will scale back hiring in counties at risk of being designated protected areas.

Prediction 1: After the establishment of the 2016 KBA Standard, firms cut hiring in areas at risk of being designated biodiversity protected areas.

While Prediction 1 considers the overall impact on hiring, there can be substantial heterogeneity underlying this effect, where firms may increase demand for some occupations while reducing others. Specifically, strategic growth option theory argues that, in the presence of uncertainty, firms retain or expand investment in capabilities that preserve future growth opportunities and competitiveness (Kulatilaka and Perotti, 1998). In the context of biodiversity transition risk, since firms operate in unprotected areas could face future land use restrictions, they may adapt by increasing hiring for workers with environmental expertise and regulatory knowledge (see, e.g., Darendeli et al., 2022; Hagendorff et al., 2025). In addition, firms may restructure their workforce by reducing demand for roles that are closely linked to local physical operations while retaining roles that can support their technical and administrative compliance efforts. Such targeted human capital investments enhance a firm’s ability to comply with emerging biodiversity protection frameworks and adjust business models as needed, thereby shifting the composition of labor demand toward compliance and adaptation roles in more exposed areas.

Prediction 2: After the establishment of the KBA Standard, firms adjust the *composition* of labor demand to mitigate risks associated with future biodiversity protection.

3 Data and methodologies

3.1 Biodiversity risk data and measure

We construct a geography-based measure of biodiversity transition risk, which arises when governments decide to designate new areas as “protected areas.” Following the adoption of

the 2016 KBA Standard, policymakers are expected to use the KBA framework to designate currently unprotected key biodiversity areas as protected areas. Building on this idea, we construct our measure in three steps.

In the first step, we identify areas of high biodiversity value using the global database of Key Biodiversity Areas (KBAs).⁹ This database designates critical sites that make significant contributions to biodiversity and ecosystem health based on the globally agreed criteria established in the 2016 KBA Standard. KBAs are essential for safeguarding threatened species and maintaining genetic diversity, and their data are widely used by governments, financial institutions, and corporations to guide conservation priorities and reduce biodiversity loss.

In the second step, we identify the areas that have already been designated as protected areas from the U.S. Geological Survey’s Protected Areas Database of the United States (PAD-US).¹⁰ This is the official GIS-based national inventory of protected area boundaries in the US. Examples of protected areas are public lands and parks, wilderness areas, national wildlife refuges, reserves, conservation easements, or marine protected areas. The PAD-US includes the Gap Analysis Project (GAP) status of the protected area, which is a measure of the conservation level of each area. Areas with GAP status 1 and 2 have permanent and legally enforceable protection from conversion of natural land cover, which restricts development in 95% of their total area. In areas with GAP status 3, extractive uses are permitted, such as logging, mining, and recreational uses. Areas with GAP status 4 lack any formal mandate for biodiversity protection. We classify an area with GAP status 1, 2 or 3 as protected. Including status 3 captures the wide range of risks firms face from both strict conservation restrictions and more flexible land uses.¹¹

In the third step, we arrive at a set of “to be protected” areas, defined as areas that are classified as KBAs but are not yet protected. While firms can still operate in these regions,

⁹see, <https://www.keybiodiversityareas.org/>

¹⁰see, <https://shorturl.at/ivt8r>

¹¹As shown in Internet Appendix IA5, our results are robust when protected areas are defined as those with GAP status 1 or 2.

there is a risk that these areas will be designated protected areas following the establishment of the 2016 KBA Standard.¹²

Of the 3,141 counties with available data, 777 (25%) have at least some areas in the county classified as KBA, while 678 (22%) have at least some areas already been designated as protected areas. Although there are expected overlaps between the KBA and the protected areas ($\text{corr} = 0.32$), they still capture some distinct variations. For example, as shown in Figure 1, while Warrick County does not have any areas classified as protected areas, it has more than 44 sq mile (or 11.5% of the county area) classified as KBA. An example of a KBA area in Warrick County is the Lynnville-Squaw Creek Mine Complex, which consists of diverse habitats such as grasslands, lakes, woodlands or wetlands, and is especially recognized as the site of the second largest population of Henslow’s Sparrow in Indiana.¹³

[Insert Figures 1 and 2]

This implies that there is meaningful variation in our definition of areas that are KBA (and are thus valuable for biodiversity) but are not yet protected. Figure 2 displays the distribution of counties with at least some areas that could potentially become protected areas. There are 774 counties (25%) having at least some of these at-risk areas, and they are highlighted in a darker color in Figure 2. These counties spread across the country, and do not cluster in any specific regions such as the West or the East Coast. Among the 774 counties with areas that could become protected, the average proportion of these at-risk areas is 7.75%. This is sizable enough to induce uncertainty over which areas will ultimately be

¹²We treat county-level biodiversity exposure ($\%Exposed$) as time-invariant because both components used to construct this measure exhibit extremely limited temporal variation. First, areas of high biodiversity value identified under the KBA Standard have not changed meaningfully over our sample period. In the continental United States, the KBA dashboard indicates that only 10 out of 667 Key Biodiversity Areas were reassessed (confirmed, revised, or newly introduced) between 2016 and 2023. See <https://www.keybiodiversityareas.org/dashboard> for the list of key biodiversity areas. Second, the spatial extent of protected areas in USGS PAD-US evolves only slowly; most updates across versions reflect improvements in data completeness, minor boundary refinements, or the incorporation of previously unmapped state, local, or NGO parcels, rather than the creation of new legally designated protected areas.

¹³Internet Appendix IA4 performs a horserace between at-risk areas and already protected areas. Consistent with at-risk areas capture future regulatory risks, firms reduce hiring in at-risk but not already protected areas.

granted protected status. Internet Appendix IA2 reports the summary statistics of different areas in our sample.

3.2 Employment and firm-level data

Our analyses draw on job postings data from Lightcast (formerly Burning Glass Technologies), covering the period 2010–2023. Lightcast uses an algorithm that continuously scrapes postings from more than 220,000 online job boards and company websites worldwide, removes duplicate postings and aggregates them, and converts the information into standardized, machine-readable formats. Each posting provides detailed information on the job title, job location, standardized occupational classification (SOC) code, and employer name. Moreover, each posting also contains rich detail on the levels of education, prior experience, and specific skills that a worker must fulfil to be eligible for the position. Carnevale et al. (2014) show that Lightcast data capture nearly the entire universe of jobs posted online, while Hershbein and Kahn (2018) demonstrate that its aggregate and industry-level vacancy trends are consistent with other sources of job vacancies information such as the Job Opening and Labor Turnover Survey.

We complement Lightcast’s job posting data with data on workforce composition and worker flows provided by Revelio Labs. Revelio collects online public profiles and transforms them into standardized resumes,¹⁴ which include the individual’s identity, job title, SOC code, employer name, job locations, and the start and end dates of employment. We aggregate the individual profiles into firm-level workforce composition, which allows us to observe the total headcounts and employee flows for each firm in each job location each year.

We merge Lightcast with Compustat-CRSP using a crosswalk provided by Lightcast, which we further enhance using a fuzzy name-matching algorithm. We then merge Lightcast-Compustat-CRSP with Revelio by the firm’s GVKEY using the crosswalk file

¹⁴To account for the overrepresentation of users with certain jobs in online public profiles, e.g., white-collar jobs in relation to blue-collar jobs, Revelio applies sampling weights to adjust for occupation and location bias. For example, if an engineer has a 90% chance of having a public profile, Revelio considers every engineer to represent 1.1 people.

provided by Revelio. Our analyses focus on job postings from manufacturing firms (two-digit NAICS codes 31–33). This ensures a homogeneous sample of firms that are likely to be similarly affected by biodiversity transition risk. Manufacturing firms also tend to be among the more pollution-intensive sectors, making them particularly exposed to increased biodiversity transition risk. We further exclude firms with missing total assets and single-location firms that operate in a single county.

Our job posting and workforce composition data are aggregated at the firm-county-year level, where county refers to the county where the job is based. We require that each firm has at least one employee in a given county-year. Our merged sample comprises 897,939 firm-county-year observations across 1,717 unique firms between 2010 and 2023. This sample is representative of public manufacturing firms in the US and exhibits substantial cross-sectional variations across firm size, sub-industry, and location.

[Insert Table 1]

Summary statistics for our Revelio-Lightcast-Compustat-CRSP sample are shown in Table 1. On average, firms list 5.5 job openings for full-time positions annually in a given county. Firms have \$6.5 billion in total book assets (or, expressed as the natural logarithm, 8.782). On average, firms borrow 60% of their total assets and generate earnings before interest and taxes equal to 8.4% of their total assets. These values are broadly consistent with existing literature (see, e.g., Brogaard et al., 2024; Nguyen and Sila, 2025).

4 Impact of the 2016 KBA Standard on employment

4.1 Empirical specification

In this section, we estimate the following continuous difference-in-differences (DiD) specification to analyze firms’ job posting activities in unprotected, key biodiversity areas following the 2016 establishment of the KBA Standard:

$$y_{ict} = \alpha + \beta PostKBA_t * \%Exposed_c + Controls_{ict} + FixedEffects + \varepsilon_{ict}, \quad (1)$$

The dependent variable y_{ict} is defined as the natural logarithm of one plus the total number of full-time job postings of firm i in county c in year t . The main coefficient of interest is the interaction between $PostKBA_t$ and $\%Exposed_c$. $PostKBA_t$ is a dummy variable that equals one from 2017 onward following the establishment of the global standard for identifying KBAs, and zero otherwise. $\%Exposed_c$ is the proportion of the county's areas that are valuable for biodiversity but are not yet protected. The larger the share of a county's land classified as valuable for biodiversity, the greater the likelihood that these areas will be designated as protected in the future, and the higher the associated risk for firms operating there. The error term ε_{ict} is clustered at the county-level, where the job is based.

Our main DiD regression includes firm and job location county fixed effects. These absorb time-invariant differences in job positing activities across firms and counties where the job is based. Our specification also includes headquarters' state \times year and job location state \times year fixed effects, which account for time-varying state specific characteristics at both the firm's headquarters and the job location, such as environmental or labor-related regulation. Finally, we include industry (defined at the two-digit NAICS code) \times year fixed effects to control for time-varying industry characteristics, such as investment opportunities and economy-wide business cycles. Collectively, the interacted fixed effects account for characteristics that could affect both labor supply as well as the quantity and nature of jobs firms seek to fill.

Following prior studies (Campello et al., 2024a), we include a comprehensive set of firm-level control variables (lagged by one year) that could affect corporate hiring. We use $\ln(1+Total\ assets)$ and *Tobin's Q* (the market value of total assets divided by book value of assets) to control for firm size and growth opportunities, respectively. We further include $EBIT/Total\ assets$ (earnings before interest and taxes divided by total assets) and $Total\ debt/Total\ assets$ to control for firm profitability and financial leverage, respectively.

We also control for *CAPEX/Total assets* (capital expenditures divided by total assets) and *PPE/Total assets* (property, plant, and equipment divided by total assets) to account for investment intensity and asset tangibility, respectively. Finally, to control for the level of existing economic activity in the local area, we include lagged $\ln(1+Employee\ count)$, defined as the natural logarithm of the firm’s total employment in a given county-year.

4.2 Setting validity

Before conducting the main analyses, we evaluate whether the parallel assumption holds in our sample. The parallel assumption states that in the absence of treatment (the establishment of the KBA Standard), the coefficient on the DiD estimator is zero. Thus, it requires a similar pre-event trend for both treatment and control observations.

[Insert Table 2]

To verify this, we compare the evolution of the main outcome variables between treated counties (i.e., those with a positive *%Exposed*) and control counties (i.e., those with a zero *%Exposed*) in 2015, as well as over a longer 2013–2015 period prior to the implementation of the KBA Standard. To calculate these pre-trends, we aggregate our data to the county-level and compare the first differences of the main outcome variables. We find in Table 2 that there are no statistically significant differences in the pre-trends of the number of full-time job postings, establishments, voluntary and involuntary departures, or the composition of jobs advertised between treatment and control counties. Thus, the results indicate that the parallel trend assumption is likely to hold in our data. We further validate the parallel trend assumption in Figure 3, showing that the effects only take place after 2016 when the KBA standard was established.

4.3 Job postings activities

Table 3 reports regression results on the effect of the 2016 establishment of KBA Standard on firms' hiring activities in exposed counties (that is, those with a greater share of land considered valuable for biodiversity but not yet protected). The dependent variable is $\ln(1+Job\ Postings)$, the natural logarithm of one plus the number of job postings for full-time positions by a firm in a given county-year. The results in Table 3 indicate that the establishment of the 2016 KBA standard has a negative impact on firms' hiring activities.

[Insert Table 3]

Specifically, across all specifications in Table 3, the interaction coefficients $\%Exposed \times PostKBA$ are negative and statistically significant. The effects are economically meaningful. The estimate in the full specification in Column 3 indicates that a one standard deviation in the county's exposure levels is associated with a 0.8% ($= 0.066 \times 0.119$) reduction in annual job postings. This corresponds to a cumulative 4% reduction in hiring over a five-year period. Section 5.2 explores variation in this effect, showing that the hiring cut is stronger in certain occupations than in others. Overall, the results in Table 3 lend support to Prediction 1 that firms respond to heightened biodiversity transition risk by reducing hiring in exposed counties.

[Insert Figure 3]

Figure 3 displays the dynamic timing effects of the 2016 KBA Standard on job posting activities in exposed counties. This figure plots the coefficients of the interaction between $\%Exposed$ and time dummies every year over the 2010-2023 sample period. We report an annual time interval, and the excluded period is 2016 when the KBA Standard was established. As shown in Figure 3, the significant treatment effects only materialize starting from 2017. From then on, exposed counties exhibit persistently lower job postings, with the magnitude of the effect increasing over time. Overall, there is little evidence of pre-trends or

anticipatory effects before the establishment of KBA Standard, further suggesting that the parallel trends assumption is likely to hold.

One concern regarding our results is that the 2016 KBA Standard is enacted around other climate-related events such as the Paris Agreement or Trump’s election in November 2016.¹⁵ Although this is unlikely to be a threat since our identification relies on variations across counties after 2016, we further address this concern by performing several placebo tests.

Our placebo test uses randomized exposed counties. The randomization process reshuffles each county’s KBA exposure levels but maintains the original data structure by drawing KBA exposure levels from the original distributions without replacement. We then use the randomized data to re-estimate the regressions in Column 3 of Table 3. We perform 10,000 simulations and plot the distribution of the coefficient estimate on $\ln(1+Job\ Postings)$ in Figure 4.

[Insert Figure 4]

As shown in Figure 4, the average coefficient estimates using the placebo data are 0.000. In contrast, the coefficient estimates using the actual data are significantly larger in absolute terms. In particular, the estimate using the actual data is -0.119 , which is several standard deviations from the mean estimate from the placebo data. The mean estimate of 0.000 using placebo data suggests that our results do not capture omitted variables that are simultaneously correlated with characteristics after 2016 and lower levels of hiring activities (otherwise, we would still observe large and statistically significant placebo estimates). Overall, the findings indicate that our main results are specifically driven by the 2016 KBA Standard and unlikely to be driven by other events around 2016.

In Internet Appendix IA4, we conduct a horserace between our measure of biodiversity transition risk, the share of a county’s area *at risk* of future protected-area designation, and

¹⁵If anything, Trump’s election works against us in detecting a hiring reduction in exposed counties after the 2016 KBA Standard. Trump is known for his active stance against biodiversity and environmental protection, which likely weakens firms’ incentives to respond to the 2016 KBA Standard.

the share of its area *already* designated as protected. Ex ante, the 2016 KBA Standard should not affect already protected areas since economic activities there are already constrained. To test this, we include the interaction between *PostKBA* and *%Protected*, the share of a county’s area already under protection. Consistent with our expectation, we find no change in job postings in already protected areas, whereas at-risk areas exhibit a decline in job postings.

Internet Appendix IA5 displays various robustness tests on the baseline findings. We show that our results are robust to using more restrictive fixed effects such as firm-year fixed effects, and are not sensitive to how standard errors are clustered. Our results also remain robust when we exclude the years of 2016 (Trump election) or 2020 (Covid). We also obtain similar results after excluding Democratic-leaning states with the large shares of unprotected KBAs: California, New York, Vermont, and Hawaii.

4.4 Heterogeneity across firms with high biodiversity dependency and impact

To better understand why firms reduce hiring after the 2016 KBA Standard, we analyze differences across firms with strong biodiversity dependencies and impacts. In particular, if firms scale back hiring due to concerns about regulatory risks following the 2016 KBA Standard, this effect should be most salient among firms making negative impact on biodiversity and thus likely to face greater regulatory exposure.

To test our predictions, we obtain data from the ENCORE platform, which provides two primary industry-level assessments of how economic activities depend on and adversely impact biodiversity: (1) a *Dependency score*, which indicates how severely an industry would

be affected by disruptions to ecosystem services;¹⁶ and (2) an *Impact score*, which captures the extent to which its activities negatively affect biodiversity.¹⁷

Following Garel et al. (2025), we transform the industry-level scores to firm-year level measures. Specifically, for firms with sales spanning multiple industries, we calculate for each firm-year the number of revenue-weighted ecosystem services and impact drivers a firm relies on. Similar to Garel et al. (2025), rather than averaging scores across sales segments, we count only the number of very high dependencies and impacts. This approach accounts for the fact that nature risks can be non-linear and can stem from very strong dependencies on a few critical services and significant impact drivers. For single-industry firms, we assign biodiversity dependency and impact scores (defined as the number of very high dependencies and impacts) based on their NAICS-6 industry classification.¹⁸

To test our hypothesis, we re-estimate Equation 1, this time including an interaction between $\%Exposed \times PostKBA$ and $Impact\ score_{20132015}$ ($Dependency\ score_{20132015}$), the three-year average biodiversity impact (dependency) score before the enactment of the 2016 KBA Standard. The dependent variable is $Ln(1+Job\ Postings)$. The triple interaction coefficients indicate whether firms with high biodiversity dependency or negative biodiversity impacts adjust their hiring differently after the establishment of the KBA Standard in 2016. Table 4 presents the results.

[Insert Table 4]

¹⁶ENCORE considers 25 ecosystem services across three categories: (1) provisioning services (e.g., the supply of food, fibre, livestock, and water), (2) regulating and maintenance services (e.g., the regulation and maintenance of air, water, soil, habitat, and climate), and (3) cultural services (e.g., cultural, educational, or recreational benefits). Our calculations exclude cultural services since they neither direct inputs nor enablers of production. For each ecosystem service relied on by an industry, ENCORE assesses how severely the industry would be affected if the ecosystem service were disrupted and classifies them into five materiality levels. Very low to medium levels imply minimal adjustments, while high or very high levels suggest production could be significantly impaired.

¹⁷ENCORE considers 13 impact drivers. Examples of these drivers are the introduction of invasive species, over-exploitation of natural resources, and the release of toxic pollutants. ENCORE similarly classifies each driver in each industry into five levels of materiality, ranging from very low to very high.

¹⁸Examples of firms with negative biodiversity impact are chemical and industrial products firms. These firms' operations could affect biodiversity through chemical emissions, land use changes, and resource extraction. Examples of biodiversity dependent firms are food and beverage manufacturing firms. These firms are heavily dependent on sustainable ecosystems for pollination, pest control, and nutrient cycling.

As shown in Columns 1 and 3 of Table 4, the triple interaction coefficients on $Impact\ score_{20132015} \times \%Exposed \times PostKBA$ are negative and statistically significant. This indicates that the reduction in hiring following the implementation of the 2016 KBA Standard is stronger among firms with greater negative impacts on biodiversity. These firms are likely to face greater public scrutiny and stricter biodiversity and environmental regulations in the future once the protected status is imposed. For example, a chemical firm could be required to obtain special permits to continue producing, storing, or extracting hazardous chemicals in biodiversity protected zones. These firms also face a higher risk of sanctions and reputational loss for activities that violate biodiversity protection frameworks. Thus, the higher expected costs increase the anticipated risks on additional human capital investment, which further discourages hiring.

In contrast, the triple-interaction coefficients between $Dependency\ score_{20132015}$ and $\%Exposed \times PostKBA$ are statistically insignificant (Columns 2–3), suggesting that hiring reductions do not differ systematically with firms’ levels of biodiversity dependency. Because their production and operations rely on nearby natural resources, these firms are likely to make similar labor adjustments to sustain production. Taken together, the results in Table 4 are consistent with the 2016 KBA Standard increasing regulatory risks and potential sanctions for firms operating in exposed counties, particular for those making significant negative impacts on biodiversity, thereby incentivizing these firms to scale back hiring.

4.5 Are the effects driven by labor supply decisions?

Having shown that firms adjust their labor demand in response to biodiversity transition risk, we next evaluate whether the results could instead be driven by changes on the labor supply side. To do this, we examine whether employees in exposed counties are less likely to leave their jobs following the 2016 KBA Standard. Finding no evidence of lower voluntary departures suggests that the observed decline in job postings is not driven by workers’ labor supply decisions but rather by firms’ reduced labor demand.

We follow Dambra et al. (2025) to distinguish voluntary departures from layoffs by using the length of time it takes a departing employee to begin working for a new employer. The intuition is that employees who resign voluntarily typically secure another job before leaving and therefore exhibit shorter gaps between consecutive employments, whereas terminated employees tend to experience longer gaps. Using employee public profiles from Revelio Labs, we measure the number of months between an employee’s job end date and the start date of their subsequent job. We define a departure as “voluntary” if an employee’s job start date at the new firm is within six months of the date they depart from the former employer, and “involuntary” otherwise.¹⁹

[Insert Table 5]

Table 5 displays the results. The dependent variables are the natural logarithm of one plus the number of voluntary (Column 1) and involuntary departures (Column 2) from a firm in a given county-year. The regressions include a set of control variables and fixed effects specified in Equation 1. Across both columns, the interaction coefficients are statistically insignificant, indicating that the 2016 KBA Standard has no detectable effect on either voluntary or involuntary departures. Thus, employees are not more likely to voluntarily leave exposed counties due to their risk of being designated protected areas, a finding at odds with the labor supply interpretation. Taken together, our results are broadly consistent with the labor demand interpretation that firms respond to heightened biodiversity transition risk by reducing new hiring.

5 Economic mechanisms

In this section, we conduct various tests to understand the mechanisms behind the reduction in hiring in exposed counties following the 2016 KBA Standard, thereby shedding light on *how* firms adjust their employment in response to heightened biodiversity transition risk.

¹⁹We obtain similar results when using alternative windows of three or twelve months.

Specifically, we explore several potential adjustment mechanisms: (1) firms may restructure their local workforce; and (2) firms may reallocate portions of their labor force to less exposed counties where regulatory risks are lower.

5.1 Workforce restructuring

Firms may adjust their workforce composition in response to increased biodiversity transition risk. Specifically, in counties where substantial portions of land are likely to be designated as protected, firms may face tighter restrictions on land use and resource extraction, as well as higher compliance and monitoring costs. Firms may respond to these pressures by restructuring their workforce in the following ways. First, firms may alter the types of occupations they recruit for if biodiversity constraints or regulatory requirements change the mix of roles needed. Second, firms may modify the skill content of jobs by embedding additional environment-related competencies within existing occupations, even when job types remain unchanged. Third, firms may adjust their overall workforce structure by shifting hiring between job role types that differ in their exposure to biodiversity constraints or their relevance for ecological adaptation. We explore each of these possibilities in turn.

We begin by examining how the KBA Standard affects the types of job roles that firms demand. Specifically, we focus on green jobs defined by O*NET’s *Taxonomy of Green Occupations*.²⁰ O*NET categorizes green occupations into three groups: (1) *Green New & Emerging*, occupations that are newly created to meet the demands of green economy activities. An example is solar installer, which did not exist at large scale before the rapid expansion of renewable energy; (2) *Green Enhanced Skills*, existing jobs that require expanded skills due to green technologies or practices. For example, architects now need additional expertise in energy-efficient building design, even though the core occupation has long existed. (3) *Green Increased Demand*, occupations where demand increases because of green economy trends, without major changes to tasks. For example,

²⁰<https://www.onetcenter.org/reports/Green.html>

environmental technicians, whose work remains similar, but are needed more as firms face greater environmental monitoring and compliance requirements. Our dependent variables are thus the share of job postings classified into each of the three green categories, as well as an overall green share capturing jobs that fall into any of these categories. Our regression specifications include a set of fixed effects and control variables similar to those in Column 3 of Table 3.

[Insert Table 6]

Panel A of Table 6 displays the results. As shown in Table 6, the share of *Green Increased Demand* occupations increases 6% in exposed counties following the establishment of the 2016 KBA Standard. In contrast, we find no significant change in the shares of *Green Enhanced Skills* or *Green New Emerging* occupations. Thus, consistent with the strategic options framework, these results suggest that firms respond to heightened biodiversity transition risk by expanding hiring in green occupations to strengthen their capacity to comply with biodiversity protection frameworks. However, the lack of significant changes in the other two green occupation categories indicates that firms' responses are primarily adaptive rather than transformative, reflecting compliance-oriented adjustments in existing roles rather than structural shifts toward new or innovation-driven capabilities.

Our second test examines whether jobs become greener at the *skill-level*, even when the occupation itself does not change. Using skill requirements reported in job postings, and following Darendeli et al. (2022), we define green skills as those belonging to the "Environment" skill cluster family.²¹ We estimate job-level regressions to examine the effect of the 2016 KBA Standard in exposed counties on (i) whether a posting contains at least one green skill (*Has green skills*); (ii) the number of green skills (*#Green skills*); and (iii) the share of green skills among all skills required in a given job (*#Green skills/#All skills*). In

²¹Lightcast systematically tags the required skills mentioned in the text of each job posting. It then categorizes skills into "skill clusters," which are in turn categorized into "skill cluster families." For example, skills such as "air emissions," "air sampling," and "air quality control" are categorized into the "air quality" skill cluster, which then belongs to the "environment" skill cluster family.

addition to the control variables and fixed effects specified in Equation 1, we further include 6-digit O*NET code fixed effects to exploit variation in green skill requirements within the same job.²²

Panel B of Table 6 reports the results. Across all three measures, we find no significant change in the number or intensity of green skills in job postings. These results are consistent with the job-level findings in Panel A that biodiversity transition risk does not lead firms to embed broader green skill requirements within the same roles.

The third test examines whether firms shift their overall workforce composition. Firms facing stricter land-use restrictions, increased biodiversity compliance costs, or heightened monitoring requirements may reduce demand for roles tied to local physical operations or activities that depend heavily on natural resource use, such as extraction, land development, or site maintenance. At the same time, they may retain roles related to regulatory compliance and adaptation since these workers can help firms comply with emerging biodiversity protection frameworks and build the capacity to adapt their business models in key biodiversity areas.

To examine this possibility, we group occupations into two broad categories according to their 2-digit SOC codes: (i) *Production roles* are job roles that require physical presence and involve on-site activities, including occupations in Construction and Extraction (47), Production (51), Transportation and Material Moving (53), Building and Grounds Cleaning and Maintenance (37), or Farming, Fishing, and Forestry (45); (ii) *Adaptation roles* are job roles that support firms' technical and administrative compliance efforts, including Legal (23), Office and Administrative Support (43), Architecture and Engineering (17), and Life, Physical, and Social Science (19). The regressions are at the firm-county-year level, and the dependent variables are the share of job postings classified as either production or adaptation. Our regression specifications include a set of fixed effects and control variables similar to those in Column 3 of Table 3.

²²We obtain similar results without O*NET fixed effects.

[Insert Table 7]

Table 7 displays the results. In line with our expectations, the estimate in Column 1 indicates that the hiring cut is more pronounced among *Production* occupations (i.e., those that are closely tied to local physical operations and reliant on natural resources) relative to the control group. In contrast, the demand for *Adaptation* jobs increases relatively, though the effect is marginally statistically significant at 10% level (Column 2). These jobs can be done remotely and play a crucial part in helping firms navigate and comply with emerging biodiversity protection frameworks and adapt their business models to the evolving conditions in key biodiversity areas. Overall, the results in Tables 6 and 7 offer new insights into how biodiversity transition risk triggers not only spatial but also occupational reallocation within firms, shifting labor demand toward compliance-oriented and adaptive capabilities.

Taken together, the results across all three tests support the strategic options framework: firms respond to increased biodiversity transition risk by adjusting the *types* of roles they demand. However, these adjustments are primarily adaptive rather than transformative. The KBA Standard increases demand for existing occupations that support compliance, monitoring, and environmental management, rather than increasing the demand for new green roles or environmental skillsets. Overall, biodiversity transition risk stimulates incremental expansion in the demand for operationally relevant green roles rather than a fundamental reconfiguration of workforce skill composition.

5.2 Labor Reallocation

In addition to restructuring workforce in counties at risk of protected-area designation, firms may also respond by reallocating portions of their labor force to less exposed counties where regulatory risks are lower. If a positive reallocation effect is observed, it would suggest that firms can mitigate the employment impact of biodiversity transition risk by shifting jobs to other locations. Conversely, firms may not be able to reallocate if they are frictions such

as reallocation costs or facility and operational constraints that prevent them from doing so (Giroud and Mueller, 2015).

To answer this question, we use the empirical strategy proposed by Giroud and Mueller (2019). In particular, we examine whether firms increase labor demand in one county when other counties in which they operate face a higher risk of land being designated as protected areas. To this end, we construct *Lower Exposure*, a dummy variable equal to 1 if a firm's *%Exposed* in a given county is lower than the same firm's average exposure across its other counties. The firm-level average exposure is computed by weighting each county's *%Exposed* by the firm's employment share in that county. We estimate the following regression:

$$y_{ict} = \alpha + \beta PostKBA_t * LowerExposure_c + Controls_{ict} + FE + \varepsilon_{ict}, \quad (2)$$

The dependent variable y_{ict} is the natural logarithm of one plus the total number of full-time job postings of firm i in county c in year t . The main coefficient of interest is the interaction between $PostKBA_t$ and $LowerExposure_c$. A positive interaction coefficient would indicate that the focal county experiences more job postings when it has a lower exposure than other counties of the same firm.

We use firm fixed effects to absorb time-invariant differences in hiring across firms. Unlike Equation 1, we are able to include job location county x year fixed effects in the reallocation regressions. This allows us to absorb all time-varying county-level characteristics that may impact firms' demand for job postings, including the county's own exposure to key biodiversity areas. Identification is possible since different firms have different establishment networks. Thus, the interaction coefficients on *Lower Exposure* and *PostKBA* compare job postings of two firms in the same county-year that have different exposures to at-risk areas in other locations. Standard errors are clustered at the county-level. Table 8 displays the results.

[Insert Table 8]

As shown in Table 8, the interaction coefficients on *Lower Exposure* x *PostKBA* are positive and statistically significant. This suggests that exposure to biodiversity transition risk in a county induces multi-location firms to increase labor demand in less affected counties. The magnitude of the estimate is economically meaningful. Specifically, counties with lower biodiversity transition risk than the firm’s average exposure exhibit 3.7% higher annual job postings. Our results suggest that risk management within firms operates not only through internal restructuring in high-risk areas but also through shifting hiring activity towards locations where future regulatory constraints are less prevalent.

6 Conclusions

This paper provides novel evidence on how corporate employment responds to increased biodiversity transition risk. We use the adoption of the Key Biodiversity Areas Standard, a global scientific benchmark to identify areas of high biodiversity importance, as a source of variation that increases the *risk* of future land-use restrictions. We find that firms respond by reducing job postings in affected areas and reallocating portions of their labor to less exposed regions. This effect is concentrated among firms that make negative impacts on biodiversity. Moreover, cuts are stronger among production roles, while hiring in green and adaptive occupations increases. The effect is not driven by changes in capital investment or workers’ labor supply decisions. Our findings highlight how the private sector internalizes the risk of natural capital regulation even before formal protection is enacted.

From a policy perspective, our findings underscore the importance of predictable and well-communicated conservation planning. Transparent criteria for KBA identification can help firms incorporate biodiversity transition risk into long-term investment and workforce decisions without inducing abrupt dislocation. At the same time, complementary policies, such as targeted transition support and incentives for green innovation, can mitigate short-term adjustment costs in affected regions and industries.

More broadly, our results suggest that the success of global biodiversity frameworks depends not only on ecological science but also on the responsiveness of economic agents to regulatory expectations. Designing biodiversity policies that balance conservation effectiveness with economic adaptability remains a central challenge for policymakers and international organizations seeking to align private incentives with planetary boundaries.

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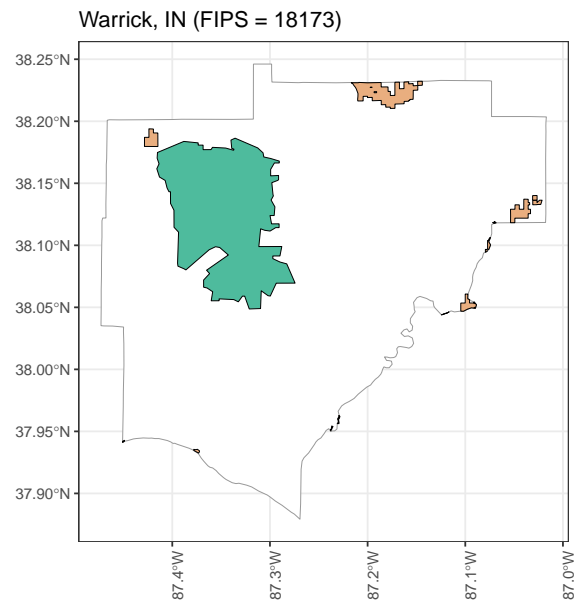


Figure 1: Warrick County, Indiana

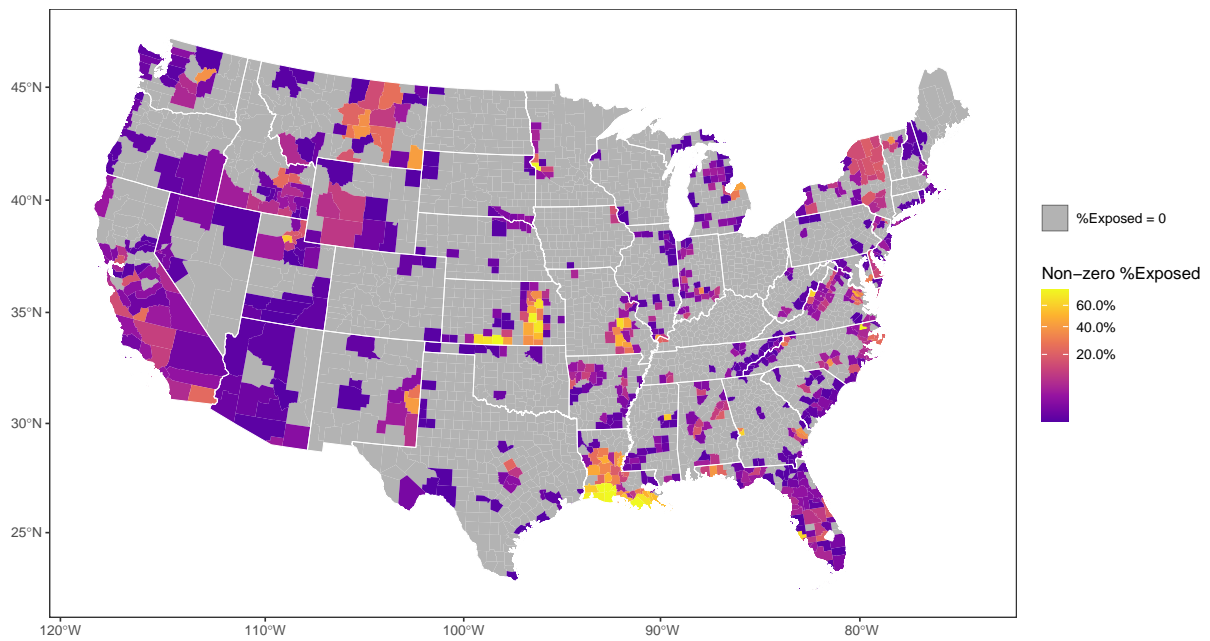


Figure 2: Counties with “to be protected” areas

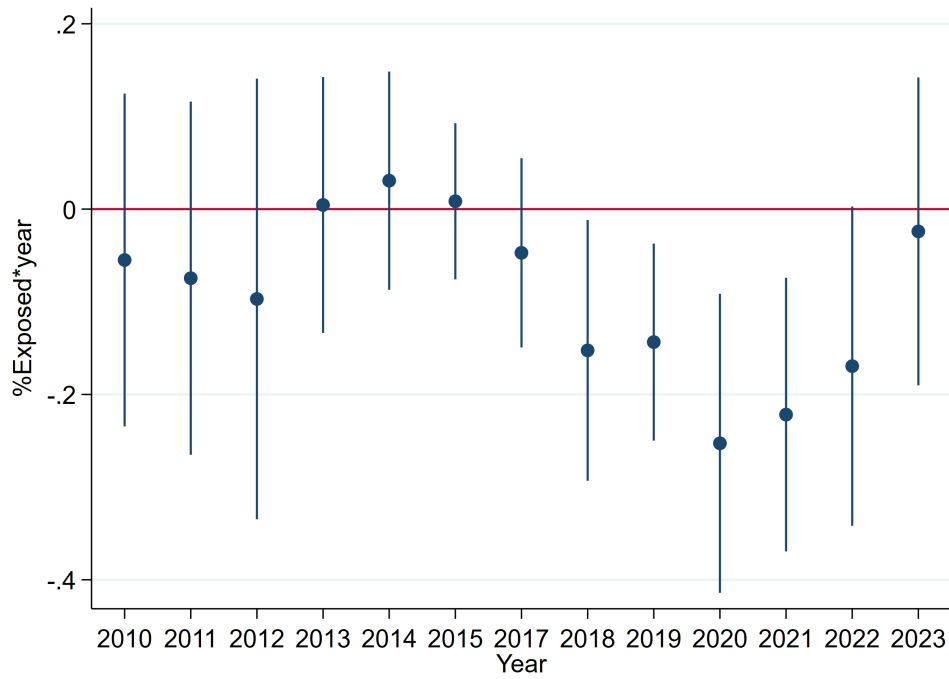


Figure 3: Dynamic effects of the 2016 KBA Standard on job posting activities

Notes: This figure displays the dynamic timing effects of the 2016 KBA Standard on job posting activities in exposed counties. This figure plots the coefficients of the interaction between *%Exposed* and time dummies every year over the 2010-2023 sample period. We report an annual time interval, and the excluded period is 2016 when the KBA Standard was established. The control variables and fixed effects are similar to those in Column 3 of Table 3. The legends indicate the 95% confidence intervals of the coefficient estimates.

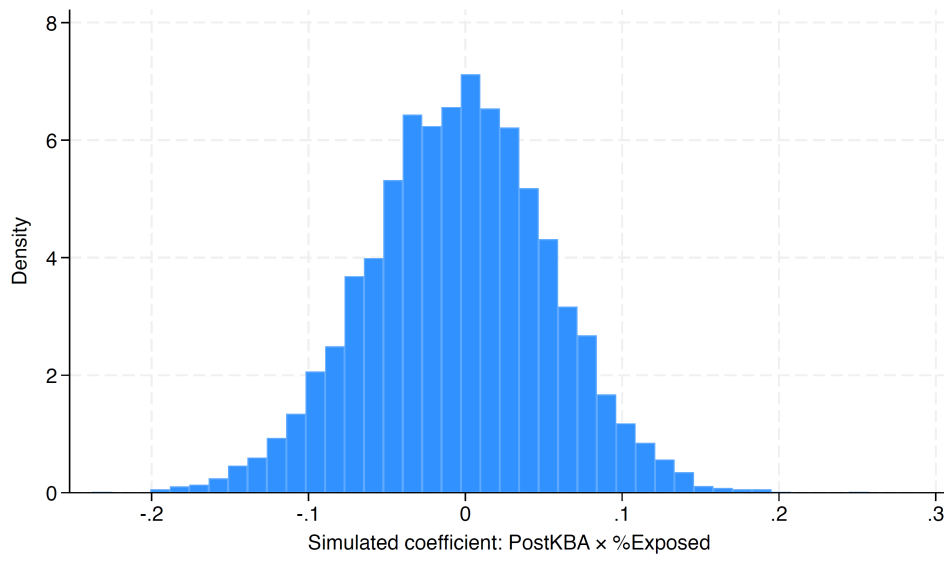


Figure 4: Placebo tests

Notes: This figure displays the distributions of the coefficient estimates on $\% \text{Exposed}$ from placebo regressions using specifications from Column 3 of Table 3. The dependent variable is $\ln(1 + \text{Job posting})$. The placebo process reshuffles a county's KBA exposure levels 10,000 times but maintains the original data structure by drawing KBA exposure levels from the original distributions without replacement.

Table 1: Summary Statistics

	#Obs	Mean	StDev	1st	99th
Exposures to KBAs					
%Exposed	897,939	0.016	0.066	0.000	0.306
Lower exposure	897,939	0.829	0.377	1.000	1.000
Outcome variables					
ln(1+ Job postings)	897,939	0.745	1.186	0.000	4.663
Number of job postings	897,939	5.527	16.660	0.000	144.000
ln(1+ Voluntary departures)	897,939	0.280	0.571	0.000	2.303
ln(1+ Involuntary departures)	897,939	0.132	0.426	0.000	2.079
ln(1+ Establishments)	237,793	0.968	0.499	0.693	3.178
ln(1+ Est openings)	237,793	0.090	0.261	0.000	1.099
ln(1+ Est closings)	237,793	0.084	0.258	0.000	1.099
%All green	327,411	0.473	0.788	0.000	4.240
%New & emerging green	327,411	0.009	0.034	0.000	0.200
%Enhanced green	327,411	0.271	0.519	0.000	3.000
%Increased demand green	327,411	0.173	0.384	0.000	2.000
%Production	346,499	0.158	0.276	0.000	1.000
%Adaptation	346,499	0.146	0.250	0.000	1.000
Firm-year controls					
ln(1+Total assets)	897,939	8.782	1.938	3.857	11.920
PPE/Total assets	897,939	0.198	0.145	0.017	0.700
CAPEX/Total assets	897,939	0.034	0.028	0.002	0.142
EBIT/Total assets	897,939	0.084	0.171	-0.517	0.315
Total debt/Total assets	897,939	0.603	0.265	0.117	1.280
Tobin's Q	897,939	1.921	0.850	0.826	4.953
Impact score ₂₀₁₃₂₀₁₅	897,939	0.812	0.875	0.000	4.000
Dependency score ₂₀₁₃₂₀₁₅	897,939	0.915	1.489	0.000	4.000
Firm-county-year controls					
ln(1+Employee counts)	897,939	1.914	1.220	0.703	5.963

Notes: This table provides descriptive statistics for the main variables used in the analyses. 'Ln' denotes that a variable is measured in natural logarithms. Variable descriptions are in Appendix Table A.1.

Table 2: Parallel trends

	(1)	(2)	(3)	(4)	(5)	(6)
	Non-exposed counties	N	Exposed counties	N	Differences	<i>t</i> -stat
Δ Number of job postings ₂₀₁₅	0.495	1,320	0.344	475	0.151	0.828
Δ Voluntary departures ₂₀₁₅	0.172	1,101	0.169	384	0.003	0.054
Δ Involuntary departures ₂₀₁₅	0.117	893	0.099	328	0.018	0.261
Δ Number of establishments ₂₀₁₅	0.043	1,324	0.046	484	-0.003	-0.212
Δ %All green ₂₀₁₅	0.458	1,111	0.327	396	0.131	0.890
Δ %Production ₂₀₁₅	0.309	1,147	0.224	394	0.085	0.539
Δ %Adaptation ₂₀₁₅	0.304	1,056	0.198	368	0.107	0.776
Δ Number of job postings ₂₀₁₃₂₀₁₅	0.612	3,759	0.512	1,364	0.585	1.069
Δ Voluntary departures ₂₀₁₃₂₀₁₅	0.209	3,154	0.162	1,145	0.196	1.032
Δ Involuntary departures ₂₀₁₃₂₀₁₅	0.062	2,595	0.052	1,000	0.059	0.275
Δ Number of establishments ₂₀₁₃₂₀₁₅	0.040	3,937	0.037	1,436	0.004	0.421
Δ %All green ₂₀₁₃₂₀₁₅	0.646	3,143	0.639	1,128	0.007	0.068
Δ %Production ₂₀₁₃₂₀₁₅	0.532	3,167	0.491	1,125	0.041	0.389
Δ %Adaptation ₂₀₁₃₂₀₁₅	0.343	2,936	0.298	1,062	0.045	0.639

Notes: This table presents the results of parallel trend tests for the main outcome variables. We aggregate the data at the county-level and compare first differences in the outcome variables for 2015 and over the longer 2013–2015 period. Exposed counties are those with a positive %*Exposed* and non-exposed counties are those those with a zero %*Exposed*. Columns 1 and 3 report the mean annual change in the dependent variables in non-exposed and exposed counties, respectively. Columns 2 and 4 display the number of observations in non-exposed and exposed counties, respectively. Column 5 shows the differences in mean values between exposed and non-exposed counties, while Column 6 reports two-tailed *t*-statistics for these differences. Variable descriptions are in Appendix Table A.1.

Table 3: 2016 KBA Standard and Job Postings

Dependent variable: $\ln(1+Job\ postings)$			
	(1)	(2)	(3)
PostKBA x %Exposed	-0.136** [0.055]	-0.108** [0.054]	-0.119** [0.052]
$\ln(1+Total\ assets)$		0.230*** [0.005]	0.167*** [0.005]
PPE/Total assets		0.436*** [0.033]	0.298*** [0.032]
CAPEX/Total assets		0.350*** [0.066]	0.281*** [0.066]
EBIT/Total assets		-0.066*** [0.008]	-0.049*** [0.009]
Total debt/Total assets		-0.009 [0.008]	-0.012 [0.007]
Tobin's Q		0.048*** [0.003]	0.042*** [0.003]
$\ln(1+Employee\ counts)$			0.598*** [0.007]
Observations	938,797	925,997	897,939
Firm FE	Yes	Yes	Yes
Job location county FE	Yes	Yes	Yes
Job location state-year FE	Yes	Yes	Yes
HQ state-year FE	Yes	Yes	Yes
NAICS2-year FE	Yes	Yes	Yes
Adjusted R^2	0.189	0.194	0.477

Notes: This table reports regression results estimating the effect of the establishment of the KBA Standard on firms' hiring activities in exposed counties. The dependent variable $\ln(1+Job\ postings)$ is the natural logarithm of one plus the number of job postings for full-time positions by a firm in a given county-year. *PostKBA* is a dummy variable that equals one from 2017 onward following the establishment of the KBA Standard, and zero otherwise. *%Exposed* is the proportion of the county's areas that are valuable for biodiversity but are not yet protected. Standard errors clustered at the job location county are reported in brackets. Variable descriptions are in Appendix Table A.1. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4: High biodiversity impact and dependency firms

Dependent variable: $\ln(1+Job\ postings)$			
	(1)	(2)	(3)
Impact score ₂₀₁₃₂₀₁₅ x PostKBA x %Exposed	-0.101*** [0.033]		-0.115*** [0.038]
Dependency score ₂₀₁₃₂₀₁₅ x PostKBA x %Exposed		-0.0001 [0.035]	-0.021 [0.037]
Observations	864,675	864,675	864,675
Control variables	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Job location county FE	Yes	Yes	Yes
Job location state-year FE	Yes	Yes	Yes
HQ state-year FE	Yes	Yes	Yes
NAICS2-year FE	Yes	Yes	Yes
Adjusted R^2	0.474	0.474	0.474

Notes: This table examines heterogeneity in the hiring reduction effects across firms with strong biodiversity dependencies and impacts. The dependent variable $\ln(1+Job\ postings)$ is the natural logarithm of one plus the number of job postings for full-time positions by a firm in a given county-year. *PostKBA* is a dummy variable that equals one from 2017 onward following the establishment of the KBA Standard, and zero otherwise. *%Exposed* is the proportion of the county's areas that are valuable for biodiversity but are not yet protected. *Impact score*₂₀₁₃₂₀₁₅ (*Dependency score*₂₀₁₃₂₀₁₅) are the three-year average biodiversity impact (dependency) score before the enactment of the 2016 KBA Standard. Control variables are similar to those in Column 3 of Table 3 and are collapsed for brevity. Standard errors clustered at the job location county are reported in brackets. Variable descriptions are in Appendix Table A.1. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 5: 2016 KBA Standard and Employee Departures

Dependent variables	$\ln(1+Voluntary\ departures)$ (1)	$\ln(1+Involuntary\ departures)$ (2)
PostKBA x %Exposed	0.004 [0.016]	0.008 [0.014]
Observations	897,939	897,939
Control variables	Yes	Yes
Firm FE	Yes	Yes
Job location county FE	Yes	Yes
Job location state-year FE	Yes	Yes
HQ state-year FE	Yes	Yes
NAICS2-year FE	Yes	Yes
Adjusted R^2	0.567	0.388

Notes: This table reports regression results estimating the effects of the establishment of the KBA Standard on workers' involuntary and voluntary departures from exposed counties. We define a departure as "voluntary" if an employee's job start date at the new firm is within six months of the date they depart from the former employer, and "involuntary" otherwise. The dependent variables are $\ln(1+Voluntary\ departures)$ and $\ln(1+Involuntary\ departures)$, the natural logarithm of one plus the number of voluntary and involuntary departures from a firm in a given county-year, respectively. *PostKBA* is a dummy variable that equals one from 2017 onward following the establishment of the KBA Standard, and zero otherwise. Control variables are similar to those in Column 3 of Table 3 and are collapsed for brevity. Standard errors clustered at the job location county are reported in brackets. Variable descriptions are in Appendix Table A.1. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 6: 2016 KBA Standard and green hiring

<i>Panel A: 2016 KBA Standard and the demand for green occupations</i>				
Dependent variables:	<i>%All green</i> (1)	<i>%New & Emerging</i> (2)	<i>%Enhanced</i> (3)	<i>%Increased demand</i> (4)
%Exposed*PostKBA	0.051 [0.046]	-0.004 [0.002]	0.013 [0.029]	0.059** [0.025]
Observations	327,153	327,153	327,153	327,153
Control variables	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Job location county FE	Yes	Yes	Yes	Yes
Job location state-year FE	Yes	Yes	Yes	Yes
HQ state-year FE	Yes	Yes	Yes	Yes
NAICS2-year FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.235	0.188	0.173	0.247
<i>Panel B: 2016 KBA Standard and green skill requirements</i>				
Dependent variables:	<i>Has green skills</i> (1)	<i>#Green skills</i> (2)	<i>#Green skills/#All skills</i> (3)	
%Exposed*PostKBA	-0.003 [0.010]	-0.006 [0.012]	-0.0004 [0.001]	
Observations	7,283,634	7,383,120	7,283,634	
Control variables	Yes	Yes	Yes	
6-digit O*NET FE	Yes	Yes	Yes	
Firm FE	Yes	Yes	Yes	
Job location county FE	Yes	Yes	Yes	
Job location state-year FE	Yes	Yes	Yes	
HQ state-year FE	Yes	Yes	Yes	
NAICS2-year FE	Yes	Yes	Yes	
Adjusted R^2	0.206	0.107	0.145	

Notes: This table reports regression results estimating the effect of the establishment of the KBA Standard on green hiring. In Panel A, the dependent variables are the share of job postings belonging to one of the following three O*NET green categories: *New & Emerging* (Column 2), *Enhanced* (Column 3), and *Increased Demand* (Column 4). We also calculate an overall green share capturing jobs that fall into any of these categories (Column 1). In Panel B, the dependent variables are: *Has green skills*, a dummy variable that equals one if a job posting contains at least one green skill (Column 1), *#Green skills*, the number of green skills required in a job posting (Column 2), and *#Green skills/#All skills*, the share of green skills among all skills required in a given job (Column 3). *PostKBA* is a dummy variable that equals one from 2017 onward following the establishment of the KBA Standard, and zero otherwise. Control variables are similar to those in Column 3 of Table 3 and are collapsed for brevity. Standard errors clustered at the job location county are reported in brackets. Variable descriptions are in Appendix Table A.1. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 7: 2016 KBA Standard and workforce restructuring

Dependent variables:	<i>%Production</i> (1)	<i>%Adaptation</i> (2)
%Exposed*PostKBA	-0.026** [0.013]	0.018* [0.011]
Observations	346,254	346,254
Control variables	Yes	Yes
Firm FE	Yes	Yes
Job location county FE	Yes	Yes
Job location state-year FE	Yes	Yes
HQ state-year FE	Yes	Yes
NAICS2-year FE	Yes	Yes
Adjusted R^2	0.330	0.163

Notes: This table reports regression results estimating the effect of the establishment of the KBA Standard on the composition of firms' job postings. The dependent variables are the share of job postings classified as production-related (Column 1) and adaptation-related (Column 2). We classify job postings into either *Production-related* or *Adaptation-related* based on their 2-digit SOC code. *Production-related* are occupations that require physical presence and involve on-site activities, including those in Construction and Extraction (47), Production (51), Transportation and Material Moving (53), Building and Grounds Cleaning and Maintenance (37), or Farming, Fishing, and Forestry (45). *Adaptation* are occupations that support firms' technical and administrative compliance efforts, including Legal (23), Office and Administrative Support (43), Architecture and Engineering (17), and Life, Physical, and Social Science (19). *PostKBA* is a dummy variable that equals one from 2017 onward following the establishment of the KBA Standard, and zero otherwise. Control variables are similar to those in Column 3 of Table 3 and are collapsed for brevity. Standard errors clustered at the job location county are reported in brackets. Variable descriptions are in Appendix Table A.1. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 8: 2016 KBA Standard and labor reallocation

Dependent variable: $\ln(1+Job\ postings)$		
	(1)	(2)
PostKBA x Lower Exposure	0.050** [0.021]	0.037** [0.017]
Observations	938,797	925,997
Control variables	No	Yes
Firm FE	Yes	Yes
Job location county FE	Yes	Yes
Job location state-year FE	Yes	Yes
HQ state-year FE	Yes	Yes
NAICS2-year FE	Yes	Yes
Adjusted R^2	0.189	0.194

Notes: This table reports regression results estimating the effect of the KBA Standard on labor reallocation. *Lower Exposure* is a dummy variable that equals to one if a firm's *%Exposed* in a given county is lower than the same firm's employee-weighted average exposure across its other counties. *PostKBA* is a dummy variable that equals one from 2017 onward following the establishment of the KBA Standard, and zero otherwise. Control variables are similar to those in Column 3 of Table 3 and are collapsed for brevity. Standard errors clustered at the job location county are reported in brackets. Variable descriptions are in Appendix Table A.1. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix Table A.1: Variable descriptions

Variable	Descriptions
Data source: KBAs and PAD-US	
%Exposed	The proportion of the county's areas that are valuable for biodiversity but are not yet protected.
Lower Exposure	= 1 if a firm's <i>%Exposed</i> in a given county is lower than the same firm's employee-weighted average exposure across its other counties.
Data source: Lightcast	
$\ln(1 + \text{Job postings})$	The natural logarithm of one plus the number of job postings for full-time positions by a firm in a given county-year.
%All green	The share of job postings belonging to any of the following O*NET green categories: New & Emerging, Enhanced, and Increased Demand.
%New & Emerging	The share of job postings belonging to O*NET's <i>Green New & Emerging</i> .
%Enhanced	The share of job postings belonging to O*NET's <i>Green Enhanced Skills</i> .
Has green skills	= 1 if a job posting requires at least one green skill.
#Green skills	The number of green skills required in a given job posting.
#Green skills/#All skills	The share of green skills among all skills required in a given job posting.
%Production	The share of job postings classified as production-related based on 2-digit SOC code: Construction and Extraction, Production, Transportation and Material Moving, Building and Grounds Cleaning and Maintenance, Farming, Fishing, and Forestry.
%Adaptation	The share of job postings classified as adaptation-related based: Legal, Office and Administrative Support, Architecture and Engineering, and Life, Physical, and Social Science.
Data source: Revelio Labs	
$\ln(1 + \text{Voluntary departures})$	The natural logarithm of one plus the number of voluntary departures from a firm in a given county-year. A voluntary departure is when the gap between an employee job's end date and the start date of their next job is less than six months.
$\ln(1 + \text{Involuntary departures})$	The natural logarithm of one plus the number of involuntary departures from a firm in a given county-year. An involuntary departure is when the gap between an employee job's end date and the start date of their next job is more than six months.
$\ln(1 + \text{Employee counts})$	The natural logarithm of one plus the number of employees in a given firm-county-year.
Data source: Compustat/CRSP	
$\ln(1 + \text{Total assets})$	Natural logarithm of one plus total assets.
PPE/Total assets	Property, Plant, and Equipment divided by total asset.
CAPEX/Total assets	Capital expenditure divided by total assets.

Appendix Table A.1: Variable descriptions – Continued

Variable	Descriptions
EBIT/Total assets	Earnings before interest and taxes divided by total assets.
Total debt/Total assets	Total debt divided by total assets.
Tobin's Q	Market value of assets (total assets + market value of common equity – common equity – deferred taxes)/(0.9*book value of assets + 0.1*market value of assets)
Data source: ENCORE	
Impact score ₂₀₁₃₂₀₁₅	The average firm-level biodiversity impact score over 2013–2015, calculated as the number of revenue-weighted “very high” impact drivers based on each firm’s industry composition.
Dependency score ₂₀₁₃₂₀₁₅	The average firm-level biodiversity dependency score over 2013–2015, calculated as the number of revenue-weighted “very high” dependency based on each firm’s industry composition.

Notes: This table provides definitions and sources of variables used in the paper.

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ISSN 2194-2188



The IWH is funded by the federal government and the German federal states.