Employment Responses to Increased Biodiversity Transition Risk

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Abstract

This paper examines how firms adjust the *number* and *type* 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. This effect is concentrated among firms that make negative impacts on biodiversity. Cuts are stronger among site-dependent roles, while hiring in green and adaptive occupations increases. There is no impact on aggregate firm-level outcomes, consistent with labor being reallocated to less exposed regions. 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, Labor Demand, Labor Supply, Key Biodiversity Areas.

JEL Codes: J01, G30, Q57

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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., 2026). 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 example, Chevron has adjusted routing and deferred infrastructure expansions near California wetlands to mitigate potential Endangered Species Act exposure.[1] Similarly, 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?

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

[2]Orlando 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 through the lens of firms' human capital investment decisions. Unlike physical capital, investment in human capital is largely irreversible, involving substantial upfront recruitment and training costs, as well as potential compensation expenses if contracts are terminated early. This makes human capital investment particularly complex and sensitive to the uncertainty stemming from evolving biodiversity regulations. Regulatory uncertainty can thus increase the option value of waiting, leading firms to delay or scale back hiring decisions (Bernanke, 1983; Dixit, 1979; Bloom et al., 2007). At the same time, human capital plays a central role in firms' ability to adapt to evolving biodiversity regulation. According to the strategic growth option theory, hiring workers with suitable environmental and compliance-related expertise can preserve future growth opportunities by enhancing firms' flexibility to operate under stricter biodiversity protection frameworks. As a result, while uncertainty encourages caution due to the irreversibility of labor investment, it may also induce selective investment in specific types of human capital that mitigate biodiversity-related regulatory risk.

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: exposed locations that are *not yet* protected but are considered valuable for biodiversity. Following the KBA Standard, firms with operations in these unprotected key biodiversity areas will be exposed to increased risk of future land-use restrictions and environmental regulation. As a result, these locations

[3]Survey 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).

represent a natural source of biodiversity transition risk since regulatory constraints are not yet in place but have become increasingly foreseeable.

Our analyses make use of big data on millions of job postings from Lightcast. Each posting contains detailed information on the employer, job title, location, and required education, experience, and skills. This setting offers several advantages. First, unlike capital investment data, which are typically observed only at the aggregate firm-level, job postings are available at a precise job-location level. This granularity allows us to directly link county-level KBA exposures to firms' demand for jobs located in the same county. Second, the rich job-level information enables us to provide novel, labor-specific insights on 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.

Using a difference-in-differences (DID) design on a firm-county-year panel of public U.S. manufacturing firms from 2010 to 2023, we document a decline in firms' job posting activities in counties with a greater share of unprotected key biodiversity areas following the introduction of the 2016 KBA Standard. *Within-firm* analyses indicate that a one standard deviation increase in the county's exposure is associated with a 0.8% reduction in annual job postings.[4] This effect accumulates to a roughly 4% reduction in hiring over a five-year period.

All regression specifications include firm, job location county, as well as headquarters' state × year, job location state × year, and industry (defined at the two-digit NAICS code) × year fixed effects. This allows us to account for a range of unobserved factors that can affect job posting activities, including time-invariant characteristics at the firm-level (e.g.,

[4]A one-standard deviation increase in KBA exposure is comparable to the difference between Greene County, New York (9.7% of land classified as unprotected, high biodiversity value) and nearby Saratoga County, New York (16.5%). The two counties are geographically proximate and share similar amenities and economic linkages.

long-run technology adoption), county-level (e.g., geographic amenities), as well as broader time-varying industry- and state-level factors, such as changes in macroeconomic conditions, industry-wide technological shocks, or state-level environmental or labor-related policies.

We next examine the economic mechanism underlying this decline in hiring. Our analyses indicate that firms' hiring responses to the 2016 KBA Standard are primarily driven by heightened regulatory risk. In particular, the reduction in hiring is concentrated among firms whose activities have larger negative impacts on biodiversity.[5] 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. The resulting increase in expected compliance and enforcement costs raises the perceived risk of expanding human capital, 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 using the placebo exposures, 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, where economic activity is already constrained and therefore should not be affected by the 2016 KBA Standard. Consistent with this, we find no change in job postings in already protected areas, whereas at-risk areas exhibit a decline in job postings.

Next, we rule out the alternative explanation that changes in capital investment drive the decline in hiring. Because capital investment is typically observed only at the aggregate firm-level, we proxy for capital investment using establishment-level activity, specifically

[5]We measure firms' biodiversity impact using data from the Exploring Natural Capital Opportunities, Risks and Exposure (ENCORE) platform. Following Garel et al. (2026), we construct firm-year impact scores as the revenue-weighted number of "very high" biodiversity impacts based on each firm's industry composition.

the opening and closing of establishments. If firms expect negative business conditions in areas that could become protected, they may opt to shut down existing establishments or refrain from opening new ones, which could in turn lead to fewer job postings. Using establishment-level data from the Toxic Release Inventory (TRI), we find no evidence of changes in the number of establishments, establishment openings, or establishment closings in exposed counties following the introduction of the KBA Standard. These findings suggest that firms primarily adjust human capital investment in response to heightened biodiversity transition risk.

We also 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.[6] We find no significant changes in either voluntary or involuntary employee departures from 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.

Our further analyses show that, beyond adjusting the *number* of job postings, firms also change the *types* of workers they hire in response to heightened 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

[6]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. Our results are not sensitive to how this gap is defined.

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.

Our further findings suggest that firms' hiring adjustments remain primarily adaptive rather than mitigating. 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.[7] 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.

In the final part of the paper, we show that firms also respond to the KBA Standard by reallocating portions of their labor force toward less exposed counties where regulatory risks are lower. Using the methodology developed by Giroud and Mueller (2019), we find that greater exposure to biodiversity transition risk in one county leads multi-location firms to increase labor demand in less affected counties.

This reallocation behavior has important implications for aggregate firm-level outcomes. Our results indicate that the introduction of the KBA Standard does not adversely affect exposed firms' operating profitability or physical capital investment. These findings suggest that by reallocating labor across locations, firms are able to insulate their profitability and physical investment from the immediate effects of increased biodiversity transition risk. In contrast, firms with greater exposure to areas at risk of future biodiversity protection exhibit weaker future growth prospects following the KBA Standard, consistent with increased regulatory uncertainty reducing exposed firms' perceived growth opportunities.

Our paper makes important contributions to various strands of the literature. We are related to an active research area that examines how biodiversity loss and the prospect of

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

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 findings that firms actively adjust their hiring in response to biodiversity transition risk build upon and extend prior studies, which show that investors perceive biodiversity-related policy signals as economically meaningful sources of risk. For example, 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. (2026) 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.

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 geographic variation, allowing us to study *within-firm* labor reallocation in response to increased biodiversity transition risk. This way, we complement existing approaches in measuring biodiversity transition and impact risk, including the biodiversity news index (Giglio et al., 2026), the corporate biodiversity footprint (Garel et al., 2024), and firm-level nature dependence (Garel et al., 2026). Our work also complements Akbari et al. (2026), 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 employement 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. 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. (2024) 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 findings highlight 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 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.[8] 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. Survey evidence from 11 countries indicates a 164% increase in key biodiversity areas following its adoption (Plumptre et al., 2025). At the same time, the 2016 KBA Standard increases the likelihood that key biodiversity areas become focal points for future protected or conserved area designations as governments and international bodies expand coverage to conserve biodiversity.[9] Consistent with this, survey evidence indicates

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

[9]Protected 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.

that the share of key biodiversity areas overlapping with protected areas increases from 25% to 32% after adoption.

This creates substantial regulatory uncertainty for firms operating within or near key biodiversity areas. Once an area is granted protected status, companies may face stricter biodiversity regulations, mandatory environmental impact assessments, or restrictions on land use and resource extraction. Importantly, firms do not need to have operations directly overlapping with key biodiversity areas to be affected. Heightened regulatory scrutiny often extends to surrounding zones and connected economic activities, meaning that nearby firms may also face tighter compliance requirements or indirect operational constraints. As a result, regulatory measures may affect not only firms located inside key biodiversity areas, but also those operating in their vicinity. Such changes increase firms' exposure to legal and compliance risks, including fines, litigation, or the potential loss of operating permits if evolving biodiversity protection frameworks are not met. To mitigate these risks, firms operating near key biodiversity areas may need to strengthen their environmental strategies, adjust business activities, scale back hiring, or, in some cases, shut down establishments altogether.

Moreover, the timing and likelihood of converting key biodiversity areas into protected areas are highly uncertain, and the magnitude of the associated costs is difficult to anticipate. Local governments may adopt different timelines, enforcement intensities, 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 2016 KBA Standard represents a source of biodiversity transition risk, generating regulatory uncertainty for business and production activities located within or near areas at risk of designation. Consequently, the greater the share of a county's land classified as valuable for biodiversity, the higher the transition risk faced by firms operating in that county.

2.2 The effect on labor demand

As discussed in Section 2.1, 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 key biodiversity areas 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).[10] 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. Key biodiversity areas are essential for safeguarding threatened species and maintaining genetic diversity, and their data are widely

[10]see, https://www.keybiodiversityareas.org/

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).[11] 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.[12]

In the third step, we arrive at a set of "to be protected" areas, defined as areas that are classified as key biodiversity areas but are not yet protected. While firms can still operate in these regions, there is a risk that these areas will be designated protected areas following the establishment of the 2016 KBA Standard.[13]

Of the 3,141 counties with available data, 777 (25%) have at least some areas in the county classified as a key biodiversity area, while 678 (22%) have at least some areas already been

[11] see, https://shorturl.at/ivt8r

[12] As shown in Internet Appendix IA3, our results are robust when protected areas are defined as those with GAP status 1 or 2.

[13] We 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.

designated as protected areas. Although there are expected overlaps between key biodiversity areas and protected areas (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 key biodiversity areas. An example of a key biodiversity 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.

[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 are geographically dispersed across the country and do not cluster in specific regions such as the West or the East Coast. In these 774 counties, 8.8% of land is, on average, unprotected and is at risk of future protection. This is sizable enough to induce uncertainty over which areas will ultimately be 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 kills 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 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 the risk of land being designated protected areas. Manufacturing firms also tend to be among the more pollution-intensive sectors, making them particularly exposed to increased biodiversity transition risk.[15] We further restrict the sample to job postings for full-time positions and exclude firms with missing total assets and single-location firms that operate in a single county.

[14] To 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.

[15] For example, firms in knowledge-based sectors are far less sensitive to the risk of land-use restrictions since their business activities do not heavily rely on physical land use.

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 Lightcast-Revelio-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 The KBA Standard and job posting quantity

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 key biodiversity areas, and zero otherwise. $\%Exposed_c$ is the proportion of county c's area that is classified as valuable for biodiversity but remains unprotected, expressed relative to the county's total unprotected land area. 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.

All regression specifications control for *%Already protected*, the share of a county's area that is *already* designated as protected areas. Already protected areas reflect past policy decisions, and economic activities in these areas are subject to existing restrictions. As a result, ex ante, we expect already protected areas to be less relevant for firms' hiring decisions. In contrast, *at-risk* areas should be more consequential because they reflect future regulatory risk. Moreover, to account for existing economic activities of the firm in the county, we include lagged *Ln(1+Employee count)*, defined as the natural logarithm of the firm's total employment in a given county-year.

Finally, 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.

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 based on two-tailed t-tests. 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 Main results: KBA Standard and job posting quantity

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* x*PostKBA* are negative and statistically significant. The estimate in the full specification in Column 3 indicates that a one standard deviation in the county's exposure levels—equivalent to the difference between Greene County, New York (9% of land classified as unprotected, high biodiversity value) and Saratoga County, New York (16%)—is associated with a 0.8% (= 0.069 x 0.116) reduction in annual job postings. This corresponds to a cumulative 4% reduction in hiring over a five-year period. While the effect appears relatively modest, subsequent sections show substantial heterogeneity underlying this result, with some firms reducing hiring more than others.

In contrast, consistent with already protected areas reflect past policy decisions, the interaction coefficients on *%Already Protected* x *PostKBA* are statistically insignificant and small in magnitude. 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 event study estimates of the dynamic effects of the KBA Standard on the number of job postings. The figure plots coefficients on interactions between year indicators and continuous county-level exposure measures, *%Exposed* and *%Already Protected*, over

the period 2010–2023, with 2016 omitted as the year in which the KBA Standard was established. The estimated effects associated with *%Exposed* are statistically insignificant prior to 2016 and begin to materialize from 2018 onward. From that point, counties with a higher share of land classified as exposed experience persistently lower job postings, with the magnitude of the effect increasing over time. In contrast, coefficients on interactions between *%Already Protected* and year indicators are statistically insignificant throughout the sample period, strengthening our interpretation that the observed decline in job postings is driven by exposure to at-risk areas and future regulatory uncertainty rather than by existing protection status.

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.[16] 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 a placebo test using randomized exposed counties. The randomization process shuffles 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 estimate using the placebo data is 0.000. In contrast, the coefficient estimate using the actual data is significantly larger in absolute terms. In particular, the estimate using the actual data is –0.116, 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;

[16] If 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.

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.

Internet Appendix IA3 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 key biodiversity areas: California, New York, Vermont, and Hawaii. This is to address the concern that Democrat states tend to adopt proactive environmental policies and this could confound our estimates.

4.4 Economic mechanisms underlying the hiring decline

To shed light on the economic mechanism underlying the decline in hiring following the 2016 KBA Standard, we examine heterogeneity across firms. In particular, if firms reduce hiring in response to heightened regulatory risk induced by the KBA Standard, this response should be most pronounced among firms whose activities exert greater negative impacts on biodiversity and face higher expected regulatory scrutiny and compliance costs.

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;[17] and (2) an *Impact score*, which captures the extent to which its activities negatively affect biodiversity.[18]

Following Garel et al. (2026), 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. (2026), 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.[19]

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]

[17] ENCORE 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.

[18] ENCORE 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.

[19] Examples 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*$_{20132015}$ × *%Exposed* × *PostKBA* are negative and statistically significant. This indicates that the reduction in hiring following the implementation of the 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* × *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. Moreover, the triple interaction coefficients on *Dependency score*$_{20132015}$ × *%Already protected* × *PostKBA* and *Impact score*$_{20132015}$ × *%Already protected* × *PostKBA* are also statistically insignificant. Since economic activities in protected areas are already restricted, firms' biodiversity impacts or dependencies do not differentially affect hiring decisions in these areas.

Taken together, the results in Table 4 indicate that firms' hiring responses to the 2016 KBA Standard are largely driven by heightened regulatory risk. As conservation protections expand, firms that make negative impacts on biodiversity face increased regulatory scrutiny and potential sanctions, raising the expected costs and uncertainty of future operations. This heightened uncertainty increases the perceived risk of additional human capital investment, leading these firms to scale back hiring.

4.5 Ruling out alternative explanations

In this subsection, we rule out alternative explanations of our main results. In particular, we show that our findings are not driven by changes in physical capital investment or by concurrent changes in workers' labor supply decisions.

4.5.1 Are the effects driven by establishment closures and openings?

One may argue that the reduction in job postings may be driven by firms reducing their physical capital investment, anticipating deteriorating business conditions in areas that may become protected. Because capital investment is typically observed only at the aggregate firm-level, we proxy for capital investment using establishment-level activity, specifically establishment openings and closures. This allows us to exploit within-firm geographic variation across locations, where differences in KBA exposure arise. In particular, we analyze firms' establishment patterns in exposed counties following the establishment of the 2016 KBA Standard.

To identify the number of establishments for each firm–county–year, we use establishment-level data from the Toxic Release Inventory (TRI). The TRI is particularly well suited for this purpose because it provides a facility-level census of environmentally regulated production sites, allowing us to directly observe the entry and exit of plants that are subject to binding environmental and land-use constraints.[20] We obtain the universe of TRI facilities from the TRI Basic files, aggregate facility records to the parent company

[20] TRI reporting is mandatory for facilities in regulated industries that exceed chemical reporting thresholds, which enables consistent tracking of individual production sites over time. This reporting design implies that the resulting sample is smaller than in broad establishment datasets (such as NETS) since TRI excludes non-production establishments, facilities operating below reporting thresholds, and firms in sectors where environmental regulation is less salient. There is substantial overlap between our sample of manufacturing firms and those covered by the TRI database.

level, and link TRI parent companies to Compustat firms by name.[21] We define a firm's establishments as distinct TRI reporting facilities, identified by facility identifiers (TRIFD).

For each firm-county-year, we count the number of active facilities reporting to TRI. To capture establishment dynamics, we construct a balanced panel of facility–year observations. Facility openings (closures) are defined as transitions from non-reporting to reporting (reporting to non-reporting) status across consecutive years. We then aggregate these measures to the firm-county-year level, yielding the total number of operating facilities and the number of facility openings and closures in each firm-county-year.

Table 5 reports the results. The dependent variables are the number of establishments, establishment openings, and establishment closures by a firm in a given county-year. The regressions include a set of control variables and fixed effects similar to those in Column 3 of Table 3.

[Insert Table 5]

As shown in Table 5, there is little evidence that firms close down establishments or refrain from opening new establishments in exposed areas following the introduction of the 2016 KBA Standard. Specifically, the interaction coefficients on $\%Exposed$ x $PostKBA$ are statistically insignificant for establishment counts (Column 1), establishment openings (Column 2), as well as establishment closures (Column 3). Overall, the results in Table 5 do not support the interpretation that the decline in job postings is driven by establishment closures or, more generally, by changes in physical capital investment in exposed areas.

4.5.2 Are the effects driven by labor supply decisions?

Next, we evaluate whether the decline in job postings could instead be driven by changes on the labor supply side. To do this, we examine whether employees in exposed counties are

[21] We standardize firm names in both TRI and Compustat by removing punctuation, legal suffixes (e.g., Inc., Corp., Ltd.), and special characters, and by harmonizing common variants. We then apply name-based fuzzy matching, retaining only exact or near-exact matches. Ambiguous cases are resolved through manual verification.

less likely to leave their jobs following the 2016 KBA Standard. Finding no evidence of lower voluntary departures would suggest 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.[22]

[Insert Table 6]

Table 6 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 similar to those in Column 3 of Table 3. 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 increased biodiversity transition risk by reducing new hiring.

[22] We obtain similar results when using alternative windows of three or twelve months.

5 The KBA Standard and job posting composition

A reduction in overall hiring may not be the only way firms adjust their labor force in response to increased biodiversity transition risk. Because biodiversity regulation changes the set of constraints under which firms operate, this could create incentives to reconfigure their workforce. Consistent with the notion of human capital as a strategic growth option, firms may respond to regulatory uncertainty by reallocating labor toward roles and skills that facilitate adaptation to stricter biodiversity protection regimes. Consequently, both investment irreversibilty and strategic growth options can operate as concurrent channels, with firms adjusting workforce composition alongside reductions in hiring.

Specifically, we hypothesize that firms may adjust the composition of their workforce in the following ways. First, firms may change the types of occupations they recruit for if biodiversity constraints or regulatory requirements alter 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 across job role types that differ in their exposure to biodiversity constraints or in 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*.[23] 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 installers, 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

[23]https://www.onetcenter.org/reports/Green.html

occupation has long existed; (3) *Green Increased Demand,* occupations where demand increases because of green economy trends, without major changes to tasks. An example is 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. The regression specifications include a set of fixed effects and control variables similar to those in Column 3 of Table 3.

[Insert Table 7]

Table 7 displays the results. We find that a one–standard-deviation increase in exposure is associated with a 3.4% (=$(0.052 \times 0.069)/0.12$) increase in the demand for *Green Increased Demand,* relative to its mean. Thus, consistent with the strategic growth option theory, firms respond to increased biodiversity transition risk by expanding hiring in green occupations to strengthen their capacity to comply with biodiversity protection frameworks. In contrast, we find no significant changes in the shares of *Green Enhanced Skills* or *Green New & Emerging* occupations. Taken together, these findings suggest that firms' responses reflect compliance-oriented adjustments within existing roles rather than structural shifts toward new or innovation-driven capabilities, indicating that green hiring responses are primarily adaptive rather than transformative.

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.[24] 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

[24]Lightcast 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.

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 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.[25]

Table 8 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 Table 7 that biodiversity transition risk does not lead firms to embed greater green skills within the same roles.

The third test examines whether firms shift their overall workforce composition. We hypothesize that firms facing stricter land-use restrictions, higher biodiversity compliance costs, or increased monitoring requirements reduce demand for roles tied to local physical operations or activities that rely heavily on natural resource use, such as extraction, land development, or site maintenance. At the same time, firms 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) *Site-dependent* are job roles that require physical presence and involve on-site activities, including occupations in Building and Grounds Cleaning and Maintenance (37), Farming, Fishing, and Forestry (45), Construction and Extraction (47), Production (51), or Transportation and Material Moving (53); (ii) *Compliance-support* are job roles that support firms' technical and administrative compliance efforts, including Management (11), Business and Financial Operations (13), Computer and Mathematical(15), Architecture and Engineering (17), Life, Physical, and Social Science (19), Legal (23), and Office and Administrative Support (43). The regressions are at the

[25]We obtain similar results without O*NET fixed effects.

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.

[Insert Table 9]

Table 9 displays the results. In line with our expectations, the estimate in Column 1 indicates that the share of *Site-dependent* roles—those closely tied to local physical operations and reliant on natural resources—decreases following the establishment of the KBA Standard. In contrast, the share of *Compliance-support* roles increases (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 7—9 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.

6 Within-firm reallocation and firm-level outcomes

6.1 Within-firm reallocation

Having shown that firms reduce and structure the composition of their new hiring in counties at risk of protected-area designation, a natural question that arises is whether they 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 there 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* as 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:

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

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.

Unlike Equation 1, we are able to include job location county × year fixed effects in the reallocation regression. 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. We also include firm fixed effects to absorb time-invariant differences in hiring across firms, and headquarters' state × year, job location state × year, and industry × year fixed effects to control for broader time-varying industry- and state-level factors. Standard errors are clustered at the county-level. Table 10 displays the results.

[Insert Table 10]

As shown in Table 10, the interaction coefficients on *Lower Exposure* x *PostKBA* are significantly positive, indicating 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 toward locations where future regulatory constraints are less prevalent.

6.2 Firm-level outcomes

In a final test, we examine whether the KBA Standard affects firms' aggregate outcomes. Although firms reduce hiring in more exposed areas, our evidence suggests that they partially offset these effects by reallocating labor toward less affected counties. Thus, the aggregate impact of the KBA Standard on firm-level outcomes is not clear ex ante. To test this, we aggregate the data to the firm-year level and run the following firm-level regression:

$$y_{it} = \alpha + \beta PostKBA_t * FirmExposure_{it} + Controls_{it} + FE + \varepsilon_{it}, \quad (3)$$

y_{it} is one of the following dependent variables: i) *Tobin's Q,* the market value of total assets divided by book value of asset; ii) *EBIT/Total assets,* earnings before interest and taxes divided by total assets, and iii) *CAPEX/Total assets*, capital expenditures divided by total assets. These outcome variables respectively capture a firm's perceived growth opportunities, operating profitability, and physical capital investment. *Firm Exposure* measures a firm's average exposure to areas at risk of future biodiversity protection, calculated as the employment-weighted average *%Exposed* across counties. All regressions include firm and year fixed effect, and a set of lagged firm-level control variables similar to those specified in Equation 1. We also control for the interaction between $PostKBA$ and a firm's average exposure to already protected areas. Standard errors are clustered at the firm-level.

[Insert Table 11]

The results in Table 11 show that, following the introduction of the KBA Standard, firms with greater exposure to areas at risk of future biodiversity protection exhibit weaker future growth prospects, although the effect is only marginally statistically significant at the 10% level (Column 1). In contrast, we find no evidence that these firms experience lower operating profitability (Column 2) or reduce physical capital investment (Column 3). The results are consistent with increased regulatory uncertainty lowering exposed firms' growth opportunities, while leaving current operations and capital investment largely unaffected. Firms appear to respond by reallocating labor across locations, thereby insulating profitability and physical investment from the immediate effects of the KBA Standard.

7 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. 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. We further show that firms with greater exposure to areas at risk of future biodiversity protection do not experience lower profitability or cut physical capital investment following the introduction of the KBA Standard. This is consistent with firms being able to reallocate portions of their labor force to less exposed regions to insulate their profitability and physical investment from the immediate effects of increased biodiversity transition risk. Overall, 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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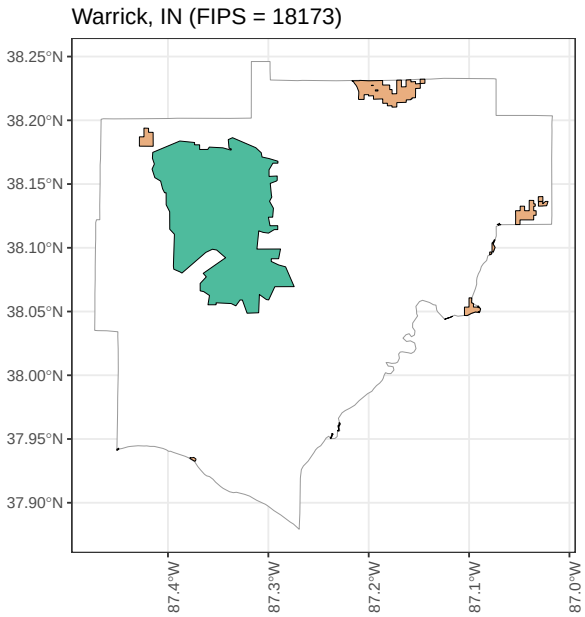


Figure 1: Warrick County, Indiana

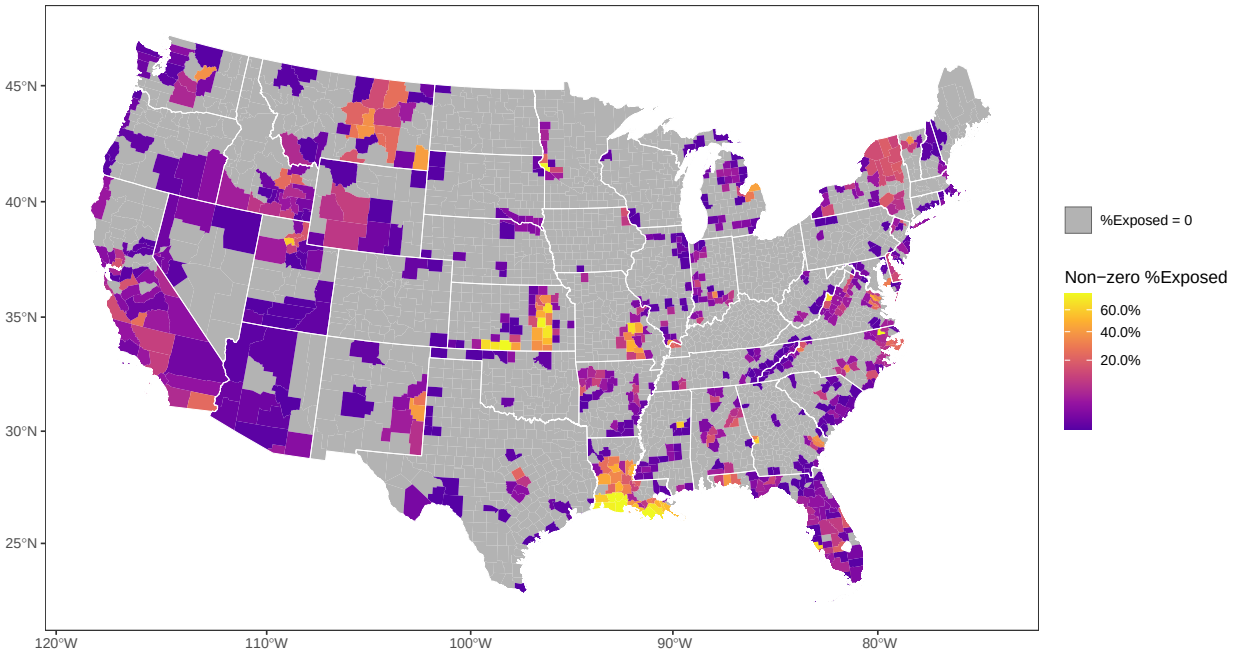


Figure 2: Counties with "to be protected" areas

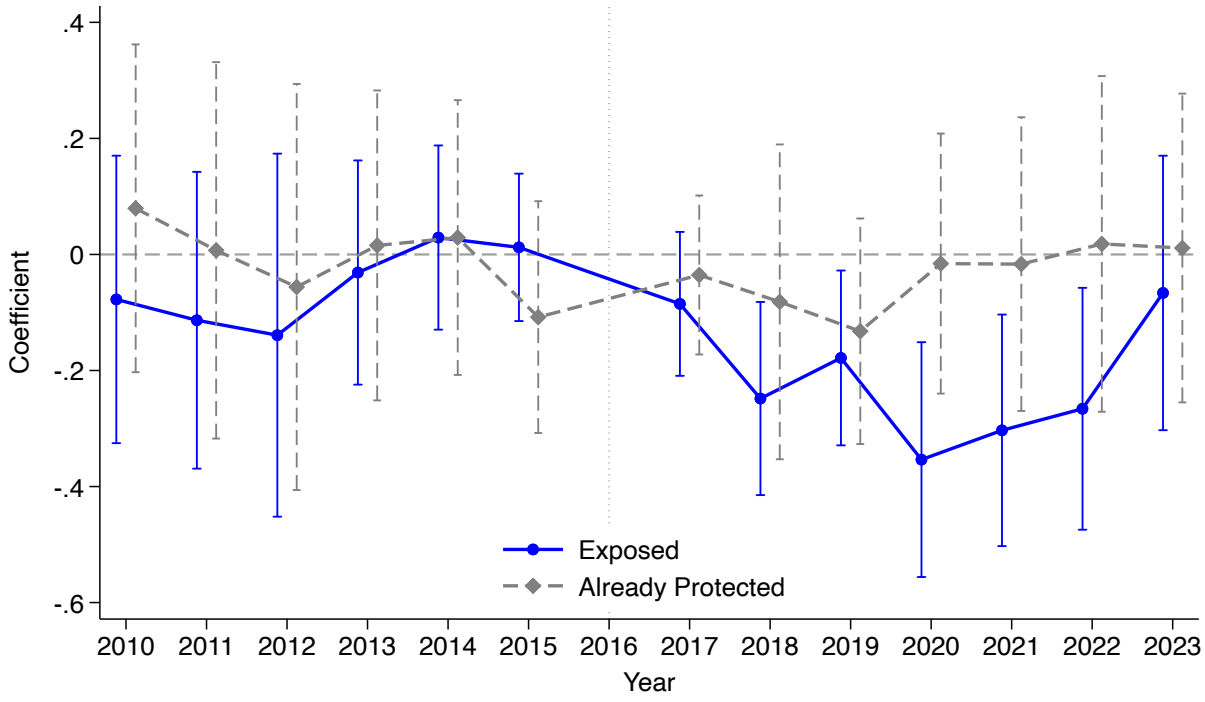


Figure 3: Dynamic effects of the 2016 KBA Standard on job posting activities

Notes:
This figure displays event study estimates of the dynamic effects of the KBA Standard on the number of job postings. The figure plots coefficients on interactions between year indicators and continuous county-level exposure measures, *%Exposed* and *%Already Protected*, over the period 2010–2023. *%Exposed* is the proportion of the county's area that is classified as valuable for biodiversity but remains unprotected, expressed relative to the county's total unprotected land area. *%Alreadyprotected* is the proportion of the county's area that is classified as protected areas. The omitted year is 2016, the year in which the KBA Standard was established. All specifications include the same control variables and fixed effects as in Column 3 of Table 3. Vertical bars denote 95% confidence intervals.

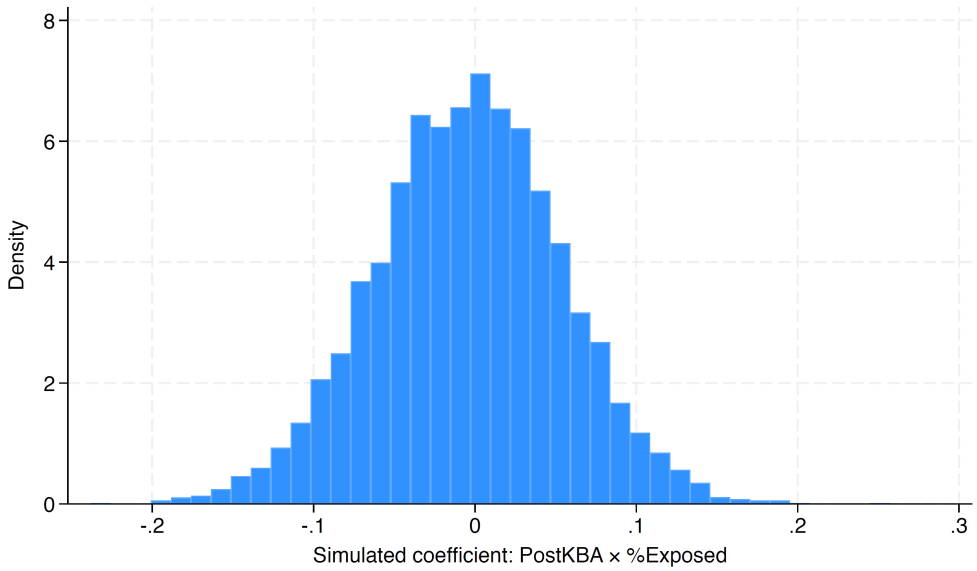


Figure 4: Placebo tests

Notes: This figure displays the distributions of the coefficient estimates on *%Exposed* from placebo regressions using specifications from Column 3 of Table 3. The dependent variable is *ln(1+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	0.017	0.069	0.000	0.313
%Already protected	897,939	0.015	0.056	0.000	0.279
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
#Establishments	36,698	0.841	0.606	0.000	3.000
#Est openings	36,698	0.035	0.185	0.000	1.000
#Est closings	36,698	0.038	0.192	0.000	1.000
%All green	307,834	0.542	0.892	0.000	5.000
%New & emerging green	307,834	0.009	0.037	0.000	0.222
%Enhanced green	307,834	0.292	0.542	0.000	3.000
%Increased demand green	307,834	0.181	0.394	0.000	2.000
%Site-dependent	346,499	0.158	0.276	0.000	1.000
%Compliance-support	346,499	0.368	0.385	0.250	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
Employee counts	897,939	19.320	53.320	1.019	387.900

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	t-stat
△Number of job postings$_{2015}$	0.495	1,320	0.344	475	0.151	0.828
△Voluntary departures$_{2015}$	0.172	1,101	0.169	384	0.003	0.054
△Involuntary departures$_{2015}$	0.117	893	0.099	328	0.018	0.261
△Number of establishments$_{2015}$	0.004	719	-0.016	243	0.020	1.020
△%All green$_{2015}$	0.461	1,107	0.332	393	0.129	0.859
△%Site-dependence$_{2015}$	0.309	1,147	0.224	394	0.085	0.539
△%Compliance-support$_{2015}$	0.063	1,152	0.043	398	0.029	0.229
△Number of job postings$_{20132015}$	0.612	3,759	0.512	1,364	0.585	1.069
△Voluntary departures$_{20132015}$	0.209	3,154	0.162	1,145	0.196	1.032
△Involuntary departures$_{20132015}$	0.062	2,595	0.052	1,000	0.059	0.275
△Number of establishments$_{20132015}$	0.006	2,139	0.001	732	0.005	0.360
△%All green$_{20132015}$	0.643	3,101	0.643	1,113	-0.0004	-0.004
△%Site-dependent$_{20132015}$	0.532	3,167	0.491	1,125	0.041	0.389
△%Compliance-support$_{20132015}$	0.243	3,220	0.132	1,162	0.111	1.903

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: The KBA Standard and Job Posting Quantity

Dependent variable: *ln(1+Job postings)*			
	(1)	(2)	(3)
%Exposed × PostKBA	-0.140**	-0.119**	-0.116**
	[0.055]	[0.051]	[0.050]
%Already protected × PostKBA			-0.020
			[0.092]
ln(1+Total assets)		0.167***	0.167***
		[0.005]	[0.005]
PPE/Total assets		0.298***	0.298***
		[0.032]	[0.032]
CAPEX/Total assets		0.281***	0.280***
		[0.064]	[0.064]
EBIT/Total assets		-0.049***	-0.049***
		[0.009]	[0.009]
Total debt/Total assets		-0.012	-0.012
		[0.007]	[0.007]
Tobin's Q		0.042***	0.042***
		[0.003]	[0.003]
ln(1+Employee counts)		0.598***	0.598***
		[0.007]	[0.007]
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
Observations	938,797	897,939	897,939
Adjusted R^2	0.189	0.477	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 area that is classified as valuable for biodiversity but remains unprotected, expressed relative to the county's total unprotected land area. $\%Alreadyprotected$ is the proportion of the county's area that is classified as protected areas. 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: Economic mechanisms: regulatory pressures

Dependent variable: *ln(1+Job postings)*	(1)	(2)	(3)
Impact score$_{2013–2015}$ × PostKBA × %Exposed	-0.107***		-0.119***
	[0.033]		[0.038]
Dependency score$_{2013–2015}$ × PostKBA × %Exposed		0.002	-0.019
		[0.033]	[0.035]
Impact score$_{2013–2015}$ × PostKBA × %Already protected	0.069		0.063
	[0.062]		[0.063]
Dependency score$_{2013–2015}$ × PostKBA × %Already protected		-0.016	-0.007
		[0.028]	[0.029]
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
Observations	864,675	864,675	864,675
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 area that is classified as valuable for biodiversity but remains unprotected, expressed relative to the county's total unprotected land area. *Impact score*$_{2013–2015}$ (*Dependency score*$_{2013–2015}$) 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: The KBA Standard and number of establishments

Dependent variables	*#Establishments* (1)	*#Est Openings* (2)	*#Est Closings* (2)
PostKBA × %Exposed	0.152	0.002	0.023
	[0.145]	[0.042]	[0.041]
PostKBA × %Already protected	0.243*	0.034	0.075
	[0.127]	[0.049]	[0.061]
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
Observations	36,677	36,677	36,677
Adjusted R^2	0.413	0.413	0.413

Notes: This table reports regression results estimating the effects of the establishment of the KBA Standard on the number of establishments in exposed counties. The dependent variables are *ln(1+Establishments*, *ln(1+Est Openings)*, and *ln(1+Est Closings)*, the natural logarithm of one plus the number of establishments, establishment openings, and establishment closings by 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. $\%Exposed$ is the proportion of the county's area that is classified as valuable for biodiversity but remains unprotected, expressed relative to the county's total unprotected land area. $\%Already protected$ is the proportion of the county's area that is classified as protected areas. 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: The KBA Standard and Employee Departures

Dependent variables	*ln(1+Voluntary departures)* (1)	*Ln(1+Involuntary departures)* (2)
PostKBA × %Exposed	0.007	0.008
	[0.015]	[0.013]
PostKBA × %Already protected	-0.009	0.013
	[0.022]	[0.015]
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
Observations	897,939	897,939
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. $\%Exposed$ is the proportion of the county's area that is classified as valuable for biodiversity but remains unprotected, expressed relative to the county's total unprotected land area. $\%Alreadyprotected$ is the proportion of the county's area that is classified as protected areas. 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: The KBA Standard and the demand for green occupations

Dependent variables:	*%All green* (1)	*%New & Emerging* (2)	*%Enhanced* (3)	*%Increased demand* (4)
%Exposed × PostKBA	0.051	-0.004	0.013	0.052**
	[0.046]	[0.003]	[0.029]	[0.027]
%Already protected × PostKBA	0.051	-0.001	-0.060	-0.019
	[0.046]	[0.005]	[0.037]	[0.027]
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
Observations	307,568	307,568	307,568	307,568
Adjusted R^2	0.220	0.187	0.170	0.246

Notes: This table reports regression results estimating the effect of the establishment of the KBA Standard on the demand for green occupations. 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). $PostKBA$ is a dummy variable that equals one from 2017 onward following the establishment of the KBA Sandard, and zero otherwise. $\%Exposed$ is the proportion of the county's area that is classified as valuable for biodiversity but remains unprotected, expressed relative to the county's total unprotected land area. $\%Already protected$ is the proportion of the county's area that is classified as protected areas. 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: KBA Standard and the demand for green skills

Dependent variables:	*Has green skills* (1)	*#Green skills* (2)	*#Green skills/#All skills* (3)
%Exposed × PostKBA	0.011	0.013	0.002
	[0.014]	[0.016]	[0.001]
%Already protected × PostKBA	-0.003	-0.006	-0.0005
	[0.010]	[0.012]	[0.001]
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
Observations	7,383,120	7,383,120	7,283,634
Adjusted R^2	0.107	0.206	0.145

Notes: This table reports regression results estimating the effect of the establishment of the KBA Standard on the demand for green skills. 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 Sandard, and zero otherwise. $\%Exposed$ is the proportion of the county's area that is classified as valuable for biodiversity but remains unprotected, expressed relative to the county's total unprotected land area. $\%Already protected$ is the proportion of the county's area that is classified as protected areas. 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 9: The KBA Standard and workforce restructuring

Dependent variables:	*%Site-dependent* (1)	*%Compliance-support* (2)
%Exposed × PostKBA	-0.027**	0.038**
	[0.013]	[0.019]
%Already protected × PostKBA	-0.005	0.021
	[0.017]	[0.027]
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
Observations	346,254	346,254
Adjusted R^2	0.330	0.359

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 *Site-dependent* or *Compliance-support* based on their 2-digit SOC code. *Site-dependent* are occupations that require physical presence and involve on-site activities, including those in Building and Grounds Cleaning and Maintenance (37), Farming, Fishing, and Forestry (45), Construction and Extraction (47), Production (51), or Transportation and Material Moving (53). *Compliance-support* are occupations that support firms' technical and administrative compliance efforts, including Management (11), Business and Financial Operations (13), Computer and Mathematical (15), Architecture and Engineering (17), Life, Physical, and Social Science (19), Legal (23), and Office and Administrative Support (43). $PostKBA$ 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 area that is classified as valuable for biodiversity but remains unprotected, expressed relative to the county's total unprotected land area. $\%Already protected$ is the proportion of the county's area that is classified as protected areas. 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 10: The KBA Standard and labor reallocation

Dependent variable: *ln(1+Job postings)*	(1)	(2)
Lower exposure × PostKBA	0.054***	0.040**
	[0.020]	[0.017]
Control variables	No	Yes
Firm FE	Yes	Yes
Job location county-year FE	Yes	Yes
HQ state-year FE	Yes	Yes
NAICS2-year FE	Yes	Yes
Observations	932,599	891,717
Adjusted R^2	0.177	0.473

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.

Table 11: The KBA Standard and aggregate firm-level outcomes

Dependent variables:	*Tobin's Q* (1)	*EBIT/Total Assets* (2)	*CAPEX/Total Assets* (3)
Exposure (firm-level) × PostKBA	-2.244**	0.849	-0.046
	[1.068]	[1.141]	[0.036]
Already protected (firm-level) × PostKBA	1.315	0.045	-0.039
	[1.393]	[0.347]	[0.029]
Exposure (firm-level)	3.381	-2.699	0.179*
	[3.730]	[1.930]	[0.107]
Already protected (firm-level)	-10.777**	2.765	-0.056
	[4.252]	[1.930]	[0.111]
ln(1+Total assets)	-0.289***	0.102***	0.003***
	[0.031]	[0.020]	[0.001]
PPE/Total assets	-0.776***	0.112	0.151***
	[0.188]	[0.173]	[0.012]
CAPEX/Total assets	1.004***	-0.271	-
	[0.339]	[0.219]	-
EBIT/Total assets	-0.120*	-	-0.002
	[0.066]	-	[0.002]
Total debt/Total assets	0.169***	-0.222***	-0.004**
	[0.049]	[0.071]	[0.002]
Tobin's Q	-	-0.018	0.004***
	-	[0.014]	[0.001]
Control variables	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	15,081	15,081	15,081
Adjusted R^2	0.650	0.187	0.574

Notes: This table reports regression results estimating the effect of the establishment of the KBA Standard on firm-level aggregate outcomes. The dependent variables are *Tobin's Q,* the market value of total assets divided by book value of asset (Column 1); ii) *EBIT/Total assets,* earnings before interest and taxes divided by total assets (Column 2), and iii) *CAPEX/Total assets*, capital expenditures divided by total assets (Column 3). *PostKBA* is a dummy variable that equals one from 2017 onward following the establishment of the KBA Sandard, and zero otherwise. *Exposure (firm-level)* is the employee-weighted average *%Exposed* across counties. *Already protected (firm-level)* is the employee-weighted average *%Already protected* across counties. 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.
%Already protected	The proportion of the county's area that is classified as protected areas.
Lower exposure	= 1 if a firm's *%Exposed* in a given county is lower than the same firm's employee-weighted average exposure across its other counties.
Data source: Lightcast	
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.
%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 *Green New & Emerging.*
%Enhanced	The share of job postings belonging to O*NET's *Green Enhanced Skills.*
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.
%Site-dependent	The share of job postings classified as site-dependent based on 2-digit SOC code: Construction and Extraction, Production, Transportation and Material Moving, Building and Grounds Cleaning and Maintenance, Farming, Fishing, and Forestry.
%Compliance-support	The share of job postings classified as compliance-support: Management, Business and Financial Operations, Computer and Mathematical, Legal, Office and Administrative Support, Architecture and Engineering, and Life, Physical, and Social Science.
Data source: Revelio Labs	
ln(1+ 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+ 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+ Employee counts)	The natural logarithm of one plus the number of emloyees in a given firm-county-year.

Appendix Table A.1: Variable descriptions – Continued

Variable	Descriptions
Data source: TRI	
#Establishments	The number of establishments a firm has in a given county-year.
#Est openings	The number of establishment openings by a firm in a given county-year.
#Est closings	The number of establishment closings by a firm in a given county-year.
Data source: Compustat/CRSP	
Ln(1+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.
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)
Exposure (firm-level)	Firm-level employee-weighted average of *%Exposed* across counties.
Already Protected (firm-level)	Firm-level employee-weighted average of *%Already protected* across counties.
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.