Review of Finance, 2025, **00**, 1–37
https://doi.org/10.1093/rof/rfaf068
Advance Access Publication Date: 6 November 2025
Article

The pricing of biodiversity risk in commodity markets

Massimo Guidolin[1,2], **Manuela Pedio**[2,3,*]

[1]Department of Finance, Bocconi University, Milan, Italy
[2]Baffi CAREFIN Centre, Milan, Italy
[3]Business School, University of Bristol, Bristol, United Kingdom

*Corresponding author: University of Bristol, Belgrave 25-27, BS8 2AA, Bristol, United Kingdom.
Email: Manuela.pedio@bristol.ac.uk

Abstract

This article provides empirical evidence that biodiversity-related transition risk is priced in global commodity markets, with particular emphasis on agricultural commodities. Using intensity-based metrics of species loss per harvested land unit, we obtain empirical evidence that commodities with higher biodiversity footprints earn significant risk premia, after controlling for commodity-specific factors. An event study around the Kunming Declaration further shows that commodities associated with greater biodiversity risk experienced negative abnormal returns following the declaration. In an aggregate-level analysis, we additionally find that commodities with higher sensitivity (beta) to biodiversity shocks earn significantly higher excess returns, reinforcing the presence of a biodiversity-related risk premium across global commodity markets. Our findings suggest that investors are increasingly internalizing the biodiversity-related risks at the commodity-asset level. The findings can be rationalized by a commodity production model, which we outline in Section 5.

Keywords: biodiversity risk; transition risk; commodity returns; biodiversity premium.
JEL classifications: G12, Q56, Q57.

1. Introduction

In recent decades, the world has witnessed a dramatic acceleration in biodiversity loss. Dirzo et al. (2014) describe this ongoing process as Anthropocene defaunation: a wave of species extinctions and, critically, pervasive declines in local species abundance. This erosion of biological diversity—driven largely by human activity—constitutes one of the most underappreciated and yet consequential forms of global environmental change (Cardinale et al. 2012; IPBES 2019). Indicators such as the Living Planet Index (LPI), which tracks wildlife population abundance over time, provide compelling evidence of this trend: the 2024 report estimates an average 73 percent decline in monitored vertebrate populations since 1970, with even sharper losses in tropical freshwater ecosystems and in Latin America (WWF 2024). While these changes often unfold incrementally, their cumulative effects can push ecosystems towards tipping points, the thresholds beyond which ecological decline becomes self-reinforcing and irreversible (Rockström et al. 2009; Barnosky et al. 2011; Lenton et al. 2019). Once a critical number of species are lost or fall below functional thresholds, ecosystems may fail to deliver essential services such as pollination, water regulation, or nutrient cycling (Hooper et al. 2012; Díaz et al. 2019).

Editor: Marcin Kacperczyk
Received: April 6, 2025. **Accepted:** September 6, 2025

As humanity approaches critical ecological limits—including the collapse in the number of pollinators, soil fertility loss, and freshwater scarcity—incremental biodiversity degradation is expected to increasingly affect commodity markets (Cardinale et al. 2012). The transition to biodiversity-friendly production is subject to finite ecological and economic windows. International policy frameworks, such as the Kunming-Montreal Global Biodiversity Framework, stress the urgency of shifting toward sustainable production systems (IPBES 2019; Convention on Biological Diversity 2022). In this context, commodities marked by intensive biodiversity footprints (e.g., palm oil, cocoa, coffee) may face rising scrutiny and financial risks, even in the absence of immediate ecological disruption. These risks may manifest through short-term value loss triggered by regulatory shifts, the introduction of market access constraints, or changes in investor and consumer preferences. Conversely, commodities with lower biodiversity footprints may enjoy transitory upward price adjustments as markets reward sustainability. However, it remains under-investigated which one of such valuation drifts may eventually prevail in the long run.

The implications of biodiversity loss for economic systems and financial markets have been increasingly acknowledged by central banks, regulators, and investors (NGFS 2023; Dasgupta 2024; FSB 2024). Biodiversity-related financial risks are generally categorized into two channels: physical risks and transition risks. Physical risks arise from the degradation of ecosystem services that support production systems, such as biomass provision, pest control, and climate regulation. In their more severe form, these risks may escalate to systemic levels if the ecological breakdown impairs entire sectors or supply chains, as seen in the case of pollinators' declines threatening crop yields globally (IPBES 2016). Transition risks, in contrast, emerge from shifts in regulation, technology, or stakeholder expectations that penalize biodiversity-harming activities, such as import bans for products that involve deforestation, mandatory due diligence regulations, or sustainability-linked capital reallocation (TNFD 2023; European Commission 2023).

In this article, we focus on transition risk. We examine whether commodities with higher biodiversity footprints, reflected in species loss intensity and land use impact, earn systematically different returns, consistent with investors pricing in the financial implications of nature-related regulatory and societal responses. Commodities offer a unique setting to test whether transition risk is priced. Their returns are observable at least at a monthly frequency across global spot and futures markets, and their biodiversity footprints can now be measured with increasing granularity using data on land use, emissions, and intensity of species loss. Moreover, unlike other economic activities, because they represent relatively standardized and tradable assets, commodities allow for comparisons of return premia across environmental risk exposures. Their uniformity across producers and geographies, combined with transparent pricing in global spot and futures markets, makes it easier to isolate the effects of biodiversity loss risk on their valuations, without the confounding influences of firm-specific characteristics, accounting differences, and sectoral heterogeneity.

Biodiversity transition risk can impact commodity prices primarily through two channels. First, biodiversity loss can directly influence production by raising input costs, reducing agricultural productivity, and reshaping regulatory environments (IPBES 2019). Second, the costs associated with adopting sustainable practices may impact investor expectations of future commodity (convenience) yields, which are recognized to be among the major drivers of returns in the commodity space (see, e.g., Han, Dam and Pohl 2025). These concepts are clearly illustrated in the commodity production model presented in Section 5, which extends Gorton Hayashi and Rouwenhorst (2012) and Yang (2013) and illustrates how, in (partial) equilibrium, commodities with a high biodiversity footprint are characterized by higher average returns.

In our baseline analysis, we leverage the availability of biodiversity footprint data for a broad set of agricultural commodities through the database assembled by the UK Joint Nature Conservation Committee (JNCC) in collaboration with the Stockholm Environment Institute

(SEI).[1] Among the commodities covered by this dataset, we are able to collect spot prices for twenty-three of them and futures prices for ten of them. Specifically, we employ a characteristic-based asset pricing framework to test whether biodiversity-related transition risks are reflected in the spot and futures returns of such commodities. Our main analysis uses intensity-based measures of species loss per unit of harvested land to proxy their biodiversity footprints. These intensity metrics enable us to abstract from scale effects and instead capture the damage a commodity causes on a per-unit basis. This approach contributes to the emerging literature on environmental risk and asset pricing and informs ongoing debates on the materiality of biodiversity loss in financial markets and the role of investor pressure and regulations in driving sustainability transitions.

Our key, novel empirical results are as follows. We find robust evidence that biodiversity transition risk is priced in the cross-section of commodity spot returns. Specifically, agricultural commodities with higher biodiversity footprints—measured by the intensity of species loss per unit of harvested land—earn a statistically and economically significant return premium. Our baseline regressions indicate a premium ranging between 20 and 60 basis points per month in commodity spot returns. These results are robust to the inclusion of controls for production growth, CO_2 emissions, and raw deforestation. Importantly, neither total species loss nor emissions alone predict commodity returns, reinforcing the importance of intensity-based measures as proxies for transition risk exposure.

We corroborate the transition risk channel in two ways. First, we conduct an event study around the Kunming Declaration in 2021 and show that commodities with high biodiversity footprints experienced significantly negative abnormal returns immediately following the declaration, consistent with markets repricing transition risk. Second, we conduct a placebo test exploiting the Paris Agreement adopted in December 2015, which aimed to address climate risk specifically, but not biodiversity loss. Consistent with the concept that biodiversity and climate transition risks are distinct, commodities with a high biodiversity footprint do not react to the Paris Agreement. Finally, we find no significant relationship between biodiversity risk and commodity futures returns. This finding is consistent with the model presented in Section 5; however, caution is needed in interpreting this result due to the small sample size of futures returns available and the consequent little power of the test.

Finally, we extend the analysis to a broader sample of commodities by estimating their exposures to aggregate biodiversity shocks, proxied by changes in the first principal components of the LPI and the Red List Index (RLI). We show that commodities with higher beta to biodiversity loss earn significantly higher excess returns, with a long-short portfolio delivering an annualized alpha of 5.4 percent after controlling for standard commodity pricing factors. These findings confirm that biodiversity-related transition risk is not only priced at the individual commodity level, but also at the aggregate market level, and may constitute a meaningful and persistent risk premium.

Rather surprisingly, given their direct link with biodiversity, the literature connecting commodity markets to nature loss is still emerging. Nonetheless, a few recent studies have begun to establish empirical and conceptual foundations for understanding how nature-related risks are reflected in asset prices. Moreover, commodities play a central role in financial markets due to their macroeconomic sensitivity, hedging potential, and inclusion in diversified investment portfolios (Basak and Pavlova 2016; Han, Dam and Pohl 2025). Their pricing reflects both real economic fundamentals and investor behavior, making them a key asset class for studying how environmental and transition risks are transmitted through global financial systems. Seminal contributions are Chaudhary and Kastner (2016)

---

[1] Agricultural commodities are particularly exposed to biodiversity transition risks because their production processes frequently involve deforestation, habitat fragmentation, and the removal of life-rich wetlands. In contrast, non-agricultural commodities—such as metals and minerals—typically affect biodiversity indirectly, primarily through pollution and broader land-use changes (Garibaldi et al. 2013; Sonter, Ali and Watson, 2018).

and Chaudhary and Brooks (2018), who have quantified the biodiversity footprints of traded commodities by linking consumption patterns to land-use impacts and species loss, offering commodity-specific measures of ecological intensity that can be paired with pricing data. However, in financial economics, early attempts to connect biodiversity degradation to asset returns have focused primarily on equities.[2] Giglio et al. (2025) and Garel et al. (2024) show that firms with large biodiversity footprints exhibit higher return sensitivity to biodiversity-related news, and that transition risk linked to biodiversity began to be priced more clearly after global policy milestones like the Kunming Declaration. More generally, at the firm level, Garel et al. (2025) introduce the Corporate Biodiversity Footprint (CBF) and NatureDep scores, which quantify a firm's impact and dependence on ecosystem services. They show that firms with large biodiversity footprints experienced significant stock price declines following major biodiversity policy announcements, suggesting that investors are beginning to price in transition risks. Kalhoro and Kyaw (2024) corroborate this with evidence that investors react positively to firms managing biodiversity risks and negatively to those with unmanaged exposures around biodiversity policy events.[3]

The rest of the article is organized as follows. Section 2 describes the measurement of biodiversity exposure using intensity-based indicators. Section 3 presents the data sources and summary statistics. Section 4 outlines the baseline results. Section 5 develops a theoretical framework to support the causal nature of our key empirical findings. Section 6 extends the analysis to test whether aggregate biodiversity risk is priced in the broader cross-section of commodities. Section 7 concludes.

2. Measuring the biodiversity footprint of commodities

A crucial aspect of our research design is our ability to appropriately measure commodities' biodiversity footprints. While a few commercial databases (see, e.g., Iceberg Data Lab 2023) have emerged that attempt to measure the biodiversity footprint of firms at the global level, we are not aware of any such dataset for commodities. However, the UK Joint Nature Conservation Committee, in collaboration with the Stockholm Environment Institute, has developed the Commodity Footprints project, which aims to measure the environmental impact (e.g., biodiversity loss, carbon emissions, deforestation) of a large set of globally traded agricultural commodities. Their data, which are collected at an annual frequency, refer to a sample period spanning from 2005 to 2022. This dataset is ideal to address our research question for several reasons. First, it is open source and therefore widely available to researchers, commodity producers and consumers, and investors.[4] Second, it uses transparent methodologies outlined in the natural sciences literature (see, e.g., Chaudhary et al. 2015; Chaudhary and Kastner 2016; Croft et al. 2024). Third, the dataset is officially used by the UK government to report on the global environmental impact of UK consumption. This further validates the idea that it contains information that is relevant to policymakers.

The primary variable of interest to our analysis is the predicted species loss, which represents an estimate of the number of species likely committed to extinction because of land use for commodity production. Importantly, these are not species that have already gone extinct. Instead, these estimates represent what is sometimes referred to as an "extinction debt"—a term coined to refer to future biodiversity losses due to past habitat destruction that have yet to materialize because of time delays in extinction (see Tilman et al. 1994).

---

[2] An exception is Kalhoro and Ahmed (2025), who examine daily correlations between four commodities (silver, gold, oil, and wheat) and a news-based measure of aggregate biodiversity risk. They find that such commodities and the news index are negatively correlated, and as a result, allegedly, they would not offer a good hedge against (aggregate, sentiment-driven) biodiversity risk.

[3] Xin et al. (2025) find that ESG biodiversity scores do not significantly predict stock returns or influence investor behavior, suggesting current disclosure mechanisms are insufficient.

[4] The data are available to the public at https://commodityfootprints.earth/.

Because during this time lag it is still possible to adopt conservation measures (e.g., restoring habitat) to preserve biodiversity (see, e.g., Wearn, Reuman and Ewers 2012), we believe that this measure is ideal for our purposes. Commodities with a high extinction debt are precisely those that policymakers may (or should) target to prevent biodiversity loss and that may trigger the types of measures and regulatory changes that are the fabric of transition risk. In the next sections, we describe how predicted species loss is measured and outline the advantages and limitations of this measure.

2.1 Species area relationship and biodiversity loss

JNCC computes the predicted species loss following the methodology outlined in Chaudhary et al. (2015), Chaudhary and Kastner (2016), and Chaudhary and Brooks (2018), which relies on a countryside species-area relationship (cSAR) model. This model seeks to predict the number of species lost of a given taxon due to land use in a specific ecoregion.[5] In particular, starting from the assumption—well established in the ecology literature (see, e.g., Liang et al. 2025—that species richness is a power function of area, a cSAR postulates:

$$S_{\mathrm{lost},g,j} = S_{\mathrm{org},g,j}\left[1 - \left(\frac{A_{\mathrm{new},j} + \sum_{i=1}^{n} h_{g,i,j}A_{i,j}}{A_{\mathrm{org},j}}\right)^{z_j}\right] \tag{1}$$

where $S_{lost,g,j}$ is the number of species lost of taxon g due to land use in eco-region j, $S_{original,g,j}$ is the number of species found in the pristine habitat area ($A_{org,j}$), $A_{new,j}$ is the remaining habitat and $A_{i,j}$ is the area of land use i (where i denotes one of the following uses: “intensive forestry”, “extensive forestry,” “annual crops,” “permanent crops,” “pasture,” and “urban”). z_j is a constant calibrated from observational data in various eco-systems (Drakare, Lennon and Hillebrand 2006) and $h_{g,i,j}$ is the affinity of the taxonomic group g for land use type i in eco-region j. At the extremes, $h_{g,i,j}$ is equal to one if the converted land is as hospitable as the original habitat to the taxon, and equal to zero if it is completely hostile. The actual value of $h_{g,i,j}$ is estimated by comparing the observed species abundance in land use i with a pristine habitat in the same eco-region. Importantly, $h_{g,i,j}$ captures the eco-region-specific differences in the responses of species to land conversion. This leads to the computation of eco-region-specific *characterization factors*, as illustrated in figure 1.

A characterization factor measures the number of species of taxonomic group g committed to extinction per m^2 of land converted to use i (Chaudhary and Kastner 2016). Taxa-aggregated characterization factors are then applied to different crops based on the area used for their production in a specific eco-region. Figure 2 shows the country-specific characterization factors from Chaudhary and Kastner (2016).[6] The figure clearly illustrates the high degree of heterogeneity of characterization factors across different countries, showing how land use in some regions (such as, for instance, tropical areas) is considerably more harmful to biodiversity than the same use in other areas.

[5] A classic SAR assumes that all natural areas converted to human-dominated areas become completely hostile to biodiversity. It also neglects that different species may respond differently to habitat loss. For instance, some species only live in pristine habitats (e.g., orangutans), while others might even benefit from the conditions found in human-modified habitats (e.g., coyotes and raccoons). cSAR models have been developed to overcome these limitations by accounting for habitat heterogeneity and taxa sensitivity (Chaudhary et al. 2015).

[6] To obtain this picture, we have started from the information supplied in Supplementary Table 1 (S1) of Chaudhary and Kastner (2016) and aggregated the total regional species lost per ton of crop across crops in each country.

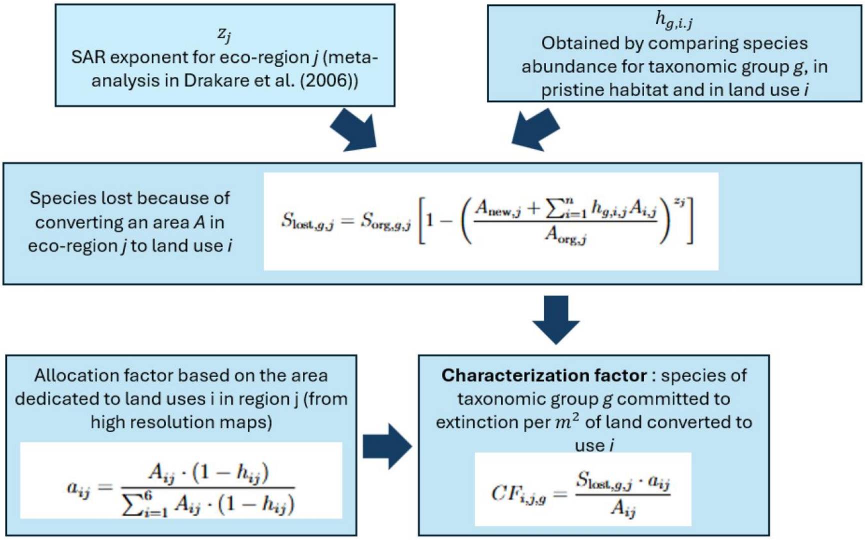

Figure 1. The calculation of eco-region-specific characterization factors. *Note*: The figure illustrates the steps involved in the calculation of eco-region-specific characterization factors. The species of the taxonomic group *g* lost because of converting an area A in eco-region *j* to land use *i* is computed using the species-area relationship and the eco-region-specific values of z_j and $h_{g,i,j}$. An allocation factor based on the area dedicated to land use *i* in eco-region *j* is then applied to compute the characterization factor for taxon *j*, land use *i*, and eco-region *j*.

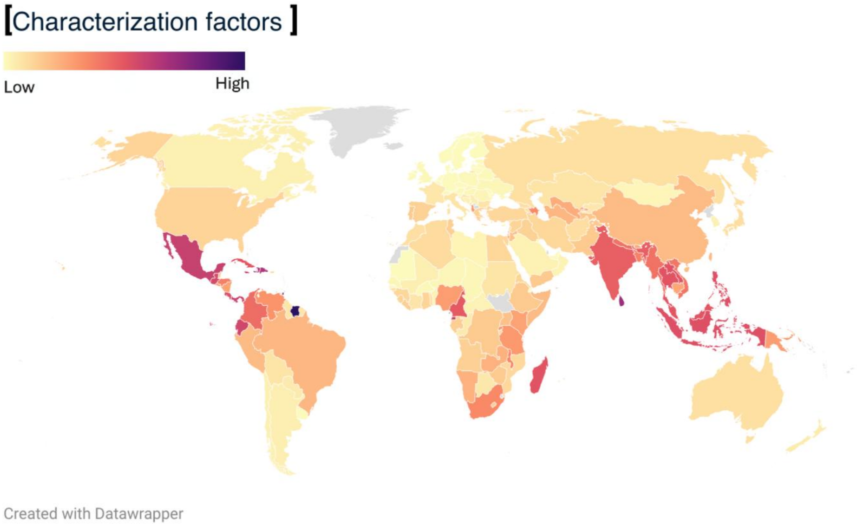

Figure 2. Country-specific characterization factors. *Note*: The figure is a plot of the country-specific characterization factors obtained by aggregating by crop the information provided in Chaudhary and Kastner (2016).

2.2 From predicted species loss to intensity of species loss

While JNCC provides the total predicted number of species expected to go extinct due to the production of each commodity in a given year, in our study, we focus on the *intensity of species loss*. To obtain this metric, we divide the total predicted species loss for year *t*

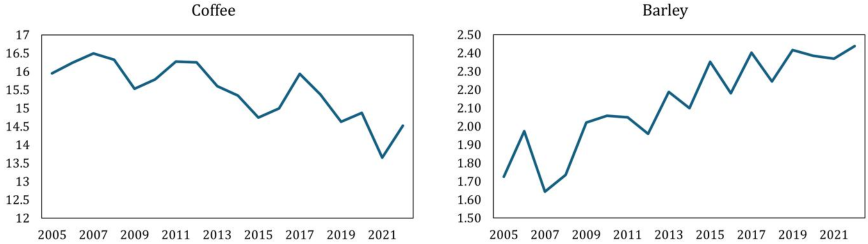

Figure 3. Intensity species loss by year. *Note*: The plot shows the time variation of the Intensity Species Loss (species lost for every 10,000 km^2 of crop area harvested) for two crops: coffee and barley. The data refer to the period 2005 through 2022.

and commodity i reported by JNCC by the corresponding area harvested. The latter is available in the JNCC database, which sources it from the Food and Agriculture Organisation (FAO). For example, figure 3 depicts the intensity of species loss for two commodities: barley and coffee. Notably, the measure is time-varying, which we shall subsequently exploit in our panel regressions. For instance, the intensity of species loss characterizing coffee is much larger than that of barley: it was equal to sixteen species per $10,000\,\mathrm{km}^2$ of area harvested in 2005, while that of Barley was less than two species. However, the intensity of species loss characterizing coffee has declined over time. This is likely in response to new trends in the production of coffee, such as the growth in the production of certified (biodiversity-friendly) coffee, and the efforts made in Ethiopia (one of the largest producers) to combat declining productivity from older trees through the adoption of a sustainable practice known as stumping.[7] To the contrary, the intensity of species loss of barley has slightly increased over time.

There are at least two reasons why we deem it preferable to employ an intensity measure rather than the total number of species (potentially) lost to the production of a given commodity. First, using the total number of species lost would give disproportionate importance to the scale of production. Figure 4 gives a clear illustration of this problem. The figure represents the number of species (expected to be) lost due to the production of coffee and barley and their intensities by country. Examining the maps, it becomes apparent that the number of species at risk of extinction due to barley production is the highest in Russia and Australia. This is mainly due to the fact that Russia and Australia are the major producers of barley. However, when we consider the corresponding intensities, one immediately notes that producing barley in the Amazon forest is much more harmful to biodiversity than producing barley in Russia.

Second, the intensity of species loss is more suitable to capture inefficiencies in the production of certain commodities. Given the multiple competing demands for land and the need to preserve biodiversity while also meeting the escalating food demands from a growing worldwide population, commodities with a high intensity of species loss are likely to face a higher transition risk than others. For instance, Phalan et al. (2011) document that, given a production target, *land sparing* achieved through higher crop yields is more effective than *land sharing*—the practice of integrating biodiversity conservation and food production on the same land using wildlife-friendly farming practices.

2.3 Limitations

Given the extreme complexity of measuring the impact of human activity on biodiversity, our measure is not without limitations. First, since it is the output of a cSAR model, the intensity of species loss measures habitat degradation due to anthropogenic land use and

---

[7] This is the practice of cutting back aging trees to stimulate new, vigorous growth.

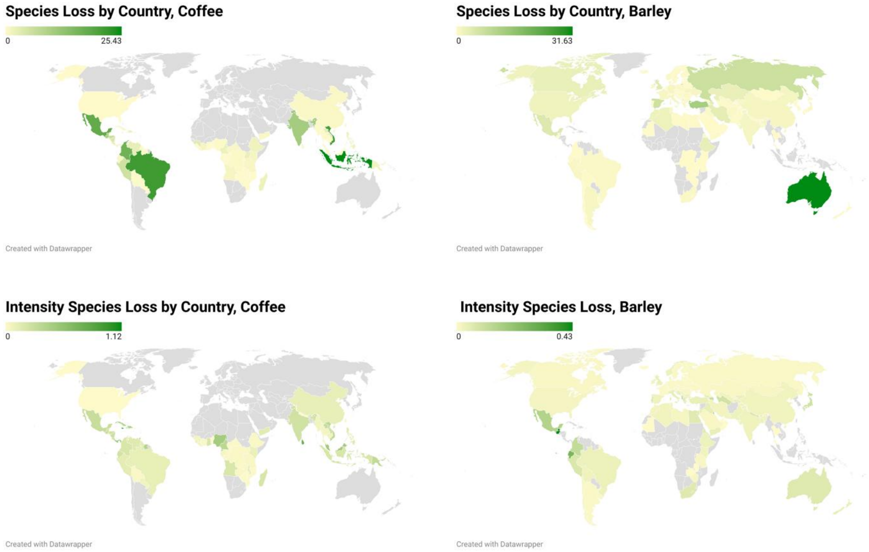

Figure 4. Species loss and intensity species loss by country. *Note*: The maps show the Species Loss (number of species) and the Intensity Species Loss (species lost for every 10,000 km^2 of crop area harvested) by country for two crops: coffee and barley. The data refer to 2022.

land use change. Therefore, it does not explicitly capture the effects on biodiversity of using chemicals (e.g., pesticides and fertilizers), the introduction of alien species, or water consumption. While this is a clear limitation of our measure, land use is widely recognized as the primary cause of biodiversity loss due to human activity (Jaureguiberry et al. 2022; Garel et al. 2024, 2025). For instance, the IPBES Global Assessment (IPBES, 2019) has ranked the direct drivers of biodiversity loss in descending order of importance as follows: changes in land and sea use, direct exploitation, climate change, pollution, and invasive alien species. Specifically, Wudu et al. (2023) report that the approximate contribution of conversion of land or sea to biodiversity loss over the past century was 34 percent (versus only 14 percent each for climate change and pollution).[8]

SAR models also fail to account for the potential harm to biodiversity caused by habitat fragmentation, which usually accompanies habitat loss, as they assume that the remaining habitat is contiguous (Chaudhary and Brooks 2018). While this leads to the underestimation of biodiversity loss due to habitat destruction, the spatially explicit data that are needed to correct for the effects of fragmentation are not yet available on a large scale (Chaudhary and Brooks 2018). Finally, another limitation of our measure is that it accounts for regional biodiversity loss without considering whether the species at risk are endemic—hence exposed to the threat of global in addition to local extinction—or are found in abundance in other areas of the world.

Despite the limitations outlined above, measures analogous to the one employed in this study are routinely used as part of the life cycle assessment of the environmental impacts of products and services (see, e.g., Souza, Teixeira and Ostermann 2015). For these reasons, our overall assessment is that—despite the inherent measurement error—the intensity of species loss remains a meaningful indicator for identifying commodities with high biodiversity-related transition risk.

---

[8] Sala et al. (2000) had already projected that, for terrestrial ecosystems, land-use change would have the largest effect on biodiversity by 2100, exceeding climate change, nitrogen deposition, biotic exchange, and elevated atmospheric CO2.

2.4 Validation

To ensure that the intensity of species loss is likely to capture transition risk, we have computed the average intensity of species loss for each commodity in our data set (see the following section for details) and compared the resulting ranking with the evidence available in the scientific literature (see Appendix A for a detailed discussion). The eight commodities with the highest average intensity of species loss are: cocoa, sugar, palm oil fruit, coffee, bananas, rubber, coconut, and tea leaves. The production of coffee (Indonesia), tea (China and India), sugar (Brazil), palm oil fruit (Indonesia and Malaysia), bananas (India, Indonesia, China, and Brazil), coconut (Indonesia, India, Philippines), cocoa (Ghana and Brazil), rubber (Thailand and Indonesia) is heavily associated with the conversion of tropical forests into cropland. Besides representing biodiversity hotspots, these ecosystems are particularly sensitive to land use change (Gibson et al. 2011). Furthermore, in a few cases, these crops have lower than optimal yields, either because their production takes place with old technology (see, e.g., cocoa in Africa, as outlined by Terazono 2014) or because their production has been expanded in suboptimal areas (e.g., rubber).

The only surprising finding from our validation analysis is the absence of soybeans among the commodities with the highest impact on biodiversity. We attribute this finding to two main reasons. First, the production of soybeans is almost equally split between Brazil (where it leads to a high impact on biodiversity) and United States (low impact on biodiversity). This is different, for instance, from coffee, which is produced in thirteen of the world's twenty-five biodiversity hotspots (Potts et al. 2017). Second, the production of soybeans has a higher yield, for instance, than coffee, rubber, or cocoa. However, with the exception of this outlier, we assess that the ranking obtained largely reflects the scientific evidence. Further discussion of each of these commodities and references to scientific studies that explain their impact on biodiversity can be found in the Supplementary Appendix A.

2.5 Climate transition risks, deforestation, and predicted species loss

Biodiversity loss and climate risk are two largely intertwined crises (see, e.g., Garel et al. 2024). In particular, converting forests, wetlands, and grasslands to farmland releases large quantities of CO_2 stored in biomass and soil. Therefore, to control for climate-related transition risk, for each commodity, we also collect data concerning the CO_2 generated from deforestation and the drainage of peatland. We obtain these data from JNCC, which in turn sources them from Chalmers University of Technology. They are estimated by quantifying the changes in carbon stock resulting from peatland drainage and subsequent land use. These represent net emissions in the sense that they are the difference between the carbon loss (the release of carbon stored in forests into the atmosphere when trees are cut down, burned, or decomposed) and the carbon that is reabsorbed when the land is turned into farming. In addition, we also collect data concerning deforestation (also available in the JNCC database). Forest loss is observed from remote sensing data and attributed to different commodities using a land-balance model, which implies that cropland expansion takes place first into pastures and then into forests (for further details see, e.g., Pendrill et al. 2019; Croft et al. 2024).

It is worthwhile noting that deforestation and CO_2 emissions are highly correlated, as CO_2 emissions are attributed to commodities using the same proportional shares of deforestation. For instance, if 10 percent of deforestation is attributed to cocoa production, then 10 percent of the CO_2 emissions resulting from deforestation are also assigned to cocoa. Therefore, in our analysis, deforestation is used as another proxy for emissions. Obviously, deforestation is also linked to biodiversity loss and, as such, it has been targeted directly by regulators (European Commission 2023). However, often these interventions do not target deforestation in general, but deforestation in biodiversity hotspots, such as the tropical forests. Therefore, a crude measure of deforestation is unlikely to capture the intended goals of regulators. In fact, species loss and deforestation display a relatively low correlation (around 0.14) precisely because species loss takes into account the specificity of the ecoregion where land use is taking place.[9]

3. Data

Our primary dataset merges several sources. Spot price data for internationally traded commodities come from the International Monetary Fund's (IMF) Primary Commodity Price System and are available at a monthly frequency.[10] The IMF collects prices from various sources to ensure that they reflect the international market conditions for each specific commodity (similar data are used, for instance, by Jacks, O'rourke and Williamson 2011; Delle Chiaie, Ferrara and Giannone 2022). The futures price data come from Pinnacle Corp (see, e.g., Kang, Rouwenhorst and Tang 2020). The futures prices are available at a daily frequency, and we compute monthly excess returns as

$$r_{i,m,t} = \frac{F^{(1)}_{i,m,t} - F^{(1)}_{i,m-1,t}}{F^{(1)}_{i,m-1,t}} \tag{2}$$

where $F^{(1)}_{i,m,t}$ is the price of the front-end future for commodity i at the end of month m of year t that does not expire in the next month and $F^{(1)}_{i,m+1,t}$ is the price of the front-end future at the end of the next month (Gorton, Hayashi and Rouwenhorst 2012).[11] Monthly commodity factor are constructed using the following commodity futures as common in the academic literature, see, for example, Boons and Prado 2019; Gong, Gozluklu and Kim 2023): feeder cattle, live cattle, cocoa, coffee, copper, corn, cotton, WTI crude, gold, heating oil, lean hogs, lumber, oats, orange, palladium, platinum, silver, soybeans, soybean meal, soybean oil, sugar, gasoline, wheat, natural gas, and rice. Specifically, each factor portfolio goes long on commodities in the bottom tercile of the sorting variable—momentum, basis, basis-momentum, hedging pressure, spreading positions, or volatility—and short on those in the top tercile. The commodity market factor is an equally weighted portfolio of the commodities mentioned above. The details of the construction of sorting variables and other commodity characteristics can be found in Appendix A.

JNCC takes as input the commodity production data from the FAO and it matches each unit of production in a given geography to the local deforestation, emissions, and species loss data. To obtain the worldwide measures of deforestation, emissions, and species loss, as well as total production, we simply aggregate across different countries. Figure 5 illustrates the logic of the database.

We are able to match the information in the Commodity Footprints dataset with twenty-three commodity spot price series available from the IMF and with ten futures price series from Pinnacole Corp. The agricultural commodities covered by the Commodity Footprints data represent the focus of our main analysis. However, in Section 6, we will expand the analysis to fifty-six commodities whose prices are available from the IMF database. The full list can be found in Appendix A. While the prices of most commodities are available for a longer sample, our main analysis spans from 2005 to 2022, which is the sample

---

[9] Scientific studies (see, e.g., Betts et al. 2017) have shown that where forest loss occurs matters as much as how much forest is lost: the probability a vertebrate species becomes threatened increases with forest loss, but the effect is disproportionately high in relatively intact landscapes. This context-dependence implies a highly non-linear relationship between area loss and species imperilment. Therefore, the linear correlation between aggregate deforestation and species loss is smaller than one would expect.

[10] These are publicly available at https://www.imf.org/en/Research/commodity-prices.

[11] The formula in equation (2) provides the excess returns for a fully collateralized position in commodity futures (this is a standard approach in the literature, see, e.g., Gorton, Hayashi and Rouwenhorst 2012; Boons and Prado 2019; Gong, Gozluklu and Kim 2023). Spot returns are obtained in a similar way from spot prices, but in this case, the US one-month T-bill rate is subtracted to obtain excess returns.

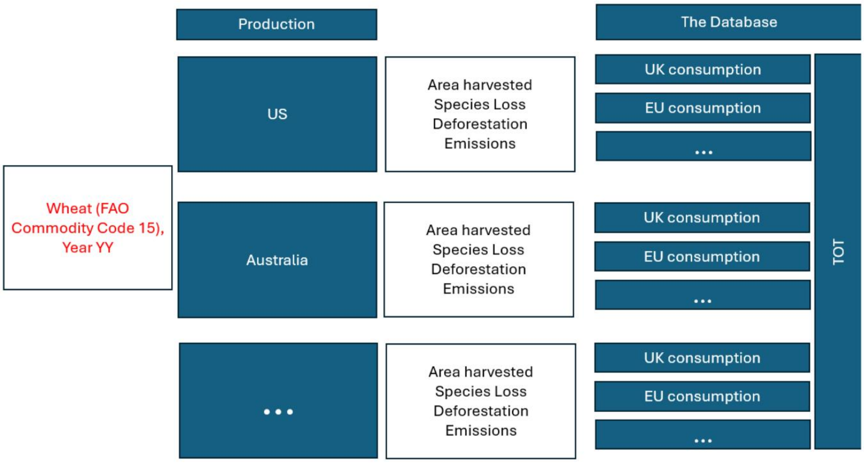

Figure 5. Logic of the JNCC database. *Note*: The picture illustrates the logic of construction of the intensity species loss, deforestation, and emission data used in the paper. JNCC starts from country-level production data from FAO and attributes to each commodity its share of emissions, deforestation, and species loss based on country-level data. Next, it matches production with consumption using an Input–Output Trade Analysis (IOTA) framework.

period covered by the Commodity Footprints project. Table 1 presents the summary statistics of the main variables used in our analysis. Our main variable of interest, the intensity of species loss, has a mean of 9.76, which implies that, on average, almost ten species are lost for every 10,000 km^2 of cultivated area. The median is smaller and amounts to 4.26. The cross-sectional standard deviation is equal to 13.47, which entails a rather large variation across different commodities. The mean of commodity spot excess returns equals 0.50 percent per month with a standard deviation of 7.61 percent. The mean of commodity futures excess returns is 0.42 percent with a standard deviation of 8.43 percent.

4. The biodiversity risk of agricultural commodities

4.1 Baseline results

In this section, we employ a characteristic-based approach (similar to Bolton and Kacperczyk 2021, 2023; Garel et al. 2024) to relate the excess returns of commodities to their biodiversity footprint, measured as the intensity of species loss calculated as discussed in Section 2. The focus is on twenty-three agricultural commodities (see Appendix A) for which we can measure the intensity of species loss, as explained in Section 3. An advantage of focusing on agricultural commodities, besides the availability of a reliable measure of their biodiversity footprint, is that they are relatively fungible and uniform across producers, compared, for instance, to crude oil, whose quality (and price) depends on differences in sulfur content, viscosity, geographic origin, etc., or to minerals, for which the methods of extraction often vary greatly.[12] Furthermore, the impact of agricultural commodities on climate change is almost exclusively driven by deforestation and peatland and wetland conversion (Pendrill et al. 2019). Therefore, because the JNCC database contains

---

[12] For instance, gold can be extracted using different methods depending on the deposit type: open-pit mining removes surface material and is used for low-grade ores; underground mining targets deeper veins; placer mining involves separating gold from river sediments; heap leaching uses cyanide to dissolve gold from crushed ore and poses chemical risks.

Table 1. Summary statistics.

Note: This table shows the summary statistics for the variables used in the analysis of agricultural commodity returns. The sample period spans from 2005 to 2022. Intensity species loss, deforestation, CO_2 emissions, production, inventory, and their growth rates are computed at an annual frequency. All the other variables are monthly. All growth rates have been winsorized using 1 percent and 99 percent thresholds. Commodity factors and other control variables are described in Appendix A.

	Mean	SD	p25	p50	p75
Panel A: deforestation, carbon, and species loss					
Intensity species loss	9.76	13.47	2.10	4.26	14.31
Deforestation, 1,000 ha (log)	3.33	1.62	2.17	3.49	4.44
CO_2 emissions, 10,000 tonnes (log)	2.23	1.82	1.04	2.40	3.58
Panel B: returns					
Excess return (spot)	0.50	7.61	−3.17	0.17	3.92
Excess return (future)	0.42	8.43	−4.69	0.06	5.27
Panel C: factors					
Market factor	0.40	4.14	−1.77	0.29	2.66
Momentum factor	0.27	4.97	−2.57	0.36	3.01
Basis momentum factor	0.63	4.37	−2.14	0.50	3.53
Basis factor	0.62	4.33	−2.53	0.88	3.03
Hedging factor	0.55	4.78	−2.08	0.49	3.36
Spreading factor	−0.66	4.70	−3.91	−0.68	1.64
Volatility factor	−0.18	4.60	−2.92	−0.44	2.57
Panel D: other characteristics					
Production (growth, %)	2.27	6.84	−1.23	2.03	5.21
Hedging pressure (HP)	0.13	0.19	−0.01	0.12	0.26
Inventory (growth %)	4.51	21.24	−8.95	2.33	15.36
Momentum (t, $t-12$)	5.32	32.62	−17.31	−1.02	21.70
Basis momentum	−8.31	218.31	−12.08	−6.18	1.59
Vol (Ret)	8.40	1.85	7.04	8.35	9.66
Basis	−4.17	22.46	−13.30	−7.18	−0.32

measures of deforestation and estimates of the CO_2 emissions that it causes, we can control for the impact of commodities on the climate in our regression.[13]

We estimate the following regression:

$$r_{i,m,t} = \beta_0 + \beta_1 IntSpeciesLoss_{i,t-1} + \beta_2 Controls_{i,t-1} + \mu_m + \gamma_i + \varepsilon_{i,m,t} \tag{3}$$

where $r_{i,m,t}$ is the spot price (in US dollars) excess return of commodity i over month m of year t, $IntSpeciesLoss_{i,t-1}$ is the intensity of species loss measured at the end of the previous year, μ_m are month–year fixed effects and γ_i are commodity fixed effects. Standard errors are double-clustered at the month–year and commodity level. A similar fixed effects specification is used, for instance, by Boons and Prado (2019). As noted in their paper, including time fixed effects removes the passive variation resulting from time variation in commodity returns, while adding commodity fixed effects eliminates the passive component from variation in the unconditional average commodity returns, thus controlling for systematic differences across the markets. We believe that this specification is particularly suitable for our case, as commodity returns are well-known to be driven by idiosyncratic factors (see,

---

[13] As explained in Section 3, the carbon emission data from JNCC's Commodity Footprint project are emissions generated from deforestation or drainage of peatlands. As a result, they are highly correlated with deforestation. Therefore, the two variables are not used in the same specification to avoid issues with multicollinearity. These are instead considered two alternative proxies of the impact of commodities on climate.

e.g., Gorton and Rouwenhorst 2006; Hong and Yogo 2012). To control for idiosyncratic shocks to demand and supply, we also include the growth rate of production in our regressions.[14]

To ensure that commodity characteristics (intensity of species loss, deforestation, and emissions) have incremental explanatory power for returns relative to the factors documented in the commodity literature, we also estimate equation (3) for the risk-adjusted returns, following the approach by Brennan, Chordia and Subrahmanyam (1998). In the baseline specification, we use a model that includes seven commodity factors obtained as discussed in Section 3: market, momentum, basis-momentum, hedging, spreading, and volatility (see, e.g., Gong, Gozluklu and Kim 2023). However, in Appendix Table B1, we report the results obtained using other specifications of the risk factor model.

Our baseline results are reported in Table 2. Panel A reports the results for raw returns, while Panel B displays the results for risk-adjusted returns. Notably, the coefficient of interest is positive and precisely estimated across all specifications. Considering, for instance, column (2) of Panel A, an additional ten species lost per 10,000 km^2 of area harvested is associated with a 58 basis point increase in the spot returns of commodities (t-stat = 4.46). The result remains very similar (56 basis points, t-stat = 3.29) when we consider risk-adjusted returns (Panel B). Such a deviation is close to the interquartile range of the intensity species loss, and it is henceforth a reasonable measure of economic significance.[15] Considering a 95 percent confidence interval, a conservative lower-bound estimate of the economic significance of changes in the intensity of species loss on spot commodity returns is around 20 basis points for an additional ten species lost per 10,000 km^2 of area harvested. In these baseline results, we link the returns on month m of year t with the intensity of species loss measured at the end of the previous calendar year ($t-1$). As a robustness check, we re-estimate equation (3) conditioning on information at $t-2$, thereby guaranteeing that all information used in the regression was available before the corresponding return was realized. The results remain qualitatively identical and are reported in Appendix Table B2.

In columns (4)–(7), we repeat the estimation over two sub-samples (pre and post January 2015). Besides splitting the sample into two equal parts, this cut-off is interesting because of the release of the Global Biodiversity Outlook 4 in 2014. GBO-4 served as a midpoint review of efforts to achieve the Aichi Biodiversity Targets, and concluded that overall progress was insufficient to meet the 2020 targets, requiring additional, significant global action. The results show that the coefficient of interest is very small and insignificant before 2015, while it becomes precisely estimated afterwards. This is consistent with the evidence in Garel et al. (2024), who find that biodiversity transition risk is a recent phenomenon.

Interestingly, the coefficients on the (log of) deforestation and CO_2 emissions turn out to be small and insignificant. While this might seem surprising at first, it has to be interpreted in the light of the fact that deforestation is not necessarily a recurring activity, as it typically takes place in bursts and discrete episodes, not as a smooth, recurring process. Once land is cleared, it is often permanently converted, reducing the frequency of repeated deforestation.[16] While the Commodity Footprints database tries to tackle the issue by attributing the deforestation to production with a lag and across an amortization period of 5 years, the sporadic nature makes deforestation a poor predictor in monthly return regressions. Similarly, while the carbon emissions generated by operating a plant tend to be stable over time if the production scale does not change (or measures are taken to reduce emissions),

---

[14] Our baseline results include the lagged growth rate of production. We also experimented with the contemporaneous growth rate, and the results do not change. These results are available upon request from the Authors.

[15] Applying a classical one-standard-deviation change (adjusted to consider the impact of all other controls in the regression, including the fixed effects) to the intensity of species loss leads to an increase of about 70 basis points in spot returns. However, we consider the interquartile range to be a more appropriate shock size because the intensity of species loss is not normally distributed.

[16] Satellite data (e.g., Hansen et al. 2013) confirm that deforestation tends to spike during specific events, and not to occur uniformly over time.

Table 2. Intensity species loss and commodity spot returns.

Note: This table reports panel regressions relating monthly spot excess returns to the intensity of species loss. The sample period is 2005–2022. All the specifications include month–year and commodity fixed effects. Standard errors clustered at the month–year and commodity level are in parentheses. Panel A refers to the raw returns of the twenty-three agricultural commodities for which the spot prices and the intensity of species loss are available. Panel B concerns risk-adjusted returns. Risk adjustment is obtained using a seven-factor model including market, momentum, basis-momentum, hedging, spreading, and volatility. Intercepts are not reported. *, **, and *** represent significance levels of 0.10, 0.05, and 0.01, respectively. Appendix A provides complete variable definitions and a list of all the commodities included in the exercise.

Panel A: raw returns

	Full sample			**Before 2015**		**2015–2022**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intensity species loss $(t-1)$	0.053***	0.058***	0.061***	−0.028	0.135***	−0.007	0.147***
	(0.011)	(0.013)	(0.015)	(0.089)	(0.022)	(0.079)	(0.028)
Production (growth $t-1, t-2$)		−0.010	−0.009	−0.038	0.038	−0.037	0.037
		(0.022)	(0.022)	(0.029)	(0.028)	(0.029)	(0.026)
Log emission $(t-1)$		−0.050		−0.671	0.349		
		(0.338)		(0.535)	(0.522)		
Log deforestation $(t-1)$			0.055			−0.320	0.712
			(0.401)			(0.891)	(0.971)
Observations	4,692	4,344	4,416	2,184	2,160	2,208	2,208
Adjusted R^2	0.138	0.143	0.143	0.186	0.089	0.186	0.090

Panel B: risk-adjusted returns

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intensity species loss $(t-1)$	0.052***	0.056***	0.059***	−0.065	0.125***	−0.046	0.136***
	(0.015)	(0.017)	(0.021)	(0.080)	(0.025)	(0.072)	(0.035)
Production (growth $t-1, t-2$)		−0.006	−0.005	−0.034	0.041*	−0.033	0.039*
		(0.021)	(0.021)	(0.025)	(0.023)	(0.025)	(0.021)
Log emission $(t-1)$		0.010		−0.658	0.408		
		(0.360)		(0.568)	(0.567)		
Log deforestation $(t-1)$			0.130			−0.375	0.925
			(0.423)			(0.916)	(1.008)
Observations	4,692	4,344	4,416	2,184	2,160	2,208	2,208
Adjusted R^2	0.092	0.093	0.093	0.123	0.057	0.123	0.058

because of the connection with deforestation, agricultural commodities produce CO_2 emissions only if there are changes in production size or location. Furthermore, all the measures of commodity environmental impact (deforestation, CO_2 emissions, and species loss) are estimated, and their estimation involves complex data collection. Therefore, they are all subject to measurement error, which can lead to an attenuation bias in their coefficients. This can also explain the lack of significance of the coefficient on deforestation (emissions). To address the possibility that climate-related transition risk is not appropriately controlled for, in Section 4.2, we also conduct an event study around the Kunming Declaration.

Finally, in Table 3, we explore whether segmentation may exist across commodities (for instance, because of financialization) and repeat the exercise after removing from our sample the six agricultural commodities that are included in the Goldman Sachs Commodity Index (GSCI): Wheat, corn, sugar, cotton, coffee, and soybeans. The GSCI is specifically chosen because it is one of the most influential commodity indices globally, heavily used by institutional investors, pension funds, and commodity traders for portfolio allocation and benchmarking, see Tang and Xiong (2012). Commodities included in the GSCI typically experience substantial investor demand driven by portfolio diversification motives, speculative trading, and hedging, often causing their price movements to reflect financial market conditions alongside fundamental supply and demand factors. The results remain

Table 3. Intensity species loss and commodity spot returns excluding commodities in the GSCI index.
Note: This table reports panel regressions relating monthly spot excess returns to the intensity of species loss when highly financialized commodities are removed. Specifically, we exclude the commodities that belong to the GSCI: wheat, corn, sugar, cotton, coffee, and soybeans. The sample period is 2005–2022. All the specifications contain month–year and commodity fixed effects. Standard errors clustered at the month–year and commodity level are in parentheses. Intercepts are not reported. *, **, and *** represent significance levels of 0.10, 0.05, and 0.01, respectively. Appendix A provides complete variable definitions and a list of all the commodities included in the exercise.

	Full Sample			Before 2015		2015–2022	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intensity species loss ($t-1$)	0.049***	0.055***	0.057***	−0.035	0.125***	−0.014	0.135***
	(0.010)	(0.013)	(0.017)	(0.090)	(0.024)	(0.081)	(0.025)
Production (growth $t-1$, $t-2$)		−0.004	−0.003	−0.035	0.053	−0.033	0.051
		(0.028)	(0.028)	(0.034)	(0.035)	(0.034)	(0.034)
Log emission ($t-1$)		0.003		−0.679	0.457		
		(0.377)		(0.626)	(0.578)		
Log deforestation ($t-1$)			0.170			−0.367	1.035
			(0.530)			(1.170)	(1.183)
Observations	3,468	3,192	3,264	1,608	1,584	1,632	1,632
Adjusted R^2	0.105	0.107	0.109	0.153	0.055	0.154	0.059

consistent with those in Table 2. For instance, in column (2), an additional ten species lost per 10,000 km^2 of area harvested corresponds to a 55 basis point increase in spot returns, very close to the 58 basis points reported above. Therefore, we conclude that our baseline results are not driven by financialized commodities.

4.2 Event study evidence

To rule out the possibility that our results might be driven by physical biodiversity risk, climate change transition or physical risks, or any other confounders that we might not have been able to control for, we conduct an event study around the date of the Kunming Declaration, similar to Garel et al. (2024). The Kunming Declaration (October 13, 2021) marked an important milestone in recognizing the role of agricultural commodities in driving biodiversity loss and called for urgent measures to address it. For instance, *Target 1* of the declaration is to address “land- and sea-use change, to bring the loss of areas of high biodiversity importance, including ecosystems of high ecological integrity, close to zero by 2030.” Similarly, *Target 16* outlines the importance of “establishing supportive policy, legislative or regulatory frameworks” to reduce the global footprint of food consumption. Therefore, we expect the declaration to heighten transition risk for commodities with a high intensity of species loss, causing their price to be revised downward, to allow for future higher average (expected) returns.

We estimate

$$r_{i,m,t} = \beta_0 + \delta_1 Post \times HighIntensitySpeciesLoss + \mu_m + \gamma_i + \varepsilon_{i,m,t} \tag{4}$$

where $r_{i,m,t}$ is the excess return of commodity i over month m of year t, *Post* is a dummy variable equal to one for the month that followed the Kunming Declaration (November 2021), and *HighIntensitySpeciesLoss* is a dummy equal to one if the intensity of species loss was above its median in 2020 (the year before the declaration). We include month–year and commodity fixed effects such that the dummies *Post* and *HighIntensitySpeciesLoss* are absorbed in them. The errors are clustered at the month–year and commodity level. The coefficient of interest is δ_1. We also estimate a dynamic version of the specification above, over a symmetric

Table 4. Commodity price reactions to the Kunming Declaration.

Note: This table reports the results of an event study around the Kunming Declaration; the event date is the month of October 2021. We report results for commodities with above versus below values of the intensity of species loss. In columns (1) and (3), *Post* is a dummy equal to one for the month that follows the Kunming Declaration. *Treated* is a dummy equal to one for commodities with an above-median intensity of species loss as of 2020. In columns (2) and (4), we compare the returns of high versus low intensity of species loss over a $[-2, +2]$ months window around the event. The baseline month is two months before the event. Intercepts are not reported. All the specifications include month–year and commodity fixed effects. Columns (1) and (2) refer to excess returns, while columns (3) and (4) refer to abnormal returns computed using the market model to estimate expected returns. Standard errors double-clustered at the month–year and commodity level are reported in parentheses. *, **, and *** represent significance levels of 0.10, 0.05, and 0.01, respectively.

	(1) Returns	(2)	(3) Abn. Returns	(4)
Post × treated	−3.587***		−2.772***	
	(0.213)		(0.204)	
Pre $(m-1)$ × treated		1.100		1.914
		(1.332)		(1.454)
Pre $(m=0)$ × treated		−2.931		−2.097
		(1.821)		(1.695)
Post $(m+1)$ × treated		−3.595***		−2.767**
		(1.124)		(0.998)
Post $(m+2)$ × treated		0.136		1.133
		(1.139)		(0.902)
Time FE	Yes	Yes	Yes	Yes
Commodity FE	Yes	Yes	Yes	Yes
Observations	4,968	4,536	4,899	4,899
Adjusted R^2	0.135	0.135	0.225	0.224

window $[-2, +2]$ months around the declaration date.[17] Finally, we estimate equation (4) using abnormal returns (similar to Garel et al. 2024). The abnormal returns are computed from a market model, where the market factor is defined as in Section 3, and the parameters are estimated recursively over the period $[-60, -1]$ months.

The results are reported in Table 4. On average, over the month following the Kunming Declaration, the returns of commodities with an above-median biodiversity footprint were lower by 3.59 percent than those with a below-median biodiversity footprint. The picture remains very similar when we adjust the returns using the market model. The abnormal returns of commodities with an above-median biodiversity footprint were 2.72 percent lower than those with a below-median biodiversity footprint, and the effect is statistically significant at a 1 percent level.

In columns (2) and (4), we report the dynamic specification of the event study as described above. The results show that the prices of commodities more exposed to transition risk reacted by declining sharply relative to commodities less exposed to it. Conversely, no differences are visible in the month before the declaration or two months after that, reinforcing our claim that what we are capturing is indeed the effect of the declaration. The results remain robust to different choices of the dynamic specification. For instance, figure 6 shows the pre- and postevent coefficients for a dynamic specification over an event window spanning the period from four months before to 4 months after the declaration. The month

---

[17] In this dynamic specification, the baseline month is two months before the event. We do not restrict the estimation period in order to retain more observations for identifying commodity fixed effects. Consequently, months outside the $[-2, 2]$ window are effectively pooled with the baseline. Restricting the sample to the event window, however, yields very similar results.

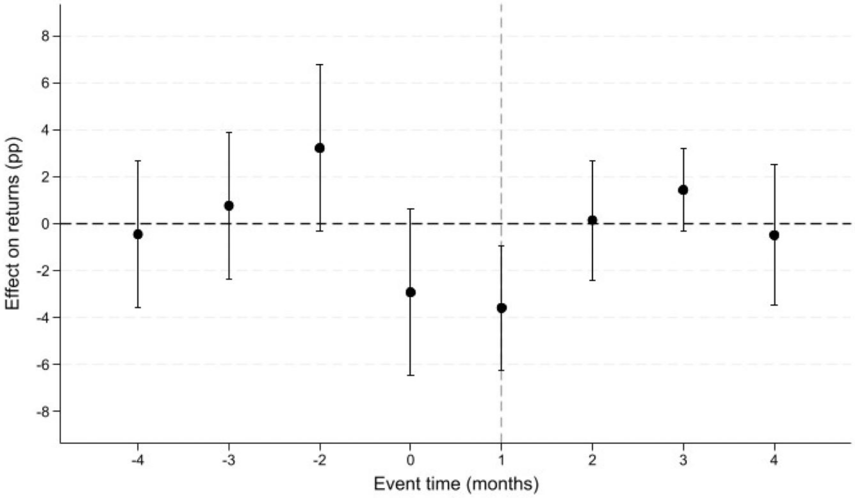

Figure 6. Event study dynamic specification. *Note*: The figure displays the estimated coefficients from a dynamic event study specification centered on the Kunming Declaration. The event window spans the period from four months before to 4 months after the declaration ($[-4, 4]$). Event time is set to zero in October 2021, the month of the Kunming Declaration. The month immediately preceding the declaration serves as the reference period and is omitted from the estimation.

immediately preceding the declaration serves as the reference period and is omitted from the estimation. The figure is largely consistent with the results presented in Table 4. It clearly shows evidence of repricing over the month following the declaration, while the parallel trend assumption held before the event.

To further validate the idea that our measure of commodity biodiversity footprint is not merely a re-labelling of a broader climate transition risk, we perform a placebo test using the Paris Agreement as an event date. More specifically, we keep the "treated" commodities fixed, but we repeat the event study using December 2015 (the date of the Paris Agreement) as the focal date. As the Paris Agreement explicitly targeted carbon emissions to tackle climate risk and had no implications for biodiversity loss intensity policies, we expect no significant differences in the returns of the treated and untreated commodities following its announcement. The results reported in Table 5 confirm our intuition. The $Post \times Treated$ coefficients in columns (1) and (3) are small and statistically insignificant. Similarly, the dynamic effects associated with $t = 0$, $t = 1$, and $t = 2$ are also statistically insignificant. This further corroborates the idea that the intensity of species loss captures a risk that is largely distinct from climate risk.

4.3 Futures returns

In this section, we re-estimate equation (3) using futures rather than spot returns, computed as explained in Section 3. Clearly, this analysis can only be conducted for commodities that have a set of traded futures contracts, which restricts our sample to coffee, cocoa, oats, cotton, rice, corn, soybeans, wheat, sugar, and orange juice (whose futures returns we use instead of oranges).[18] Also in this case, the main coefficient of interest is the one associated with the intensity of species loss. To control for other factors that the literature has identified as explanatory for commodity futures returns, we employ two alternative methods. In

---

[18] The results reported below remain qualitatively similar if we add Rubber, Palm Oil, and Canola. We exclude these futures from our main analysis because their contracts are significantly less liquid. The results remain available upon request.

Table 5. Placebo test around the Paris Agreement.

Note: This table reports the results of a placebo test that uses December 2015 (the date of the Paris Agreement) as the event date. In columns (1) and (3), *Post* is a dummy equal to one for the month that follows the Paris Agreement. *Treated* is a dummy equal to one for commodities with an above-median intensity of species loss as of 2020. In columns (2) and (4), we compare the returns of high versus low intensity of species loss over a $[-2, +2]$ months window around the event. The baseline month is 2 months before the event. Intercepts are not reported. All the specifications include month–year and commodity fixed effects. Columns (1) and (2) refer to excess returns, while columns (3) and (4) refer to abnormal returns computed using the market model to estimate expected returns. Standard errors double-clustered at the month–year and commodity level are reported in parentheses. *, **, and *** represent significance levels of 0.10, 0.05, and 0.01, respectively.

	(1) Returns	(2)	(3) Abn. Returns	(4)
Post × Treated	0.275		0.299	
	(0.200)		(0.205)	
Pre $(m-1)$ × treated		2.816**		2.673**
		(1.319)		(1.168)
Pre $(m=0)$ × treated		0.287		0.310
		(0.583)		(0.679)
Post $(m+1)$ × treated		−1.147		−1.292
		(1.540)		(1.544)
Post $(m+2)$ × treated		0.920		0.861
		(1.204)		(1.291)
Time FE	Yes	Yes	Yes	Yes
Commodity FE	Yes	Yes	Yes	Yes
Observations	4,968	4,536	4,899	4,899
Adjusted R^2	0.135	0.135	0.225	0.224

columns (1) through (5), we directly control for futures-specific characteristics such as basis, basis-momentum, momentum, volatility, hedging pressure, and inventory growth.[19] In columns (6) to (7), instead of using such characteristics, we adjusted returns for risk by regressing them on the commodity factors similar to what we did in Section 4.1. Similarly, to Section 4.1, we also control for either deforestation or the CO_2 emissions caused by deforestation.

The results are presented in Table 6. The specifications in columns (1) and (4) refer to all ten commodities mentioned above. The remaining specifications include only nine commodities because hedging pressure could not be calculated for Rice. Notably, the estimated coefficient on the intensity of species loss turns out to be negative and not statistically significant in all specifications.

The small cross-sectional sample size obviously represents a limitation of this exercise and could be driving the lack of significant results. For instance, taking the specification in column (1) of Table 6, and given the large robust standard error of 0.413, the minimum detectable effect with an 80 percent power (using a normal approximation) would correspond to a coefficient of 1.16. This amounts to a change in returns of about 1.16 percent for one additional species lost over 10,000 ha of area harvested. This would clearly be a very large effect, and therefore, our test is underpowered.

In Appendix Table B4, we re-estimated the regressions in columns (1) and (2), and (6) and (7) on a matched sample of spot returns. The estimates of the coefficients are very similar to those reported in Table 2, validating the idea that the results are not an artifact of the

---

[19] Details on how these characteristics have been constructed can be found in Appendix A. The commodity-specific characteristics are not directly used in the spot analysis above, as constructing them requires the existence of traded futures, significantly restricting the sample.

Table 6. Intensity species loss and commodity futures returns.

Note: This table reports panel regressions relating monthly futures excess returns to the intensity of species loss. The details concerning the commodities included in the exercise can be found in Appendix A. The sample period is 2005–2022. All the specifications contain month–year and commodity fixed effects. Columns (1) through (5) concern raw returns. Columns (6) and (7) concern risk-adjusted returns. Risk adjustment is obtained using a seven-factor model including market, momentum, basis-momentum, hedging, spreading, and volatility. Intercepts are not reported. Standard errors clustered at the month–year and commodity level are in parentheses. Intercepts are not reported. *, **, and *** represent significance levels of 0.10, 0.05, and 0.01, respectively. Appendix A provides complete variable definitions.

	(1) Return	(2) Return	(3) Return	(4) Return	(5) Return	(6) adj ret	(7) adj ret
Intensity species loss ($t-1$)	−0.349	−0.392	−0.474	−0.452	−0.463	−0.066	−0.101
	(0.413)	(0.416)	(0.429)	(0.462)	(0.464)	(0.394)	(0.398)
Log deforestation ($t-1$)		−0.784	−0.886	−0.507	−0.042		−0.625
		(0.652)	(0.650)	(0.712)	(0.748)		(0.651)
Basis ($t-1$)			−0.002	0.000			
			(0.011)	(0.011)			
Momentum ($t-1$, $t-12$)			−0.009	−0.018*	−0.015		
			(0.009)	(0.010)	(0.012)		
Basis momentum ($t-1$)			0.036	0.048	0.044***		
			(0.047)	(0.047)	(0.010)		
Log emissions ($t-1$)	−0.695					−0.477	
	(0.629)					(0.612)	
Growth inventory ($t-1$,$t-2$)				−0.037***	−0.038***		
				(0.011)	(0.012)		
Hedging pressure ($t-1$)					−1.589		
					(1.778)		
Return volatility ($t-1$)					−0.254		
					(0.185)		
Observations	2,040	2,040	2,009	1,889	1,704	2,040	2,040
Adjusted R^2	0.276	0.276	0.281	0.293	0.313	0.019	0.019

sample choice. However, in this case, the coefficients are not statistically significant, with *P*-values around 0.25, consistent with the lack of power discussed above. However, one interesting fact is that the estimated sign of the coefficient on the intensity of species loss is negative for the futures returns and positive for the spot returns, even when a matched sample is used (and across different specifications). Such evidence, although difficult to robustly validate empirically due to data availability limitations, is consistent with the theoretical framework presented in Section 5.

4.4 Other Measures of Biodiversity Risk

We have also experimented with using the (log of) species loss rather than its intensity. The results, which are reported in Appendix Table B3, show that the coefficient of interest is insignificant across all the specifications. This is not entirely surprising. As we explained in Section 2, total species loss is not, in our opinion, a good measure of commodities' biodiversity footprint for several reasons. For instance, total species loss is largely driven by the production scale. Accordingly, this measure can fluctuate in ways that do not capture commodities' exposure to transition risk but merely reflect demand and supply dynamics.

In contrast, the commodities characterized by a high intensity of species loss—such as palm oil, cocoa, and coffee—face inherent sustainability risks. This derives from the fact that high-intensity commodities tend to be environmentally destructive by nature, for example, requiring deforestation in biodiversity hotspots as we have discussed in Section 2. As outlined in Section 2, the commodities identified by our measure as having a high biodiversity footprint are typically grown in tropical rainforest regions with exceptional biodiversity. Their expansion often involves clearing primary forests and peatlands, causing irreversible habitat destruction. Even small-scale production can lead to significant ecological damage due to the overlap with habitats of endangered species. To the contrary, commodities with high overall species loss are those such as wheat, whose production is extensive but does not primarily happen in tropical forests. Arguably, the latter are less likely to be the target of regulations or to come under the scrutiny of environmentally concerned consumers.

5. The conceptual framework: an investment model of commodity pricing

To support the causal nature of our empirical results and building on Gorton, Hayashi and Rouwenhorst (2012) and Yang (2013), we develop a two-period production model in which commodity spot and futures prices are endogenously linked to physical investment decisions and the risk posed by shifts in climate and biodiversity regulations. Supplementary Appendix B provides full details and a small set of simulations that showcase the model implications. The model features two categories of agents, one producer (farmer–hedger) for each commodity $c = 1, 2, \dots, C$ and one commodity-specialized investor-speculator.[20] Both agents are risk-averse and, for simplicity, they feature (locally) mean–variance preferences (Gorton, Hayashi and Rouwenhorst 2012). We consider discrete times $t, t+T$. The risk-free rate is set to zero. Two markets open in each period. In the first period (t), investors and farmers–hedgers trade in the spot market at price S_t^c and in the futures market at price $F_{t,T}^c$. In the second period ($t+T$), the spot market clears to yield the final price S_T^c, and the futures expires. There are three shocks that are realized at time T described by random variables that are unknown as of time t:

- $\tilde{\delta}_T^c$, the idiosyncratic capacity depreciation rate[21];
- $\tilde{\tau}_T$, the carbon-price affecting per-unit output cost and homogeneously applied to all commodities;
- $\tilde{B}_T$, the biodiversity-transition pressure consisting in changes of the regulatory penalty rates—both scale- and intensity-based—uniformly across all commodities.

All these random variables are assumed to be mutually independent and, calling a generic one L (henceforth, L_t will be $\tilde{\delta}_T^c$, $\tilde{\tau}_t$, or $\tilde{B}_t$), the first three have the following, simple Bernoulli structure with $l > 0$ (below l is δ, τ, and b, respectively) and for a given L_t:

$$L_T = \begin{cases} L_t + l & \text{with prob. } q_l, \\ L_t & \text{with prob. } 1 - q_l. \end{cases}$$

so that $E[L_T] = L_t + q_l l$ and $\text{Var}[L_T] = q_l(1 - q_l)l^2$. At this point, if we assume that $q_l \simeq 0$, because

$$\frac{dE[\Delta L_T]}{dq_l} = l > 0, \quad \frac{d\text{Var}[L_T]}{dq_l}\bigg|_{q_l=0} = (1 - 2q_l)l^2\bigg|_{q_l=0} = l^2 > 0,$$

---

[20] Following Yang (2013), we assume the economy to be competitive, with each commodity involving many identical producers, allowing their behavior to be reduced to a single representative producer problem.

[21] This can also capture an idiosyncratic yield shock hitting the production of c by the farmer; in this case, the shock to $\tilde{\delta}_T^c$ could be negative to capture a positive yield shock.

we have that for marginal, positive changes in the probability q_l starting from $q_l \simeq 0$, both $dE[L_T]$ and $d\mathrm{Var}[L_T]$ are positive and increasing in $l > 0$. Moreover, the square of l becomes a simple, local overall measure of the risk of change in the phenomenon measured by L_T (as in Deaton and Laroque, 1992).

At the beginning of period t, the farmer c has on hand an exogenous (endowment-like) amount $z_t^c > 0$ of the commodity. This endowment can be either sold immediately in the spot market or re-invested to generate future production capacity. The farmer c selects $X_t^c \leq S(Q_t)z_t^c$ to be the dollar amount of capacity investment, required to be nonnegative. Therefore the farmer sells $S(Q_t)z_t^c - X_t^c$ in the spot market in period t and invests X_t^c, so that her period t profit, π_t^c, is $\pi_t^c = S(Q_t^c)z_t^c - X_t^c$, where $S(\cdot)$ denotes the inverse demand function assumed to be decreasing in its argument and differentiable.

Each commodity c farmer produces physical output using a linear technology:

$$Q_T^c = (1 + \eta^c)(X_T^c)^{\upsilon}.$$

Production is assumed to be deterministic, so $\upsilon = 1$, indicating constant returns to scale as in Yang (2013). The capital accumulates as:

$$X_T^c = (1 - \tilde{\delta}_T)X_t^c.$$

The adoption of a non-neutral technology, however, is costly. The total cost to the farmer in period t comprises[22]:

1) $X_t^c + h(\eta^c)$ (Intensity costs) with $h'(\eta) > 0$ (cleaner production increases marginal costs)
2) $\tilde{\tau}_T Q_T^c$ (carbon emissions tax cost)
3) $\lambda_B \tilde{B}_T[\phi Q_T^c - (1 - \phi)(\eta^c - \eta)]$ (biodiversity penalty/reward) with $0 \leq \phi \leq 1$.

When $\phi = 1$, the random biodiversity penalty acts as a per-unit of output tax; when $\phi = 0$, it is instead an abnormal (versus the cross-sectional commodity average) intensity tax; in the intermediate cases, the regulatory system mixes per-unit output and intensity taxes. Realistically, the carbon taxes are only imposed on a per-unit-of-output basis. In this setup, $\tilde{\tau}_T$ can be interpreted as either a tax on CO_2 emissions or as a per-unit carbon price if permits need to be purchased (after production occurs). b is the random biodiversity-transition shock (e.g., new habitat regulations, ecosystem-value taxes). λ_B scales the strength of biodiversity regulations and the financial impact of the biodiversity shock b on the farmer's profits.

After t, each farmer c chooses a short hedging position in futures ($H_t^c < 0$). The corresponding final, time T gross revenue is $S(Q_T^c)(Q_T^c - H_t^c) + F_{t,T}^c H_t^c = S(Q_T^c)Q_T^c + H_t^c(F_{t,T}^c - S(Q_T^c))$. Therefore, the total final profit is:

$$\begin{aligned}\pi_T^c &= S(Q_T^c)Q_T^c + H_t^c(F_{t,T}^c - S(Q_T^c)) - h(\eta^c)] - \tilde{\tau}_T Q_T^c - \lambda_B \tilde{B}_T[\phi Q_T^c - (1 - \phi)\tilde{\eta}^c] \\ &= (Q_T^c - H_t^c)S(Q_T^c) + H_t^c F_{t,T}^c - h(\eta^c)] - \tilde{\tau}_T Q_T^c - \lambda_B \tilde{B}_T[\phi Q_T^c - (1 - \phi)\tilde{\eta}^c],\end{aligned}$$

where $\tilde{\eta}^c \equiv (\eta^c - \eta)$ is the normalized, abnormal technology intensity index. The sequence of events between t and T is as follows:

1) The futures market clears at price $F_{t,T}$.
2) At T, the shocks δ, τ, and b realize.

---

[22] We owe the idea to account for both CO_2 emission taxes and for biodiversity penalties and rewards in the manner specified below to Markus Leippold, who has provided numerous suggestions in his discussion.

3) Producers obtain output Q^c_T, sell $Q^c_T + H^c_t$ on the spot market at S^c_T, deliver H^c_t via futures at $F^c_{t,T}$. Profits π^c_T are realized and the futures contract is settled.

5.1 Overview of the implications of the model

The hedger–farmer problem is:

$$\max_{X^c_t, H^c_t} \pi^c_t + E[\pi^c_T] - \frac{1}{2}\gamma^f_c \mathrm{Var}[\pi^c_T] \quad \text{s.t.} \quad H^c_t \leq 0,\, \eta^c > -1, \tag{5}$$

(here $H^c_t \leq 0$ means hedging), which implies the two FOCs:

$$\frac{\partial \mathcal{L}}{\partial H^c_t} = F^c_{t,T} - E[S(Q^c_T)] - \gamma^f_c (Q^c_T - H^c_t)\mathrm{Var}[S(Q^c_T)] = 0 \tag{6}$$

$$\Rightarrow \quad H^c_t = \frac{E[S(Q^c_T)] - F^c_{t,T}}{\gamma^f_c \mathrm{Var}[S(Q^c_T)]} - Q^c_T \tag{7}$$

that is, the mean–variance optimal hedge minus the term $-Q^c_T$ (this is called natural exposure and derives from the very nature of the farming activity).[23]

$$\frac{\partial \mathcal{L}}{\partial X^c_t} = -1 + \kappa^c \{E[S(Q^c_T)] - E[\tilde{\tau}_T] - \lambda_B \phi E[\tilde{B}_T]\} - \gamma^f_c [V^c_{1_T} + V^c_{2_T}] X^c_t = 0 \tag{8}$$

$$\Rightarrow \quad \widehat{X}^c_t = \frac{\kappa^c \{E[S(Q^c_T)] - E[\tilde{\tau}_T] - \lambda_B \phi E[\tilde{B}_T]\} - 1}{\gamma^f_c [V^c_{1_T} + V^c_{2_T}]} \tag{9}$$

where $\mathrm{Var}[\pi^c_T] = [V^c_{1_T} + V^c_{2_T}](X^c_t)^2$, $\kappa^c \equiv (1 - \delta_t - \delta)(1 + \equiv (\eta^c)$, $d^c \equiv \delta(1 + \equiv (\eta^c)^2$ (how much quantity is exposed to spot prices), $V^c_{2_T} = (\kappa^c)^2 d^c$, and

$$V^c_{1_T} \equiv \mathrm{Var}[S(Q^c_T)](d^c + (\kappa^c)^2) + (E[S(Q^c_T)])^2 d^c = \text{Spot variance risk} + \text{Reg-shock risk}$$

bundles together all the profit-variance coming from the combination of spot-price risk and the depreciation–shock risk operating through the producer's output.[24] However, because the expression for $\widehat{X}^c_t$ depends on expected future spot prices which, in their turn, depend on $\widehat{X}^c_t$, in general, equation (9) is a nonlinear equation that requires numerical solution methods.

The commodity $c = 1, 2, \ldots, C$ investor's problem, who starts out with wealth W^c_t, is:

$$\max_{\omega^c_t} E[W^c_T] - \frac{1}{2}\gamma^I_c \mathrm{Var}[W^c_T] \quad \text{s.t.} \quad W^c_T = W^c_t + \omega^c_t (S^c_T(Q^c_T) - F^c_{t,T}), \tag{10}$$

where ω^c_t is the investment in long futures positions, which implies the FOC:

---

[23] The classical risk-neutral condition, $F_{t,T} = E[S(Q^c_T)]$ (zero risk premium) in this case would imply a hedging demand equal to the entire production as the hedger/farmers are risk-averse and hedging at a zero premium in the presence of spot price risk would remove all risk while such an insurance would come at no cost.

[24] The expression for X^c_t holds as long as the numerator is positive, otherwise $X^c_t = 0$ represents the optimum, the so-called stock-out state in which $Q^c_T = 0$ as no capital expenditure is made and the shocks are multiplicative.

$$(\text{w.r.t. }\omega_t^c)\quad \frac{\partial \mathcal{L}^c}{\partial \omega_t^c} = E[S_T^c(Q_T^c)] - F_{t,T}^c - \omega_t^c \gamma_c^I \text{Var}[S_T^c(Q_T^c)] = 0 \Rightarrow \omega_t^c = \frac{E[S_T^c(Q_T^c)] - F_{t,T}^c}{\gamma_c^I \text{Var}[S_T^c(Q_T^c)]},$$

or $\omega_t^c = \frac{F_{t,T}^c}{\gamma_c^I \text{Var}[S_T^c(Q_T^c)]}$ times commodity c's futures risk premium, so if and only if the risk premium is positive/negative (hence, $E[S_T^c(Q_T^c)] \gtrless F_{t,T}^c$) the investor wants to go long (short).

Because $E[S_T^c(Q_T)] > F_{t,T}^c$ is necessary and sufficient for $H_t^c < 0$ but at the same time this guarantees $\omega_t^c > 0$, in equilibrium, because futures are in zero net supply, $\omega_t^c + H_t^c = 0$ which means that the average individual position taken by the farmer–hedger is

$$H_t^c = \min\left\{0, \frac{F_{t,T}^c - E[S_T^c(Q_T^c)]}{\gamma_c^f \text{Var}[S_T^c(Q_T^c)]}\right\} = \frac{F_{t,T}^c - E[S_T^c(Q_T^c)]}{\gamma_c^I \text{Var}[S_T^c(Q_T^c)]} \propto \text{ Futures Risk Premium} < 0.$$

Because this implies

$$\omega_t^c = \frac{F_{t,T}^c - E[S_T^c(Q_T^c)]}{\gamma_c^I \text{Var}[S_T^c(Q_T^c)]} = -\min\left\{0, \frac{F_{t,T}^c - E[S_T^c(Q_T^c)]}{\gamma_c^f \text{Var}[S_T^c(Q_T^c)]}\right\},$$

it follows that in equilibrium:

$$\frac{E[S_T^c(Q_T^c)] - F_{t,T}^c}{F_{t,T}^c} = \gamma_c^I \frac{\text{Var}[S_T^c(Q_T^c)]}{F_{t,T}^c} \min\left\{0, \frac{F_{t,T}^c - E[S_T^c(Q_T^c)]}{\gamma_c^f \text{Var}[S_T^c(Q_T^c)]}\right\}.$$

5.2 A decomposition for expected spot returns

The Supplementary Appendix B derives a first-order decomposition based on linearizing the full stochastic pricing relation of the expected spot return into a basis term and two covariance premia generated by (1) stochastic storage/depreciation and (2) biodiversity transition intensity risk. Let us approximate the unknown (in closed-form) stochastic discount factor (SDF) with a linear affine one consistent with the model's environment

$$M_{t+1} = \bar{M} - \varphi_t \xi_{t+1} - \lambda_\delta \tilde{\delta}_T - \lambda_B \tilde{B}_T, \tag{11}$$

where ξ_{t+1} is the futures-spanned payoff shock (the one priced through hedging pressure), orthogonal to $\tilde{\delta}_T$ and $\tilde{B}_T$ by construction[25]; $\varphi_t > 0$ captures the endogenous aggregate risk tolerance; and $\lambda_\delta, \lambda_B > 0$ are the prices of storage–cost and biodiversity risks, respectively.

With a zero risk-free rate, for any payoff X_{t+1} we have

$$S_t = E_t[M_{t+1}S_T], \quad F_{t,T} = \frac{E_t[M_{t+1}S_T]}{E_t[M_{t+1}]} = E_t[S_T] - \frac{Cov_t(M_{t+1}, S_T)}{E_t[M_{t+1}]}. \tag{12}$$

Because the futures payoff equals S_T, the futures risk premium is entirely driven by $Cov_t(M_{t+1}, S_T)$. Using the expression for the approximate SDF and $E_t[M_{t+1}] = \bar{M}$, we have:

[25] ξ_{t+1} is the shock that affects both producers' net exposure and speculators' hedging positions so that $E_t[S_T] - F_{t,T} \propto Cov_t(S_T, \xi_{t+1})$ and is the only source of uncertainty that the single traded futures contract actually spans and prices. The shocks $\tilde{\delta}_T$ (storage-cost) and $\tilde{B}_T$ (biodiversity) affect the spot price and agents' marginal utility but are not spanned by the single traded futures contract. Therefore, by construction (i.e., by model design) we impose $Cov_t(\xi_{t+1}, \tilde{\delta}_T) = Cov_t(\xi_{t+1}, \tilde{B}_T) = 0$, i.e., ξ_{t+1} is orthogonal (uncorrelated) to $\tilde{\delta}_T$ and $\tilde{B}_T$.

$$E_t[S_T] - F_{t,T} = \frac{1}{\bar{M}} \varphi_t Cov_t(S_T, \xi_{t+1}), \tag{13}$$

which is the *basis* component driven by the hedging (spanned) shock.

Starting from the definition of expected spot return $E_t[r_{S,t+1}] = (E_t[S_T] - S_t)/S_t$ and adding/subtracting $F_{t,T}$,

$$E_t[r_{S,t+1}] = \frac{E_t[S_T] - F_{t,T}}{S_t} + \frac{F_{t,T} - S_t}{S_t}.$$

the results above yield that:

$$\frac{F_{t,T} - S_t}{S_t} = -\frac{1}{S_t}\frac{Cov_t(M_{t+1}, S_T)}{E_t[M_{t+1}]} = \frac{1}{S_t}\left(\lambda_\delta Cov_t(S_T, \tilde{\delta}_T) + \lambda_B Cov_t(S_T, \tilde{B}_T)\right),$$

Collecting terms, we obtain:

$$E_t[r_{S,t+1}] = \underbrace{\frac{E_t[S_T] - F_{t,T}}{S_t}}_{\text{basis (hedgeable)}} + \underbrace{\frac{\lambda_\delta Cov_t(S_T, \tilde{\delta}_T)}{S_t}}_{\text{storage-cost volatility (non-hedgeable)}} + \underbrace{\frac{\lambda_B Cov_t(S_T, \tilde{B}_T)}{S_t}}_{\text{intensity premium (non-hedgeable)}}.$$

The storage-cost term arises because $\tilde{\delta}_T$ perturbs Q_T and hence S_T and marginal utility, creating a covariance–priced component that cannot be hedged away with the single futures payoff. Under the model's Bernoulli shocks and mean–variance preferences, $\lambda_\delta, \lambda_B > 0$, so positive co-movement of S_T with either shock raises the expected spot return. This decomposition provides the theoretical mapping for our empirical tests: the first (basis) term corresponds to the return spread across commodities sorted by basis, while the two nonhedgeable components underpin the cross-sectional relation between spot returns and measures of storage-cost (hence, convenience yield) volatility and biodiversity intensity documented in Section 4.[26]

5.3 One explicitly solved example

Under the assumption simple Bernoulli shocks and of a simple, linear inverse demand function, we can derive closed-form expressions for $\widehat{X}^c_T$, $\widehat{\Sigma}^c_T$, and $\widehat{F}^c_{t,T}$ as a function of the forcing state variables $(\delta_t, \tau_t, B_t, S_t)$ and of the parameters $(\alpha, \theta, \beta, q_\delta, \delta, q_\tau, \tau, \lambda_B, \varphi, q_B, b)$. Defining $\kappa^c \equiv (1 - \delta_t - \delta)(1 + \alpha \equiv (\eta^c) > 0$, the net expected return per unit invested is:

$$\kappa^c \left\{ \underbrace{[\alpha - \beta \mathbb{E}[Q^c_T]]}_{\text{Expected future spot price}} - \underbrace{[\tau_t + \tau + \lambda_B \varphi \mathbb{E}[\tilde{B}_T]]}_{\text{Expected regulatory costs}} \right\} - 1 \tag{14}$$

where $\alpha - \beta \mathbb{E}[Q^c_T]$ derives from the assumed linear demand function. Moreover, the fact that $Q^c_T = (1 - \tilde{\delta}_T) X^c_t (1 + \alpha \equiv (\eta^c)$ implies:

$$\text{Var}[Q^c_T] = q_\delta (1 - q_\delta) \delta^2 (1 + \alpha \equiv (\eta^c)^2 (X^c_t)^2,$$

while $\text{Var}[S^c_T] = \beta^2 \text{Var}[Q^c_T] = \beta^2 q_\delta (1 - q_\delta) \delta^2 (1 + \alpha \equiv (\eta^c)^2 (X^c_t)^2$ and

---

[26] Effectively, our empirical tests use standard commodity factors to control for basis and convenience yield risk and explicitly test for the cross-sectional impact of biodiversity intensity risk.

$$\mathrm{Var}[\tau_t + \tau + \lambda_B \varphi(B_t + b)] = (1 + \alpha \equiv (\eta^c)^2 (X_t^c)^2 [q_\tau(1 - q_\tau)\tau^2 + \lambda_B^2 \varphi^2 q_B (1 - q_B) b^2].$$

Using the general formula, we obtain:

$$(X_t^c)^3 = \frac{\phi_{0,t} + \phi_{1,t} X_t^c}{\gamma_f^c (V_{Q,t} + V_{\mathrm{reg},t})} \tag{15}$$

where $\phi_{0,t} \equiv -\kappa^c[\tau_t + \tau + \lambda_B \varphi(B_t + b) - \alpha] - 1$, $\phi_{1,t} \equiv -\kappa_t^c \beta(1 - \delta_t - \delta)(1 + \alpha \equiv (\eta^c) < 0, V_{Q,t} \equiv q_\delta(1 - q_\delta), \delta^2(1 + \alpha \equiv (\eta^c)^2$, $V_{\mathrm{reg},t} \equiv (1 + \alpha\psi_t^c)^2 [q_\tau(1 - q_\tau)\tau^2 + \lambda_B^2 \varphi^2 q_B(1 - q_B) b^2]$. This is a nonlinear equation in X_t^c, but it can be solved exactly. In fact, it is a polynomial equation of the form:

$$(X_t^c)^3 - \frac{\phi_1}{\gamma^c (V_Q + V_{\mathrm{reg}})} X_t^c - \frac{\phi_0}{\gamma^c (V_Q + V_{\mathrm{reg}})} = 0, \tag{16}$$

(also known as the depressed cubic equation) with general solution[27]:

$$\widehat{X}_t^c = \max\left\{0, \sqrt[3]{\frac{1}{\gamma^c g}\left(\sqrt[3]{\frac{\phi_0}{2} + \sqrt{\frac{\phi_0^2}{4} + \frac{\phi_1^3}{27\gamma^c g}}} + \sqrt[3]{\frac{\phi_0}{2} - \sqrt{\frac{\phi_0^2}{4} + \frac{\phi_1^3}{27\gamma^c g)}}}\right)}\right\} \tag{17}$$

where $g \equiv (V_Q + V_{\mathrm{reg}})$. Given this expression for $\widehat{X}_t^c$, we obtain:

$$Q_T^c = (1 - \tilde{\delta}_T)(1 + \alpha \equiv (\eta^c) \widehat{X}_t^c, S_T^c = \alpha - \beta(1 - \tilde{\delta}_T)(1 + \alpha \equiv (\eta^c) \widehat{X}_t^c$$

which makes for quick simulation as these are linear transformations of $\widehat{X}_t^c$.

The simulations in the Supplementary Appendix B show that the expected spot prices and returns rise steadily as the biodiversity intensity loss caused by a commodity increases. This reflects the fact that lower clean-tech efficiency reduces the effective productivity of capacity investment, so the same level of capacity generates less output. Moreover, as discussed above, expected spot returns reflect three components: the basis premium, the storage-cost volatility premium, and the biodiversity-intensity premium. For those commodities for which clean-tech intensity is low (with high biodiversity impact, hence most likely to be hit by restrictive regulations), the unhedgeable intensity premium is larger, and investors require higher expected spot returns as compensation. As clean-tech adoption rises, the marginal return to environmental conservation declines, and the expected spot return curve flattens, consistent with a fading marginal intensity reward. This effect is consistent with the empirical finding that, as shown in Section 4, investors increasingly exhibit aversion towards commodities characterized by a high biodiversity intensity threat, and may be demanding a premium even in the absence of impending regulatory action (Díaz et al. 2019). In fact, the resulting spot risk premium may simply arise from environmental policy uncertainty, unclear regulatory responses, and shifting consumer attitudes.[28]

[27] This solution is guaranteed to be real (and positive, as $\widehat{X}_t^c = 0$ does not solve the cubic equation) as long as:

$$\frac{\phi_0^2}{4} + \frac{\phi_1^3}{27\gamma^c (V_Q + V_{\mathrm{reg}})} = \frac{\{[\tau_t + \tau + \lambda_B \varphi(B_t + b) - \alpha] - 1\}^2}{4} - \frac{\kappa^c \{\beta(1 - \tilde{\delta}_T)(1 + \alpha \equiv (\eta^c)\}^3}{27\gamma^c (V_Q + V_{\mathrm{reg}})} \geq 0.$$

[28] However, expected spot returns modestly rise as the total size of the transition risk shocks b increases. In fact, the impact on spot prices of $\equiv (\eta^c$ and b appears to be largely independent, even though this possibly derives from the simple nature of our model. Expected spot returns increase in both dimensions: weak clean-tech

As for the closed-form expression for $F^c_{\tau,T}$, because in equilibrium $\widehat{\omega}^c_\tau + \widehat{H}^c_\tau = 0$, it follows that[29]:

$$\frac{\mathbb{E}[S^c_T(Q^c_T)] - F^c_{\tau,T}}{\gamma^I_c \mathrm{Var}[S^c_T(Q^c_T)]} + \frac{\mathbb{E}[S^c_T(Q^c_T)] - F^c_{\tau,T}}{\gamma^f_c \mathrm{Var}[S^c_T(Q^c_T)]} = \kappa^c \widehat{X}^c_t \tag{18}$$

$$\Rightarrow \left(\mathbb{E}[S^c_T(Q^c_T)] - F^c_{\tau,T}\right)\left(\frac{1}{\gamma^I_c} + \frac{1}{\gamma^f_c}\right) = \mathrm{Var}[S^c_T(Q^c_T)]\kappa^c \widehat{X}^c_t. \tag{19}$$

The simulations in the Supplementary Appendix B show that the expected futures returns remain essentially flat around zero for a range of alternative values for η^c, consistent with the model's general properties for futures prices. The small positive expected futures returns correspond to a mild contango state, as the futures price lies slightly above the expected spot due to the equilibrium risk premium, even though the compensation for the risk posed by the variance of spot prices brings the overall expected futures return in the positive range. This is a case in which the increase in the convenience yield caused by biodiversity transition risk would essentially balance the induced, small negative futures risk premium caused by the adverse future negative effect of transition risk, thus bringing average realized futures return to hardly react to changes in biodiversity intensity loss.

6. Aggregate biodiversity risk in the cross-section of commodities

In Section 4, we tested whether commodities with a high biodiversity footprint earn a premium that compensates for the transition risk they are exposed to. We now investigate whether aggregate biodiversity risk is also priced in the cross-section of commodity returns. The reasoning is as follows: if *biodiversity risk* is a priced risk factor, then commodities that generate positive returns in the presence of an aggregate biodiversity risk shock, thus offering a hedge against it, should earn lower returns on average. Conversely, commodities offering negative returns in the face of a biodiversity risk shock ought to command a premium on average, over the long run.

We follow a methodology similar in spirit to the one employed, for instance, by Ang et al. (2006) and in which sorting occurs on the basis of the exposure of stocks to some aggregate risk driver (see also Alekseev et al. 2022). To measure the aggregate biodiversity risk, we extract the first principal component from two popular indices of the state of the world's *biological diversity*: the LPI and the global Red List Index. Because, at the time of writing, both series are jointly available only for the period 1993–2020, we use this period for our analysis.[30] A declining LPI (RLI) trend indicates that the risk of extinction among the species included in the index is increasing. The same applies to their first principal component, which we henceforth refer to as the aggregate biodiversity loss index (BLI). Figure 7 plots BLI as well as LPI and RLI. Notably, despite being computed using different methodologies, the LPI and RLI are highly correlated and both reflect a general downward trend in biodiversity. The average annual growth rate in BLI is −2 percent, with a minimum of −3.66 percent and a maximum of 0.20 percent.

---

adoption and larger biodiversity shocks reduce convenience yields by raising unhedgeable penalties and volatility, so investors demand higher premia.

[29] Hirshleifer (1990) was the first one to suggest that commodity futures premia include a component related to spot price volatility beyond traditional systematic risk.

[30] The LPI is published by the World Wildlife Fund (WWF). The data can be retrieved at https://www.livingplanetindex.org/latest_results. The RLI is published by the International Union for Conservation of Nature (IUCN) and is available at https://www.iucnredlist.org/search. The world RLI index is obtained as an average of the national RLI indices. The first principal component explains approximately 98 percent of the total variation of the two indices. The variables are standardized before performing the principal component analysis, as the two indices have different scales. The relevant loadings are then applied to the unscaled variables to get the first principal component.

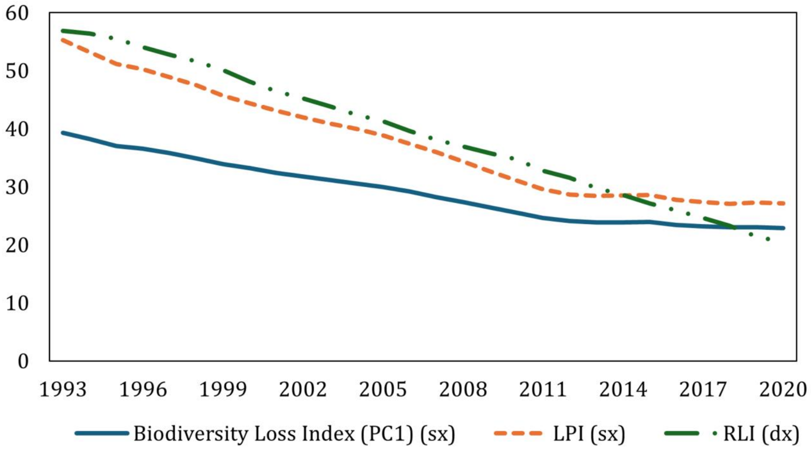

Figure 7. Aggregate biodiversity loss index. *Note*: The solid line (left axis) shows the first principal component extracted from the LPI and RLI. The dashed line (left axis) plots the LPI, while the solid line with small circular markers (right axis) depicts the RLI. The sample period is 1993–2020.

Notably, when we use BLI, we can no longer distinguish between transition and physical biodiversity risk. However, one advantage is that, because this exercise does not require the measurement of commodity-specific biodiversity footprint, we can extend our analysis to the spot returns of both agricultural and nonagricultural commodities, that is, to a much wider cross-section than what has been considered so far. Moreover, physical biodiversity deterioration serves as a leading indicator for transition risk, as local biodiversity/ecosystem vulnerabilities are most likely to cross tipping points, provoking the collapse of human communities, with implications for extra-local economies and security (Brook et al. 2013). This arguably makes the BLI's conflation of physical and transition risks theoretically appropriate given their causal relationship.[31]

We obtain the sensitivity of each commodity to shocks to aggregate biodiversity by estimating the following time series regression for each individual commodity i:

$$r_{i,t} = \beta_0 + \beta_{i,MKT} MKT_t + \beta_{i,BLI} \Delta BLI_t + \varepsilon_t, \tag{20}$$

where ΔBLI_t is BLI's growth rate and MKT_t is the excess return of the sectoral index to which the commodity belongs (see Appendix A for details on the sectoral classification applied).[32,33] As it is typical in the asset pricing literature (see, e.g., Bali, Engle and Murray 2016, the regression in equation (20) is estimated recursively over windows of 5 years (60 months) of data. Next, we sort commodities into three tercile portfolios based on $\beta_{i,BLI}$. The portfolios are rebalanced at the beginning of every year based on the $\beta_{i,BLI}$ observed at the end of the previous year. Because BLI is a measure of biodiversity abundance, commodities that offer positive returns when the index declines (that is, commodities with a

---

[31] Environmental tipping points significantly affect the cost-benefit assessment of climate policies, and such threshold often come from physical tipping elements in the environmental system, creating a direct causal link where slowly accumulating physical biodiversity risks justify immediate policy interventions, see, e.g., Cai et al. (2015).

[32] To check the robustness of our results, in Appendix B (Table B3), we use changes in LPI instead of changes in BLI. The results remain qualitatively identical.

[33] As noted by Ang et al. (2006) with reference to the VIX, because BLI is very persistent (the autoregressive coefficient is equal to 0.947), changes to the index are an adequate proxy of shocks to the index. In fact, the correlation between changes to the index and innovations from an autoregressive model on BLI is very high (0.82). The advantage of this approach is that the computation of the growth rate does not require estimating a model, thereby avoiding the introduction of additional noise and a look-ahead bias in the design.

Table 7. Portfolios sorted by exposure to aggregate biodiversity shocks.

Note: Column (1) contains the average $\beta_{i,BLI}$ of the commodities included in each tercile portfolio at the time of portfolio formation. Columns (2) and (3) report the sample mean and standard deviation of the excess returns of the tercile portfolios and the high-beta minus low-beta portfolio. Column (4) reports the intercept of a regression of the excess returns of each portfolio on seven commodity factors: market, basis, momentum, basis-momentum, spreading, volatility, and hedging. The returns are expressed as percentages. Newey-West standard errors are reported in parentheses. T-statistics based on the Newey-West standard errors are in squared brackets. *, **, and *** represent significance levels of 0.10, 0.05, and 0.01, respectively.

Rank	(1) Preformation beta	(2) Mean excess return	(3) Std. Dev. excess return	(4) Alpha
1	− 1.439	0.177 (0.275)	3.274	0.042 (0.190)
2	− 0.043	0.404 (0.289)	3.266	0.279 (0.188)
3	1.554	0.539** (0.255)	3.187	0.458** (0.179)
3-1		0.361* (0.192) [1.88]	2.969	0.416** (0.204) [2.04]

negative beta) can be considered a hedge against aggregate biodiversity loss, in line with the reasoning above. Therefore, if aggregate biodiversity risk is priced in the cross-section of commodity returns, we would expect commodities with high beta to earn higher returns on average than commodities with low or negative beta.

In Table 7, we report the average monthly excess returns of the tercile portfolios and of the high-beta minus low-beta hedge portfolio. We also report the intercept of the regression of the portfolios' excess returns over seven commodity factors: market, basis, momentum, basis-momentum, spreading, volatility, and hedging (see Appendix A, in which the methodology used to construct the factors is also explained). Newey–West standard errors are reported in parentheses. The truncation parameter is set equal to four lags, following the rule of thumb that sets it equal to $floor(T^{1/4})$.[34] This can be interpreted as the alpha unexplained by a traditional commodity factor model.

Column (1) in Table 7 shows that the average $\beta_{i,BLI}$ at the time of portfolio formation is negative for commodities in the bottom tercile and positive for commodities in the top tercile. Therefore, the bottom tercile collects commodities that offer a hedge against biodiversity risk. Notably, the monthly mean excess returns display a monotonic increase from 0.18 percent on the low- (negative) beta portfolio to 0.54 percent on the high-beta portfolio. The monthly mean excess return of the long-short spread portfolio is 0.36 percent, which compounds to around 4 percent in annualized terms and is statistically significant at a 10 percent test size level. A similar pattern is visible in column (4) with reference to the estimated alphas of the tercile and hedge portfolios with respect to a classical set of commodity factors. The alpha increases from close to zero on the low-beta portfolio to 0.46 percent on the high-beta portfolio. The high- minus low-beta portfolio yields an alpha of 0.42 percent, which is equal to 5.3 percent on an annualized basis and it is statistically significant at a 5 percent level. All in all, the results suggest that aggregated biodiversity risk is priced in the cross-section of commodity returns and the resulting biodiversity premium is sufficiently large in an economic sense to provide a basis for the hedging of short-run biodiversity shocks.[35]

---

[34] The results remain robust when we use different specifications, such as including only four (market, momentum, basis, and basis-momentum) or five (market, momentum, basis, basis-momentum, and spreading) factors. These additional results are available upon request from the Authors.

[35] For comparison, Boons and Prado (2019) reports that long-short portfolios sorted by momentum earn an excess return of 15.02 percent and those sorted by basis-momentum earn an excess return of 18.38 percent.

7. Conclusions

This article provided empirical evidence that biodiversity-related transition risks are priced in commodity markets. Using intensity-based measures of species loss per unit of harvested land, we showed that commodities with higher biodiversity footprints earn a significant return premium. This premium is robust to controls for production scale, emissions, and deforestation. An event-study approach further confirmed the transition risk channel: commodities with higher biodiversity footprints experienced significant negative abnormal returns following the Kunming Declaration. This aligns with the notion that, in response to a shock to the regulatory environment, the price of commodities with a high biodiversity footprint should decrease to allow for future larger returns. Notably, a placebo test that exploits the Paris Agreement showed that commodities with a high-biodiversity footprint are not affected by shocks related to climate transition risk. This supports the idea that biodiversity and transition risks are two interrelated but distinct risks. Interestingly, we find that the biodiversity transition risk premium does not extend to futures markets, although this result is based on a small sample of futures, with obvious problems concerning the power of the test. In Section 5, extending Gorton, Hayashi and Rouwenhorst (2012) and Yang (2013), we offered a production model that rationalizes these findings. In such a model, expected spot returns entail three components: the basis premium, the storage-cost volatility premium, and the biodiversity-intensity premium. However, the biodiversity–intensity premium is washed out from futures returns by the presence of a risk-driven convenience yield change that compensates the futures risk premium contribution.

Our results contribute to the emerging literature on the financial implications of biodiversity loss and extend it to commodity markets, a domain where nature-related risks are immediate, physical, and directly measurable. They also complement firm-level studies such as Garel et al. (2024, 2025), who document that the dependence on the environment is associated with downside risk but remains largely absent from corporate disclosures. In contrast, the biodiversity premium identified in this article suggests that investors are beginning to internalize nature-related risks at the asset level, even in the absence of firm-level transparency.

Future work could extend this analysis along several dimensions. First, while this study mostly focuses on agricultural commodities, a broader mapping of biodiversity risk should incorporate nonagricultural commodities, such as metals and fossil fuels, which can drive habitat destruction through pollution and land-use change. Unfortunately, as of the time of this writing, our data source, the Commodity Footprints project, is only focused on agricultural commodities. Second, our measure of interest, the intensity of species loss, is focused on land use. As more data become available, the biodiversity footprint data used here could be enriched using multi-dimensional biodiversity data that capture taxonomic, functional, and geographic variation in biodiversity loss. Finally, future research could explore the financial implications of different sub-components of biodiversity loss, such as species abundance, genetic diversity, or ecosystem degradation, and test whether markets differentiate between them. As new biodiversity data sources and taxonomies (e.g., ENCORE, IUCN Red List, NatureDep) become available, asset-level and firm-level pricing of biodiversity risk is likely to become a richer and more policy-relevant area of investigation.

Acknowledgments

The authors thank the participants of the two editions of the Biodiversity and Natural Resource Finance Conference Workshop (Cambridge 2024; London 2025), and Max Croce for his insightful discussion of their proposal. The authors are indebted to Markus Leippold for his extensive discussion of the first draft of this article and for his numerous suggestions that have undeniably contributed to its development. Manuela Pedio is grateful to her colleagues at the University of Bristol for their useful comments during a Brownbag presentation of an early draft of the paper. The authors are also grateful to Marcin Kacperczyk, Laura Starks, and Elroy Dimson (the editors) for their useful comments and guidance.

Supplementary material

Supplementary material is available at *Review of Finance* online.

Funding

Massimo Guidolin's research is funded by the European Union—Next Generation EU, in the framework of the GRINS—Growing Resilient, Inclusive and Sustainable—Project (GRINS PE0000000—CUP E63C22002140007). The views and opinions expressed are solely those of the Authors and do not necessarily reflect those of the European Union, and the European Union cannot be held responsible for them.

Conflict of interest: None declared.

Data availability

The data concerning the commodity spot prices, inventories, and commodity environmental footprints, as well as the Living Planet Index and the Red List Index are publicly available from the sources outlined in the article. The data concerning futures returns were provided by Pinnacle Corp under license. It is our understanding that any researcher who wishes to purchase any of the data may freely do so.

References

Alekseev, G., S., Giglio, Q. Maingi, J. Selgrad, and J. Stroebel. 2022. "A quantity-based approach to constructing climate risk hedge portfolios." Working paper. *Available at SSRN 4283192*.

Ang, A., R. J. Hodrick, Y. Xing, and X. Zhang. 2006. "The Cross-Section of Volatility and Expected Returns." *Journal of Finance* 61: 259–99.

Bali, T. G., R. F. Engle, and S. Murray. 2016. *Empirical Asset Pricing: The Cross Section of Stock Returns*. Hoboken, NJ: John Wiley & Sons.

Barnosky, A. D., N. Matzke, S. Tomiya, G. O. U. Wogan, B. Swartz, T. B. Quental, C. Marshall, et al. 2011. "Has the Earth's Sixth Mass Extinction Already Arrived?" *Nature* 471: 51–57.

Basak, S., and A. Pavlova. 2016. "A Model of Financialization of Commodities." *Journal of Finance* 71: 1511–56.

Betts, M. G., C., Wolf, W, J. Ripple, B. Phalan, K. A. Millers, A. Duarte, S. H. M. Butchart, and T. Levi. 2017. "Global Forest Loss Disproportionately Erodes Biodiversity in Intact Landscapes." *Nature* 547: 441–444.

Bolton, P., and M. Kacperczyk. 2021. "Do Investors Care about Carbon Risk?" *Journal of Financial Economics* 142: 517–49.

Bolton, P., and M. Kacperczyk. 2023. "Global Pricing of Carbon-Transition Risk." *Journal of Finance* 78: 3677–54.

Boons, M., and M. P. Prado. 2019. "Basis-Momentum." *Journal of Finance* 74: 239–79.

Brennan, M. J., T. Chordia, and A. Subrahmanyam. 1998. "Alternative Factor Specifications, Security Characteristics, and the Cross-Section of Expected Stock Returns." *Journal of Financial Economics* 49: 345–73.

Brook, B. W., E. C. Ellis, M. P. Perring, A. W. Mackay, and L. Blomqvist. 2013. "Does the Terrestrial Biosphere Have Planetary Tipping Points?" *Trends in Ecology & Evolution* 28: 396–401.

Cai, Y., K. L. Judd, T. M. Lenton, T. S. Lontzek, and D. Narita. 2015. "Environmental Tipping Points Significantly Affect the Cost- Benefit Assessment of Climate Policies." *Proceedings of the National Academy of Sciences* 112: 4606–11.

Cardinale, B. J., J. E. Duffy, A. Gonzalez, D. U. Hooper, C. Perrings, P. Venail, A. Narwani, et al. 2012. "Biodiversity Loss and Its Impact on Humanity." *Nature* 486: 59–67.

Chaudhary, A., F. Verones, L. de Baan and S. Hellweg. 2015. "Quantifying Land Use Impacts on Biodiversity: Combining Species–Area Models and Vulnerability Indicators." *Environmental Science & Technology* 49: 9987–95. https://doi.org/10.1021/acs.est.5b02507

Chaudhary, A., and T. Kastner. 2016. "Land Use Biodiversity Impacts Embodied in International Food Trade." *Global Environmental Change* 38: 195–204.

Chaudhary, A., and T. M. Brooks. 2018. “Land Use Intensity-Specific Global Characterization Factors to Assess Product Biodiversity Footprints.” *Environmental Science & Technology* 52: 5094–04.

Convention on Biological Diversity. 2022. “Kunming-Montreal Global Biodiversity Framework.” https://www.cbd.int/gbf/. Date accessed April 3, 2025

Croft, S., C. West, M. Harris, J. Green, A. Molotoks, V. Harris, C. Egan, E. Wood, T. Ball and L. Way. 2024. Technical documentation for an official statistic estimating the global environmental impacts of consumption: 2024 version. Technical Report JNCC Report 786 Joint Nature Conservation Committee.

Dasgupta, P. 2024. *The Economics of Biodiversity*. Cambridge University Press. https://www.cambridge.org/core/books/economics-of-biodiversity/C81ED65223BB4C6BB52BA5748CFE3EA0

Deaton, A. and G. Laroque. 1992. “On the Behaviour of Commodity Prices.” *Review of Economic Studies* 59: 1–23.

Delle Chiaie, S., L. Ferrara and D. Giannone. 2022. “Common Factors of Commodity Prices.” *Journal of Applied Econometrics* 37: 461–76.

Díaz, S., J. Settele, E. S. Brondízio, H. T. Ngo, J. Agard, A. Arneth, P. Balvanera, et al. 2019. “Pervasive Human-Driven Decline of Life on Earth Points to the Need for Transformative Change.” *Science* 366: eaax3100.

Dirzo, R., H. S. Young, M. Galetti, G. Ceballos, N. J.B. Isaac, and B. Collen. 2014. “Defaunation in the Anthropocene.” *Science* 345: 401–6.

Drakare, S., J. J. Lennon and H. Hillebrand. 2006. “The Imprint of the Geographical, Evolutionary and Ecological Context on Species-Area Relationships.” *Ecology Letters* 9: 215–27.

European Commission. 2023. “Regulation on Deforestation-Free Products.” https://environment.ec.europa.eu/topics/forests/deforestation/regulation-deforestation-free-products_en. Date accessed: April 5, 2025.

FSB. 2024. “2024 Resolution Report: From Lessons to Action – Enhancing Resolution Preparedness.” Date accessed: April 5, 2025. https://www.fsb.org/2024/12/2024-resolution-report-from-lessons-to-action-enhancing-resolution-preparedness.

Garel, A., A. Romec, Z. Sautner and A. F. Wagner. 2024. “Do Investors Care about Biodiversity?” *Review of Finance* 28: 1151–86.

Garel, A., A. Romec, Z. Sautner and A. F. Wagner. 2025. Firm-Level Nature Dependence. Technical report European Corporate Governance Institute (ECGI) – Finance Working Paper No. 1050/2025, Swiss Finance Institute Research Paper No. 25-44, HKU Jockey Club Enterprise Sustainability Global Research Institute Paper No. 2025/036, Review of Finance, forthcoming, Available at SSRN: https://ssrn.com/abstract=5196826 or http://dx.doi.org/10.2139/ssrn.5196826

Garibaldi, L. A., I. Steffan-Dewenter, R. Winfree, M. A. Aizen, R. Bommarco, S. A. Cunningham, C. Kremen, et al. 2013. “Wild Pollinators Enhance Fruit Set of Crops Regardless of Honey Bee Abundance.” *Science* 339: 1608–11.

Gibson, L., T. M. Lee, L. P. Koh, B. W. Brook, T. A. Gardner, J. Barlow, C. A. Peres, et al. 2011. “Primary Forests Are Irreplaceable for Sustaining Tropical Biodiversity.” *Nature* 478: 378–81.

Giglio, S., T. Kuchler, J. Stroebel, and X. Zeng. 2025. Biodiversity risk. *Review of Finance*. https://doi.org/10.1093/rof/rfaf063

Gong, Y., A. E. Gozluklu and G. H. Kim. 2023. Spreading Positions and the Commodity Futures Risk Premium. In WBS Finance Group Research Paper, WFA 2020 Annual Meeting.

Gorton, G. B., F. Hayashi, and K. G. Rouwenhorst. 2012. “The Fundamentals of Commodity Futures Returns.” *Review of Finance* 17: 35–105.

Gorton, G., and K. G. Rouwenhorst. 2006. “Facts and Fantasies about Commodity Futures.” *Financial Analysts Journal* 62: 47–68.

Han, M., L. Dam, and W. Pohl. 2025. “What Drives Commodity Price Variation?” *Review of Finance* 29: 315–47.

Hansen, M. C., P. V. Potapov, R. Moore, M. Hancher, S. A. Turubanova, A. Tyukavina, D. Thau, et al. 2013. “High-Resolution Global Maps of 21st-Century Forest Cover Change.” *Science* 342: 850–3.

Hirshleifer, D. 1990. “Hedging Pressure and Futures Price Movements in a General Equilibrium Model.” *Econometrica: Journal of the Econometric Society* 411–28.

Hong, H., and M. Yogo. 2012. “What Does Futures Market Interest Tell us about the Macroeconomy and Asset Prices?” *Journal of Financial Economics* 105: 473–90.

Hooper, D. U., E. C. Adair, B. J. Cardinale, J. E. K. Byrnes, B. A. Hungate, K. L. Matulich, A. Gonzalez, J. E. Duffy, L. Gamfeldt, M. I. O'Connor, 2012. “A Global Synthesis Reveals Biodiversity Loss as a Major Driver of Ecosystem Change.” *Nature* 486: 105–108.

Iceberg Data Lab. 2023. Corporate Biodiversity Footprint—Methodological Guide.

IPBES. 2016. “The methodological assessment report on scenarios and models of biodiversity and ecosystem services.” https://files.ipbes.net/ipbes-web-prod-public-files/downloads/pdf/2016.methodological_assessment_report_scenarios_models.pdf. Date accessed: April 5, 2025.

IPBES. 2019. “Global assessment report on biodiversity and ecosystem services.” Available at: https://ipbes.net/global-assessment. Date accessed: 12 April 2025.

Jacks, D. S., K. H. O'Rourke, J. G. Williamson, 2011. “Commodity Price Volatility and World Market Integration since 1700.” *Review of Economics and Statistics* 93: 800–13.

Jaureguiberry, P., N. Titeux, M. Wiemers, D. E. Bowler, L. Coscieme, A. S. Golden, C. A. Guerra, et al. 2022. “The Direct Drivers of Recent Global Anthropogenic Biodiversity Loss.” *Science Advances* 8: eabm9982.

Kalhoro, M. R., and K. Ahmed. 2025. “Dynamic Linkages and Spillover Effects of Biodiversity Risk in Socially Responsible Investment and Commodity Markets.” *Journal of Environmental Management* 374: 124144.

Kalhoro, M. R., and K. Kyaw. 2024. “Manage Biodiversity Risk Exposure?” *Finance Research Letters* 61: 104989.

Kang, W., K. G. Rouwenhorst, and K. Tang. 2020. “A Tale of Two Premiums: the Role of Hedgers and Speculators in Commodity Futures Markets.” *Journal of Finance* 75: 377–417.

Lenton, T. M., J. Rockström, O. Gaffney, S. Rahmstorf, K. Richardson, W. Steffen, and H. J. Schellnhuber. 2019. “Climate Tipping Points—Too Risky to Bet against.” *Nature* 575: 592–5.

Liang, M., Q. Yang, J. M. Chase, F. Isbell, M. Loreau, B. Schmid, E. W. Seabloom, D. Tilman and S. Wang. 2025. “Unifying Spatial Scaling Laws of Biodiversity and Ecosystem Stability.” *Science* 387: eadl2373.

NGFS. 2023. “NGFS Annual Report 2023.” https://www.ngfs.net/system/files/import/ngfs/medias/documents/ngfs_ar2023_en.pdf. Date accessed: April 5, 2025.

Pendrill, F., U. M. Persson, J. Godar and T. Kastner. 2019. “Deforestation Displaced: trade in Forest-Risk Commodities and the Prospects for a Global Forest Transition.” *Environmental Research Letters* 14: 055003.

Phalan, B., M. Onial, A. Balmford and R. E. Green. 2011. “Reconciling Food Production and Biodiversity Conservation: Land Sharing and Land Sparing Compared.” *Science* 333: 1289–91.

Potts, J., V. Voora, M. Lynch, and A. Mammadova. 2017. “Standards and Biodiversity: The Role of Voluntary Sustainability Standards”. State of Sustainability Initiatives Policy Brief. International Institute for Sustainable Development. https://www.iisd.org/system/files/publications/voluntary-sustainability-standards-biodiversity-policy-brief.pdf

Rockström, J., W. Steffen, K. Noone, A. Persson, F. S. Chapin, E. F. Lambin, T. M. Lenton, et al. 2009. “A Safe Operating Space for Humanity.” *Nature* 461: 472–75.

Sala, O. E., F. S. Chapin, J. J. Armesto, E. Berlow, J. Bloomfield, R. Dirzo, E. Huber-Sanwald, et al. 2000. “Global Biodiversity Scenarios for the Year 2100.” *Science* 287: 1770–74.

Sonter, L. J., Saleem H. Ali, and J. E. M. Watson. 2018. “Mining and Biodiversity: Key Issues and Research Needs in Conservation Science.” *Proceedings of the Royal Society B* 285: 20181926.

Souza, D. M., R. F. M. Teixeira, and O. P. Ostermann. 2015. “Assessing Biodiversity Loss Due to Land Use with Life Cycle Assessment: are we There yet?” *Global Change Biology* 21: 32–47.

Tang, K., and W. Xiong. 2012. “Index Investment and the Financialization of Commodities.” *Financial Analysts Journal* 68: 54–74.

Terazono, E. 2014. “African farming: Initiatives about to increase cocoa yields.” *Financial Times*, https://www.ft.com/content/8218cfbc-5dc8-11e3-95bd-00144feabdc0. Date accessed: August 2, 2025.

Tilman, D., R. M. May, C. L. Lehman and M. A. Nowak. 1994. “Habitat Destruction and the Extinction Debt.” *Nature* 371: 65–6.

TNFD. 2023. “Recommendations of the taskforce on nature-related financial disclosures.” https://tnfd.global/wp-content/uploads/2023/08/Recommendations_of_the_Taskforce_on_Nature-related_Financial_Disclosures_September_2023.pdf. Date accessed: April 5, 2025

Wearn, O. R., D. C. Reuman and R. M. Ewers. 2012. “Extinction Debt and Windows of Conservation Opportunity in the Brazilian Amazon.” *Science* 337: 228–32.

Wudu, K., A. Abegaz, L. Ayele and M. Ybabe. 2023. “The Impacts of Climate Change on Biodiversity Loss and Its Remedial Measures Using Nature Based Conservation Approach: A Global Perspective.” *Biodiversity and Conservation* 32: 3681–01.

WWF. 2024. “Living Planet Report 2024.” https://www.worldwildlife.org/publications/2024-living-planet-report. Date accessed: April 5, 2025.

Xin, W., L. Grant, B. Groom, and C. Zhang. 2025. “Noisy Biodiversity: The Impact of ESG Biodiversity Ratings on Asset Prices.” *Ecological Economics* 236: 108662.

Yang, F. 2013. “Investment Shocks and the Commodity Basis Spread.” *Journal of Financial Economics* 110: 164–84.

Appendix A. Commodity list and data.

Table A1. Commodity list.

Note: The table contains the list of all the commodities used in our exercises. *Commodity name* is the name of the commodity in the IMF database. The spot returns of tea are obtained as a simple average of the different tea qualities available in the database. Similarly, the returns of coal have been obtained by averaging coal from Australia and South Africa; returns of natural gas are a simple average across the three main producers (EU, US, and Japan). Coffee is an index produced by the IMF as a weighted average of various prices from different parts of the world. The market index is the sectoral index to which each commodity belongs. The column *Species Loss?* indicates whether a commodity is featured by the Commodity Footprint databases. FAO Code is the FAO Commodity Code that identifies the commodities in the Commodity Footprint databases. The last column indicates whether the futures returns are available.

Commodity Name	Market Index	Species Loss?	FAO Code	Futures?
Beef	Food index			
Shrimp	Food index			
Tin	All Metals EX GOLD Index			
Cobalt	All Metals EX GOLD Index			
Zinc	All Metals EX GOLD Index			
RapeseedOil	Agriculture index	Y	270	
Coffeeindex	Agriculture index	Y	656	(Coffee, KC)
WTICrude	Energy index			
Cocoa	Agriculture index	Y	661	(Cocoa, CC)
Tea	Agriculture index	Y	667	
NonCitrusFruitApple	Agriculture index	Y	515	
PalmOil	Agriculture index	Y	254	
OliveOil	Agriculture index	Y	260	
Coal	Energy index			
Swine	Food index			
Silver	Precious Metals Price Index			
Rubber	Agr. Raw Material Index	Y	836	
FishMeal	Food index			
WoolFine	Agr. Raw Material Index			
Palladium	Precious Metals Price Index			
LegumesChickpea	Energy index			
NaturalGas	Energy index			
Copper	All Metals EX GOLD Index			
Platinum	Precious Metals Price Index			
Lead	Agriculture index			
Oats	Agriculture index	Y	75	(Oats, ZO)
BrentCrude	Energy index			
Gasoline	Energy index			
Gold	Precious Metals Price Index			
Cotton	Agr. Raw Material Index	Y	328	(Cotton, CT)
RiceThailand	Agriculture index	Y	27	(Rough Rice, ZR)
Nickel	All Metals EX GOLD Index			
Groundnuts	Agriculture index	Y	242	
Corn	Agriculture index	Y	56	(Corn, ZC)
TimberIndex	Agr. Raw Material Index			
Poultry	Food index			
WoolCoarse	Agr. Raw Material Index			
SoybeanMeal	Agriculture index			
IronOre	All Metals EX GOLD Index			
SunflowerOil	Agriculture index	Y	267	
Soybeans	Agriculture index	Y	236	(Soybeans, ZS)
Wheat	Agriculture index	Y	15	(Wheat, W_)
CoconutOil	Agriculture index	Y	249	

(continued)

Table A1. (continued)

Commodity Name	Market Index	Species Loss?	FAO Code	Futures?
Barley	Agriculture index	Y	44	
SoftLogs	Agr. Raw Material Index			
Aluminum	All Metals EX GOLD Index			
VegetablesTomato	Agriculture index	Y	388	
SugarNo11World	Agriculture index	Y	156	(Sugar #11, SB)
DubaiCrude	Energy index			
Lamb	Food index			
Fish	Food index			
Sorghum	Agriculture index	Y	83	
Bananas	Agriculture index	Y	486	
Orange	Agriculture index	Y	490	(Orange Juice, JO)
SoybeansOil	Agriculture index			
HeatingOil	Energy index			

Table A2. Variable description.
Note: This table describes the variables used in the analysis.

Variable name	Variable description
Spot excess returns (monthly)	The spot excess returns for commodity i in month m of year t are computed as: $r_{i,m,t} = \frac{S_{i,m,t} - S_{i,m-1,t}}{S_{i,m-1,t}} - rf_{m,t}$ where $S_{i,m,t}$ is the price of commodity i at the end of month m of year t , $S_{i,m-1,t}$ is the price of the same commodity at the end of the previous month, and $rf_{m,t}$ is the US 1 month T-bill rate. Spot prices are sourced from the International Monetary Fund. The 1 month T-bill is sourced from the Federal Reserve of St. Louis repository (FRED).
Futures excess returns (monthly)	The futures excess returns for commodity i in month m of year t are computed as: $r_{i,m,t} = \frac{F^1_{i,m,t} - F^1_{i,m-1,t}}{F^1_{i,m-1,t}}$ where $F^1_{i,m,t}$ is the price of the next to expiry future contract that does not expire on the following month of commodity i at the end of month m of year t, and $F^1_{i,m-1,t}$ is its price at the end of the previous month. The position is assumed to be fully collateralized. Futures prices are sourced from Pinnacole Corp.
Intensity species loss (annual)	The intensity of species loss is calculated as: $\text{IntSpeciesLoss}_{i,t} = \frac{\text{PredictedSpeciesLoss}_{i,t}}{\text{CroplandAreaHarvested}_{i,t}}$ This is the number of species lost per 10,000 km^2. Both variables come from the Commodity Footprints database.
Deforestation (annual)	Deforestation is obtained from the Commodity Footprints dataset, which sources it from the Chalmers University of Technology. Forest loss from remote sensing is attributed to agricultural commodities using a national-level land-balance model (subnational for Brazil and Indonesia). Cropland expansion is modeled to first replace pasture, then forests. Forest loss is distributed across expanding cropland and then among crops in proportion to their harvested area.

(continued)

Table A2. (continued)

Variable name	Variable description
CO_2 emissions (annual)	CO $_2$ emissions due to deforestation and peatland drainage are obtained from the Commodity Footprints dataset, which sources them from the Chalmers University of Technology. Emissions are estimated based on changes in carbon stocks (above-ground biomass, below-ground biomass, and soil organic carbon) resulting from forest loss and subsequent land use.
Production (annual)	Production data are from the Commodity Footprints dataset, which sources them from FAO, "Production—Crop and livestock products" dataset. The growth rate is computed year-on-year.
Inventory (annual)	When available, the inventory data come from the World Agricultural Supply and Demand Estimates (WASDE) report retrieved from the United States Department of Agriculture Foreign Agricultural Service (https://apps.fas.usda.gov/psdonline/app/index.html). Specifically, we take the ending stock for the world as of the end of the calendar year. For cocoa, we take the data from the ICE report "Historical Cocoa Warehouse Stocks: 2002—Present" (available at: https://www.ice.com/report/300).
Hedging pressure (monthly)	The hedging pressure is computed using the Commitment of Traders report as of the end of the month. The hedging pressure from commodity i is computed as $$\mathrm{HP}_{i,m,t} = \frac{\mathrm{CS}_{i,m,t} - CL_{i,m,t}}{OI}_{i,t}$$ Namely, HP, for commodity i is defined as the net short (short minus long) position of commercial traders in commodity futures contracts divided by total open interest.
Momentum (monthly)	The commodity-specific futures returns' momentum is computed as the cumulative futures returns between month m and month $m{-}11$: $$Mom_i, m, t = \prod_{s=m-11}^{m} (1 + R^{T_1}_{i,s,t})$$
Basis (monthly)	The commodity-specific basis is computed as in Gorton, Hayashi and Rouwenhorst (2012). Specifically, it is given by $$\mathrm{Basis}_{i,m,t} = \left(\frac{\mathrm{F}^1_{i,m,t}}{\mathrm{F}^2_{i,m,t}} - 1\right) \times \frac{365}{D^2_{i,m,t} - D^1_{i,m,t}}$$ where $\mathrm{F}^1_{i,m,t}$ is the price of the front-end future, $\mathrm{F}^2_{i,m,t}$ is the price of the next nearby future, and $D^2_{i,m,t}$, $D^1_{i,m,t}$ are the number of days until the last trading date of the respective contracts.
Basis momentum (monthly)	The commodity-specific basis-momentum is computed as in Boons and Prado (2019). Specifically, it is $$BM_i, m, t = \prod_{s=m-11}^{m} (1 + R^{T_1}_{i,s,t}) - \prod_{s=m-11}^{m} (1 + R^{T_2}_{i,s,t}).$$ where R^{T_1} is the return of the front-end future and R^{T_2} is the return of the next nearby future.
Spreading (monthly)	Spreading is computed as in Gong, Gozluklu and Kim (2023) using the Commitment of Traders report as of the end of the month. The spreading for commodity i is computed as $$\mathrm{spreading}_{i,m,t} = \frac{\mathrm{spreader}_{i,m,t}}{OI_{i,m,t}}$$ Namely, spreading for commodity i is defined as the spreading positions in commodity futures contracts divided by total open interest.

(continued)

Table A2. (continued)

Variable name	Variable description
Volatility (monthly)	The volatility for commodity i is computed as the volatility of the futures return over the past 36 months.
Market factor	The market factor is the equal average of future returns for the following commodities: feeder cattle, live cattle, cocoa, coffee, copper, corn, cotton, WTI crude, gold, heating oil, lean hogs, lumber, oats, orange, palladium, platinum, silver, soybeans, soybean meal, soybean oil, sugar, gasoline, wheat, natural gas, rice.
Basis factor	The basis factor is obtained as a long-short portfolio based on sorting the following commodities according to their basis: feeder cattle, live cattle, cocoa, coffee, copper, corn, cotton, WTI crude, gold, heating oil, lean hogs, lumber, oats, orange, palladium, platinum, silver, soybeans, soybean meal, soybean oil, sugar, gasoline, wheat, natural gas, rice. Portfolio construction is based on terciles. The basis is constructed as discussed above.
Basis-momentum factor	The basis-momentum factor is obtained as a long-short portfolio based on sorting the following commodities according to their basis-momentum: feeder cattle, live cattle, cocoa, coffee, copper, corn, cotton, WTI crude, gold, heating oil, lean hogs, lumber, oats, orange, palladium, platinum, silver, soybeans, soybean meal, soybean oil, sugar, gasoline, wheat, natural gas, rice. Portfolio construction is based on terciles. Basis-momentum is constructed as discussed above.
Momentum factor	The momentum factor is obtained as a long-short portfolio based on sorting the following commodities according to their momentum: feeder cattle, live cattle, cocoa, coffee, copper, corn, cotton, WTI crude, gold, heating oil, lean hogs, lumber, oats, orange, palladium, platinum, silver, soybeans, soybean meal, soybean oil, sugar, gasoline, wheat, natural gas, rice. Portfolio construction is based on terciles. Momentum is constructed as discussed above.
HP factor	The HP factor is obtained as a long-short portfolio based on sorting the following commodities according to their HP: feeder cattle, live cattle, cocoa, coffee, copper, corn, cotton, WTI crude, gold, heating oil, lean hogs, lumber, oats, orange, palladium, platinum, silver, soybeans, soybean meal, soybean oil, sugar, gasoline, wheat, natural gas, rice. Portfolio construction is based on terciles. HP is constructed as discussed above.
Spreading factor	The spreading factor is obtained as a long-short portfolio based on sorting the following commodities according to their spreading positions: feeder cattle, live cattle, cocoa, coffee, copper, corn, cotton, WTI crude, gold, heating oil, lean hogs, lumber, oats, orange, palladium, platinum, silver, soybeans, soybean meal, soybean oil, sugar, gasoline, wheat, natural gas, rice. Portfolio construction is based on terciles. Spreading positions are constructed as discussed above.
Volatility factor	The volatility factor is obtained as a long-short portfolio based on sorting the following commodities according to their volatility: feeder cattle, live cattle, cocoa, coffee, copper, corn, cotton, WTI crude, gold, heating oil, lean hogs, lumber, oats, orange, palladium, platinum, silver, soybeans, soybean meal, soybean oil, sugar, gasoline, wheat, natural gas, rice. Portfolio construction is based on terciles. Volatility is constructed as discussed above.

Appendix B. Additional results

Table B1. Intensity species loss and commodity risk-adjusted spot returns.

Note: This table reports panel regressions relating monthly risk-adjusted spot excess returns to the intensity of species loss. The sample period is 2005–2022. All the specifications contain month–year and commodity fixed effects. Standard errors clustered at the month–year and commodity level are in parentheses. In Panel A, the risk-adjustment model contains the market, momentum, basis, and basis momentum factors. In Panel B, the risk-adjustment model contains the market, momentum, basis, basis momentum, and hedging factors. In Panel C, the risk-adjustment model contains the market, momentum, basis, basis momentum, hedging, and spreading factors. Intercepts are not reported. *, **, and *** represent significance levels of 0.10, 0.05, and 0.01, respectively.

Panel A			
	(1)	**(2)**	**(3)**
Intensity species loss ($t-1$)	0.050***	0.055***	0.058***
	(0.015)	(0.017)	(0.020)
Production (growth $t-1$, $t-2$)		−0.006	−0.005
		(0.022)	(0.022)
Log emission ($t-1$)		−0.017	
		(0.358)	
Log deforestation ($t-1$)			0.108
			(0.412)
Adjusted R^2	0.092	0.092	0.092
Panel B			
Intensity species loss ($t-1$)	0.049***	0.054***	0.057***
	(0.014)	(0.016)	(0.020)
Production (growth $t-1$, $t-2$)		−0.005	−0.004
		(0.021)	(0.021)
Log emission ($t-1$)		−0.012	
		(0.363)	
Log deforestation ($t-1$)			0.116
			(0.424)
Adjusted R^2	0.092	0.093	0.093
Panel C			
Intensity species loss ($t-1$)	0.051***	0.056***	0.059***
	(0.015)	(0.017)	(0.020)
Production (growth $t-1$, $t-2$)		−0.004	−0.003
		(0.021)	(0.021)
Log emission ($t-1$)		−0.008	
		(0.359)	
Log deforestation ($t-1$)			0.119
			(0.423)
Adjusted R^2	0.092	0.092	0.093

Table B2. Commodity returns and different lags of the conditioning variables.

Note: This table reports panel regressions relating monthly risk-adjusted spot excess returns to the intensity of species loss measured at the end of year $t-2$. The sample period is 2005–2022. All the specifications contain month–year and commodity fixed effects. Standard errors clustered at the month–year and commodity level are in parentheses. Risk adjustment is obtained using a seven-factor model including market, momentum, basis-momentum, hedging, spreading, and volatility. Intercepts are not reported. *, **, and *** represent significance levels of 0.10, 0.05, and 0.01, respectively.

	Raw returns			Risk-adjusted returns		
	(1)	(2)	(3)	(4)	(5)	(6)
Intensity species loss ($t-2$)	0.062***	0.070***	0.068***	0.055***	0.067***	0.064***
	(0.012)	(0.019)	(0.017)	(0.017)	(0.023)	(0.021)
Production (growth $t-2$, $t-3$)		−0.024	−0.024		−0.022	−0.023
		(0.017)	(0.018)		(0.018)	(0.018)
Log emission ($t-2$)		−0.083			0.027	
		(0.288)			(0.309)	
Log deforestation ($t-2$)			−0.198			−0.109
			(0.389)			(0.425)
Adjusted R^2	0.143	0.145	0.148	0.094	0.095	0.097

Table B3. Alternative measures of biodiversity footprint and commodity returns.

Note: This table reports panel regressions relating monthly spot excess returns to Log Species Loss. The sample period is 2005–2022. All the specifications contain month–year and commodity fixed effects. Standard errors clustered at the month–year and commodity level are in parentheses. The results refer to all twenty-three agricultural commodities for which the spot prices and the species loss are available. Intercepts are not reported. *, **, and *** represent significance levels of 0.10, 0.05, and 0.01, respectively. Appendix B provides complete variable definitions and a list of all the commodities included in the exercise.

			Before 2015		2015–2022	
	(1)	(2)	(3)	(4)	(5)	(6)
Intensity species loss ($t-1$)	−0.102	0.241	−2.955	3.518	−2.798	4.634
	(0.942)	(1.060)	(2.134)	(3.121)	(2.106)	(3.502)
Production (growth $t-1$, $t-2$)	−0.009	−0.009	−0.027	0.025	−0.026	0.019
	(0.021)	(0.021)	(0.028)	(0.027)	(0.028)	(0.027)
Log emission ($t-1$)	−0.073		−0.649	0.350		
	(0.344)		(0.534)	(0.495)		
Log deforestation ($t-1$)		0.004			−0.259	0.783
		(0.422)			(0.893)	(0.945)
Adjusted R^2	0.142	0.143	0.187	0.088	0.187	0.090

Table B4:. Commodity spot returns for a sample matched with the futures.
Note: This table reports panel regressions relating monthly spot excess returns and risk-adjusted spot returns to the intensity of species loss for a sample restricted to the commodities for which futures returns are available. The sample period is 2005–2022. All the specifications contain month–year and commodity fixed effects. Standard errors clustered at the month–year and commodity level are in parentheses. Risk adjustment is obtained using a seven-factor model including market, momentum, basis-momentum, hedging, spreading, and volatility. Intercepts are not reported. *, **, and *** represent significance levels of 0.10, 0.05, and 0.01, respectively.

	Raw Returns		**Risk Adj. Returns**	
Intensity species loss $(t-1)$	0.051	0.051	0.051	0.052
	(0.045)	(0.045)	(0.044)	(0.045)
Log emission $(t-1)$	−0.102		−0.038	
	(0.349)		(0.343)	
Log deforestation $(t-1)$		−0.104		−0.009
		(0.455)		(0.446)
Adjusted R^2	0.138	0.138	0.092	0.092

Table B5. Portfolios sorted by exposure to an alternative measure of biodiversity shocks.
Note: This table reproduces Table 7 in the main text when percentage changes to LPI are used instead of percentage changes to the first principal component extracted from the LPI and RLI. Column (1) contains the average $\beta_{i,LPI}$ of the commodities included in each tercile portfolio at the time of portfolio formation. Columns (2) and (3) report the sample mean and standard deviation of the excess returns of the tercile portfolios and the high-beta minus low-beta portfolio. Column (4) reports the intercept of a regression of the excess returns on each portfolio over seven commodity factors: market, basis, momentum, basis-momentum, spreading, volatility, and hedging. The returns are expressed as percentages. Newey–West standard errors are in parentheses. The truncation parameter is set equal to four lags, following the rule of thumb that sets it equal to $floor(T^{1/4})$. *, **, and *** represent significance levels of 0.10, 0.05, and 0.01, respectively.

Rank	**(1) Preformation Beta**	**(2) Mean excess return**	**(3) Std. Dev. excess return**	**(4) Alpha**
1	−1.174	0.227	3.087	**0.095**
		(0.255)		(0.185)
2	−0.035	0.327	3.423	**0.239**
		(0.313)		(0.218)
3	1.088	0.570**	3.235	0.447**
		(0.270)		(0.182)
3-1		0.343	2.881	0.353*
		(0.185)		(0.187)

Review of Finance, 2025, 00, 1–37
https://doi.org/10.1093/rof/rfaf068
Article