Biodiversity Entrepreneurship*

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Abstract

We study an emerging class of start-up organizations focused on biodiversity conservation and the challenges they face in financing these ventures. By fine-tuning a large language model (LLM), we identify 630 biodiversity-linked start-ups in PitchBook and compare their financing dynamics with those of other ventures. Biodiversity start-ups raise less capital but attract a broader coalition of investors, including not only venture capitalists ("value investors") but also mission-aligned impact funds and public institutions ("values investors"). Values investors provide incremental capital rather than substituting value investors, but funding gaps persist. We show biodiversity-linked start-ups use social media (Twitter) activity to help connect with value investors. Our findings can inform policy and practice for mobilizing private capital toward biodiversity preservation, emphasizing hybrid financing models and strategic communication.

JEL Classification: G11, G23, G24, H41, Q57, D83
Keywords: Biodiversity Finance, Entrepreneurship, Venture Capital, Sustainable Investing, Fine-Tuning, Large Language Model (LLM), Social Media, Twitter.

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1. Introduction.

Biodiversity loss – the decline in the number, genetic variation and variety of species and biological communities – is one of the most pressing environmental issues today with significant implications for businesses in terms of their operations, reputation, and financial success. Consider, for example, how pharmaceutical companies rely on Limulus amebocyte lysate (LAL), an extract from the blood of horseshoe crabs, which is crucial for detecting bacterial endotoxins in medical products and serves as a vital tool for ensuring the sterility of injectable drugs, vaccines, and medical devices. The diminishing population of horseshoe crabs presents a significant challenge, as no known natural alternative is as effective. Indeed, every company, regardless of size, industry, or location, helps drive biodiversity loss through vectors such as land and sea use changes, consumption of water and other biological resources, as well as pollution and the production of waste. Even service-oriented companies contribute indirectly through their supply chains and procurement practices. According to the Kunming-Montreal Global Biodiversity Framework (GBF) in 2022, *"Biodiversity is fundamental to human well-being, a healthy planet, and economic prosperity for all people, including for living well in balance and in harmony with Mother Earth. We depend on it for food, medicine, energy, clean air and water, security from natural disasters as well as recreation and cultural inspiration, and it supports all systems of life on Earth."*[1]

Biodiversity issues are distinct from conventional climate issues for at least two reasons. First, the impact of biodiversity loss is irreversible (Karolyi and Tobin-de la Puente, 2023). Once the damage is done, it is permanent and can be irremediable. Second, compared to climate-change-linked start-up companies, biodiversity start-ups face more challenges in delivering financial returns to investors, which may make it more difficult to raise capital. In the climate sector, generating revenue to service debt payments is arguably more straightforward. A proposed green energy project produces power, generating cash flows to repay investors. However, the paradox of biodiversity finance lies in its goal of generating revenue by conserving a natural resource rather than transforming it, the typical method of monetizing natural resources (Karolyi and Tobin-de la

[1] The Kunming-Montreal Global Biodiversity Framework was adopted by the Conference of the Parties to the Convention on Biological Diversity, December 7-19, 2022 (Montreal, Canada). The Framework seeks to respond to the Global Assessment Report of Biodiversity and Ecosystem Services issued by the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES), the fifth edition of the Global Biodiversity Outlook, and other scientific documents that provide evidence that biodiversity is deteriorating worldwide.

Puente, 2023; Flammer, Giroux, and Heal, 2025a). These factors compel research to address biodiversity issues separately from climate issues, particularly in venture financing challenges.

In this article, we propose to study a new type of biodiversity-linked corporate organization that has received little scholarly attention to date – what we call "biodiversity start-ups" or "biodiversity ventures." The conversation regarding biodiversity and corporate responsibility has largely focused on relatively large, publicly listed and well-established companies (e.g., Google with its project Wildlife Insights). However, unlike these large public firms where biodiversity projects may be side initiatives, we scour the Crunchbase and PitchBook databases to identify private ventures that are exclusively focused on biodiversity. These start-ups and smaller-/ medium-sized private organizations are fully dedicated to biodiversity and could become significant forces in conservation, much as small start-ups grew into industry giants or "unicorns," ultimately the leading forces of the tech sector (Davydova, Fahlenbrach, Sanz, and Stulz, 2024).

While these organizations have the potential to alleviate biodiversity loss, they can face additional hurdles in attracting investment compared to conventional start-ups. A 2020 study by the Paulson Institute, The Nature Conservancy, and Cornell's Atkinson Center for Sustainability estimated that the biodiversity financing gap is such that an additional $700 billion annually would be needed to reverse the decline in biodiversity by 2030. In terms of biodiversity start-ups, there can be extra funding challenges compared to climate start-ups. According to a 2023 report, nature tech companies (a proxy for biodiversity start-ups) received only $1.56 billion in venture capital (VC) investments in 2023, while climate tech companies received $41 billion.[2] The report points to several reasons behind the financing gap for biodiversity ventures. For example, biodiversity start-ups often lack the resources to organize road shows to attract potential investors. Besides resource constraints, their targeted investor base is limited as they engage with impact investors who prioritize environmental and social benefits, while most investors focus on financial returns. Last, mainstream financial media also tends to focus on large corporations, limiting coverage of early-stage ventures with environmental and social impact. Lack of promotion from traditional

[2] See State of Nature Tech Report (2023) by Nature4Climate (N4C), MRV Collective, and Serena. They define nature tech as: "supporting the development of nature-based solutions (NbS)…through the development and implementation of tools and techniques in projects and on the ground, by automating processes and by providing the accurate and reliable data needed to develop the market further." Further, they argue: "While climate tech focuses primarily on reducing greenhouse gas emissions and mitigating the impacts of climate change, nature tech is more comprehensive, addressing a wider range of environmental challenges, including habitat destruction, deforestation, soil degradation, water pollution and species loss." (p. 6)

media makes biodiversity finance even more challenging because biodiversity loss is a relatively new concept in business, and many investors, including those involved in impact investing, may not fully understand its importance and urgency. Although hardly an exhaustive list, these potential reasons motivate us to better understand how biodiversity-linked start-ups can close the nature financing gap.

We first develop a novel approach to identify biodiversity-focused start-ups by combining keyword screening with machine learning methods. Using Crunchbase as our starting point, we apply biodiversity-related keywords, such as those from the Biodiversity Dictionary by Giglio et al. (2023), alongside manual verification, to compile a verified sample of 173 biodiversity start-ups. To improve classification beyond keyword limitations – such as ambiguous phrases like "pollinator-friendly agriculture" or "rewilding efforts" – we train a machine learning model, a fine-tuned large language model (LLM), Llama-3.1-8B, using this verified sample alongside a balanced set of non-biodiversity start-ups (what we will term "general sustainability ventures" and "generic start-ups"). Our model achieves a 96% accuracy rate in distinguishing biodiversity ventures and allows us to then identify 630 biodiversity start-ups in the PitchBook VC datasets for which we have their fundraising details and information about investors. We also conduct manual verification of all 630 PitchBook biodiversity start-ups and compare them with the 173 Crunchbase biodiversity start-ups in the training set. We find that they are highly similar, with no domain-shift concerns. This sample of 630 PitchBook biodiversity start-ups is the focus of our analysis.

In light of the importance of these unexplored biodiversity start-ups and the growing curiosity about their financing landscape, our study focuses on the following questions: (1) how to best classify, or create a taxonomy of, biodiversity start-ups and their investors; (2) what types of VC investors match with which kind of biodiversity start-ups; and, (3) what strategies can improve the funding outcomes among VC investors for biodiversity start-ups.

First, our study pioneers a taxonomy of biodiversity start-ups, revealing critical insights into their operational diversity. We categorize biodiversity start-ups based on their ecological foci: *marine biodiversity*, *forest biodiversity*, *agricultural biodiversity*, *animal biodiversity* (terrestrial or freshwater), and *multi-functional biodiversity*. Among these, the *multi-functional biodiversity* category, which contributes positively to biodiversity across multiple ecological fields, accounts for the most in start-up counts in our sample (26.5% or 167) and in total funding (43% or $7.33 billion). The category of *forest biodiversity* ties with *marine biodiversity* in total counts of biodiversity start-ups (25.7% or 162), but *forest* biodiversity accounts for 33.7% (or $5.75 billion) of total funding, while *marine biodiversity* accounts for 10.6% (or $1.8 billion). We next categorize biodiversity start-ups based on whether they have *direct* or *indirect* impact in guiding new capital toward positive nature-based outcomes. Notably, over half (53.8%) of our biodiversity start-ups employ *indirect* conservation strategies (by means of awareness campaigns, environmental consulting, education products), securing 55.2% of total financing.[3]

We also provide descriptive statistics on the biodiversity start-up's financing dynamics, and compare them to other non-biodiversity, or generic, start-ups. To do this analysis, we pair the biodiversity start-ups to non-biodiversity-linked generic start-ups using a propensity score matching (PSM) approach. Temporal analysis uncovers a surge in biodiversity entrepreneurship post-2017, with annual new venture launches peaking at around 60 during 2019–2021 paralleled by accelerating fundraising tied to policy momentum like the Kunming-Montreal Global Biodiversity Framework in December 2022. Yet, despite their growth, biodiversity start-ups remain a niche; the total and average deal sizes for matched biodiversity ventures are slightly below half those of matched non-biodiversity start-ups. The total and average deal sizes are $9.8 million and $3.2 million, respectively, for biodiversity start-ups, while they are $22.5 million and $6.6 million for matched non-biodiversity start-ups. Biodiversity start-ups are nevertheless significantly more likely to receive financing deals involving impact investors, regardless of their ecological focus or operational approach (whether direct or indirect).

Second, our analysis of PitchBook data offers a first-of-its-kind taxonomy of biodiversity start-up-linked investors that reveals distinct characteristics of funds and investors who finance biodiversity start-ups. Those funds exhibit strong "values-driven" motivations and priorities (Starks, 2023). Over 20% explicitly target impact investments, while a notable share prioritizes ESG (Environmental, Social, and Governance) and MWBE (Minority- and Women-Owned Business Enterprises) initiatives—levels higher than those observed among generic start-up investors. They also disproportionately favor minority stakes and syndication relative to other funds, signaling their preferences for collaborative and risk-mitigating investment strategies. Beyond traditional VC funds, biodiversity finance also attracts diverse actors, including

[3] Consider, as an example, iNaturalist, a social network that maps and shares biodiversity information, connecting people to nature through technology. This is different from what we call a *direct* biodiversity-linked start-up like rrreefs, an environmental company operator that provides ecosystem services toward restoring reefs. Our analysis highlights considerable heterogeneity in specialties and approaches to protect biodiversity.

government-sponsored accelerators/incubators, government investment agencies, and sovereign wealth funds, each playing an outsized role compared to their presence in the broader VC investment landscape. The participation of venture capital firms, accelerators, government, and niche impact funds further highlights the hybrid financing landscape, merging ecological stewardship with profit motives and a willingness to take investment risks.

Next, our analysis reveals pronounced differences in financing patterns between biodiversity-focused start-ups and the broader start-up ecosystem. Biodiversity ventures rely disproportionately on impact-driven capital: 15% of their deals involve at least one impact investor, compared to 5% for all PitchBook start-ups, while impact-driven funding accounts for 10% of their total fundraising versus 3% in the broader startup market. Similarly, blended finance—which we define as deals involving at least one public or philanthropic investor—plays a catalytic role in biodiversity entrepreneurship (Flammer, Giroux, and Heal, 2025a). Half of all biodiversity start-up transactions include public investors (versus 40% for all PitchBook start-ups), and blended finance contributes 30% of their total funds raised (double the 15% observed across PitchBook). Results from logit regressions indicate that, relative to matched generic start-ups, biodiversity start-ups exhibit 2.20 times higher odds (or more than twice the likelihood) of securing funding from impact investors and 1.26 times higher odds (a 26% increase in likelihood) of attracting public investors, even after controlling for company size, age, and deal stage. Financial deals for biodiversity start-ups tend to be significantly smaller, but impact investors are usually associated with larger deal sizes.

Last, we examine the role of social media—specifically Twitter—in mitigating the financing challenges faced by biodiversity start-ups. Our work is inspired by Wang, Wu, and Hitt (2023) on how social media can alleviate VC funding inequality. Biodiversity start-ups with an active presence on Twitter raise significantly more funding. Our analysis distinguishes between two tests on the extensive and intensive margins: simply having a Twitter account is associated with a 35.8% increase in total funds raised, while greater engagement—measured by tweet volume conditional on having a Twitter account—plays a modest enhancing role. Our evidence shows that using Twitter helps biodiversity start-ups attract more funding from "minds-unalike" *value investors* than "minds-alike" *value investors* (such as impact investors and public capital sources), bridging the information gap between biodiversity start-ups and more profit-oriented *value investors*.

Echoing two important research calls (Karolyi and Tobin-de la Puente, 2023, for biodiversity finance; Goldstein, Jiang, and Karolyi, 2019, for fintech), we hope to demonstrate how alternative data can be used to address biodiversity-related questions in finance. Indeed, this emerging area lacks the kind of structured data to which scholars are accustomed. Among existing biodiversity finance studies, our new findings on emerging biodiversity start-ups contribute in several ways. Our work is closely related to Flammer, Giroux, and Heal (2025a), and Junge, Feuer, and Sassen (2023) who study how private capital can help finance the conservation and restoration of biodiversity or at least limit biodiversity loss. In addition, Giglio et al. (2024) model the economic consequences of biodiversity loss in an ecologically founded framework, which provides theoretical foundations for empirical research on biodiversity linked to financial economics. Our paper provides empirical support for reducing biodiversity loss and thereby mitigating its negative economic consequences. We also complement another group of recent working papers that study the pricing of biodiversity risks, such as Garel et al. (2024), Giglio et al. (2023), Coqueret and Giroux (2023), and Xiong (2023). Other papers focus on the relation between biodiversity loss and financing costs in capital markets; for example, Rizzi (2022) and Chen et al. (2023) investigate the relation between natural capital and municipal bond yields, while Hoepner et al. (2023) study the influence of biodiversity loss and pollution on the CDS term structure. And Soylemezgil and Uzmanoglu (2024) examine biodiversity risks and the borrowing costs of corporate bonds.

Our study also contributes by linking the broader sustainable finance literature to that of entrepreneurial finance. Biodiversity finance is an emergent and crucial area of ESG/sustainable finance (Edmans and Kacperczyk 2022; Starks 2023). Our work complements a stream of influential climate finance literature such as Bolton and Kacperczyk (2021, 2023), Bolton, Eskildsen, and Kacperczyk (2024), Krueger, Sautner, and Starks (2020), and Ilhan et al. (2023). Our work also builds on other ESG finance and socially responsible investing (SRI) literature including, among others, Dimson, Karakaş, and Li (2015, 2018), Hoepner et al. (2023), Horan et al. (2022), Seltzer, Starks, and Zhu (2022), and Starks, Venkat, and Zhu (2025). For studies of private equity and entrepreneurial finance, our study will identify a new challenge for entrepreneurial finance – biodiversity start-ups – and provide implications for remedying these difficulties, thus adding to the series of emerging studies related to Lerner et al. (2018), Lerner and Leamon (2023), Lerner, Li, and Liu (2023), Maurin, Robinson, and Strömberg (2023), Kisseleva, Mjøs, and Robinson (2023a, 2023b), Chen and Ewens (2021), and Ewens and Farre-Mensa (2022). Our study also adds to the interdisciplinary literature on SRI in private markets and sustainable organizations, such as Gupta, Kopytov, and Starmans (2021), and Geelen, Hajda, and Starmans

(2022). In addition, Barber, Morse, and Yasuda (2021) show that impact investors of dual-objective VC funds accept lower returns as they derive nonpecuniary utility from investing. Other impact investing articles include Geczy et al. (2021), Jeffers, Lyu, and Posenau (2024), Cole et al. (2023), Oehmke and Opp (2025), Green and Roth (2025), and Berk and Van Binsbergen (2025).

Additionally, our research relates to how social media and networks can support entrepreneurial finance, as they can influence capital allocations by raising investor awareness and facilitating information transmission. Wang, Wu, and Hitt (2024) note that utilizing Twitter can help start-ups secure venture financing and increase the visibility of women and other underrepresented minority entrepreneurs who may lack social capital (i.e., the less-connected entrepreneurs), thereby addressing the funding disparities faced by start-ups founded by these groups. They further highlight that social media can reduce information asymmetry between investors and entrepreneurs. Peng and Zhang (2024) document the substantial influence of social networks in crowdfunding markets for entrepreneurial finance, which leverages the power of the Internet to promote communication between potential investors and entrepreneurs.

The remainder of the article is as follows. Section 2 presents our data and the methodology to construct our sample. Section 3 provides the descriptive and empirical results of our study. Section 4 concludes this article.[4]

2. Data and Sample.

2.1 Identifying Biodiversity Start-Ups.

To construct a comprehensive sample of biodiversity start-ups, we leverage both the Crunchbase and PitchBook databases, two leading private market databases widely used in prior research (among many others, see Cole et al., 2023). Our access to PitchBook's comprehensive dataset includes the start-up's profiles, historical fundraising records, and investor profiles, while our access to Crunchbase only includes the start-up's profiles.

Our methodology for identifying biodiversity-related start-ups integrates biodiversity keyword searches with large language model (LLM) fine-tuning. We first curate a training sample of biodiversity start-ups from Crunchbase, leveraging its granular categorization of ventures, such as

[4] This study was developed from our pre-registered proposal submitted in August 2024 to the *Review of Finance* "Call for Research Proposals: Special Issue on Biodiversity and Natural Resource Finance." The paper has since evolved through feedback and discussions at two *Review of Finance* workshops on biodiversity and natural resource finance. For a detailed record of revisions from our pre-registered hypotheses to the final paper, see Appendix 1.

sustainability start-ups, and we use this sample to fine-tune an LLM. The model is then applied to classify biodiversity start-ups within PitchBook, a dataset better suited for detailed financial and operational analysis. We employ Crunchbase as the training source for two key reasons. First, biodiversity-focused start-ups exhibit nuanced distinctions from broader sustainability ventures—such as those centered on climate change—that require precise differentiation. Crunchbase's explicit sustainability labeling helps the LLM discern these subtleties, ensuring accurate categorization. Second, while our Crunchbase access is limited to company profiles, PitchBook provides richer data on fundraising and investor dynamics. By training on Crunchbase's granular definitions for precision and applying the LLM to PitchBook, we harmonize the strengths of both.

This approach advances upon conventional keyword methods by leveraging the semantic and contextual capabilities of large language models (LLMs). Keyword searches rely on pre-specified, non-exhaustive term lists and frequently miss domain-specific or emerging language (e.g., "pollinator-friendly agriculture," "mycorrhizal inoculation"), leading to both false positives and negatives. In contrast, LLMs interpret meaning in context, recognize synonyms and semantically related expressions, and adapt flexibly to evolving terminology. Fine-tuning enables the model to identify biodiversity-linked start-ups even when firm descriptions use implicit or novel phrasing. Specifically, the procedure includes three steps:

Step 1: Positive Label Construction. We begin by applying keyword searches to start-up business descriptions in Crunchbase, using biodiversity keywords from Giglio et al. (2023). Following this initial identification, each candidate start-up undergoes manual verification through a review of its corporate website. This process yields 173 confirmed biodiversity start-ups, which serve as the positive-labeled dataset for fine-tuning the LLM.

Step 2: Negative Label Construction. To train the LLM effectively, we complement the positive sample with two groups of non-biodiversity-related start-ups (negative labels). First, we extract sustainability-focused start-ups from Crunchbase's sustainability category, excluding those explicitly tied to biodiversity. Due to the imbalance between sustainability and biodiversity start-up counts, we employ propensity-score matching to select 173 sustainability start-ups that mirror the biodiversity sample in textual description length and industry focus (e.g., Natural Resources, Biotechnology, Data & Analytics). This group highlights the distinctions between general sustainability efforts (e.g., carbon capture) and biodiversity-specific activities (e.g., habitat restoration). Second, we randomly sample 173 generic start-ups from Crunchbase, unrelated to either sustainability or biodiversity. Combining these groups with the positive sample produces a balanced and hybrid training dataset of 519 start-ups. Company business descriptions and assigned biodiversity labels are then used to fine-tune the LLM.

Step 3: LLM Fine-Tuning Process. Fine-tuning adapts the pre-trained LLM—Meta's open-source Llama 3.1 Instruct model (8 billion parameters)—to our specialized classification task. This was our best choice when we started the work in the summer of 2024; we acknowledge that LLMs are rapidly evolving. While pre-trained LLMs excel as generalists, fine-tuning improves task-specific performance by aligning outputs with factual accuracy, reducing hallucinations, and prioritizing relevance. Given the model's 8-billion parameter count vastly exceeds our sample size, we apply the Low-Rank Adaptation (LoRA) technique. LoRA enhances learning efficiency and mitigates overfitting by updating only a small subspace of model parameters, significantly lowering computational costs. Performance is validated through 10-fold cross-validation, achieving average accuracy of 96.58% across training folds and 96.15% on a holdout test set. Full fine-tuning details are in Appendix A.2.

Applying the fine-tuned LLM to PitchBook identifies 630 biodiversity start-ups.[5] To analyze their focus areas, we classify each start-up by biodiversity type or the ecological system focus (marine, agriculture, animal, forest) using business descriptions. Start-ups addressing multiple domains (e.g., iNaturalist, the social network company mentioned above) are labeled as multi-functional. Table 1 presents examples of manually identified Crunchbase start-ups and compares them to the LLM-classified PitchBook start-ups to demonstrate the alignment between keyword-based and LLM-driven methods. Among Crunchbase companies listed, take note of Conservation Contracts Northwest (CCNW), a specialist contracting and consultancy company specializing in forest conservation, landscape management, and ecology, which we classify in the forest biodiversity category, and Re:wild, an animal biodiversity start-up, which works to safeguard wildlands and support guardians and which is co-founded by actor Leonardo DiCaprio. Among the Pitchbook examples, the parallel identified companies include Land Life, a provider of reforestation services, and WildLife Partners, an operator of a wildlife conservation company. Their similarities based on description suggest a closeness that affirms our LLM algorithms.

[5] We manually review all 630 PitchBook startups and confirm that they are very similar to the Crunchbase training set, and the vast majority of them are related to biodiversity and nature.

Subsequent analysis focuses exclusively on PitchBook start-ups due to our access to the comprehensive historical fundraising and investor data.

Methodologically, our approach aligns with and extends recent research on LLM - based text classification in finance and economics, e.g., Cao et al. (2020) and Cao et al. (2024), which has demonstrated superior accuracy, adaptability, and scalability compared to rule - based methods. Cunha, Rocha, and Gonçalves (2025) demonstrate that LLMs outperform traditional classifiers by up to 26 percentage points in accuracy across diverse text-classification benchmarks. Wang, Pang, and Lin (2023) highlight that zero-shot and prompt-based LLMs achieve competitive performance without extensive labeled data, making them highly effective for novel or specialized domains. Together, these insights support our use of an LLM framework, which provides a robust, flexible, and future-proof method for identifying biodiversity start-ups at scale.

2.2 The Sample of Biodiversity Start-Ups.

Our study aims to understand the financing of biodiversity start-ups. To benchmark the fundraising patterns of biodiversity start-ups against those of generic start-ups in our empirical analysis, we employ propensity score matching to identify the best-matched generic start-ups for each biodiversity start-up. Specifically, a generic start-up qualifies as a match if it operates in the same industry sector and geographic region. We then refine the matching process based on founding year and the most recent employee count reported in PitchBook, ensuring that biodiversity and non-biodiversity start-ups are comparable in terms of size and age. Due to missing data on the founding year and employee count for some biodiversity start-ups, we are only able to successfully pair 605 of the 630 biodiversity start-ups with closely matched generic counterparts.

Table 2 presents summary statistics. We will focus on the biodiversity-linked (left panel) and matched generic start-ups (right panel) throughout our empirical analysis. Our analysis examines biodiversity and non-biodiversity start-ups and their financing at both the *company* level (Panel A, two groups of 605 firms each) and the financial *deal* level (Panel B, 2483 observations given the 1210 firms average 2.1 deals each). Panel A shows that, by design, the matching procedure ensures that both groups have similar sizes (measured by the log of employee count) around 18.95 employees for biodiversity-linked companies and 17.17 for others, and ages (measured as the time between a start-up's founding and its most recent financing deal).

The start-up's financing deals vary by type and can be importantly influenced by a start-up's age. Younger start-ups typically secure early-stage financing of smaller amounts. We define early-stage deals as "grants, angel investments, seed rounds, and accelerator/incubator funding," as classified in PitchBook. Panel A reports the proportion of early-stage deals among all deals. Since the two groups have similar ages (7.9 years for biodiversity-linked start-ups compared to 6.9 years for the generic start-ups), approximately 60% of their deals qualify as early-stage financing. For some financing deals, PitchBook records the start-up's EBITDA at the time of fundraising. We define a variable, Positive Profit, as the fraction of a start-up's deals reporting positive EBITDA. Among biodiversity start-ups, 3.5% of deals report positive profitability, slightly higher than the 2.8% observed for matched generic start-ups.

We also examine the investors that finance biodiversity start-ups. In addition to private capital, including venture capital funds, biodiversity start-ups receive funding from impact investors and public capital. We classify a deal as an *impact* deal if it involves at least one impact investor and as a *blended* deal if it is partially or fully financed by public capital. We define an investor as an "impact investor" if they are explicitly designated as such by PitchBook or if they manage at least one fund explicitly targeting impact investing, ESG (Environmental, Social, and Governance) criteria, or MWBE (Minority and Women-Owned Business Enterprises). Our definition of "public capital" or "public investors" in blended finance deals adopts the framework of Flammer, Giroux, and Heal (2025a), encompassing both public-sector institutions (e.g., government agencies, economic development agencies, sovereign wealth funds, public-funded accelerators/incubators, and public pension funds) and non-profit sources (e.g., not-for-profit venture capital, foundations, universities, and endowments). Section 3.2 below offers further discussion regarding the investors.

Panel A of Table 2 shows that 16.9% of biodiversity start-up deals are impact deals, compared to only 8.0% for matched generic start-ups, highlighting the significant role of impact investors in financing biodiversity start-ups. Additionally, 32.3% of biodiversity start-up deals are blended deals that involve at least some public capital, slightly higher than the 30.2% observed for matched generic start-ups. The last three rows of Panel A summarize the overall fundraising activity of both groups. On average, biodiversity start-ups secure 2.39 financing deals over time, comparable to the 2.17 deals for matched generic start-ups. However, biodiversity start-ups raise significantly smaller amounts per deal, with an average deal size of only $3.19 million—approximately half the size of deals secured by matched generic start-ups. Consequently, the total amount raised by biodiversity start-ups averages $9.8 million, substantially lower than the $22.5 million raised by generic start-ups.

Panel B presents deal-level summary statistics for the financing deals of both biodiversity and matched generic start-ups. For this deal-level analysis, we identify whether a deal qualifies as an impact or blended deal by leveraging investor information from PitchBook. We construct indicator variables for both impact (15.9% of the sample) and blended deals (44.1% of the sample). Other variables are defined consistently with the company-level summary statistics, except for *Age*, which is measured as the difference in years between a start-up's founding and the date of the financing deal (on average, 5.326 years).

Finally, Panel C reports Twitter usage and engagement by biodiversity and matched generic start-ups. Of the 605 biodiversity start-ups in our sample, 229, or 37.9%, maintain active Twitter accounts during the period of study.[6] By December 2024, the total number of posted tweets across these accounts averages 301, with a standard deviation of 298. The 25th percentile for posted tweets is 36, while the 75th percentile is 578. As indicated by the results of the mean comparison test, the summary statistics are very close to those of the matched generic start-ups (235 of the 605 startups have Twitter accounts, or 38.8%), reflecting a similar level of variations in Twitter engagement across start-ups within each of the paired groups.

3. Results.

3.1. Taxonomy and Descriptives of Biodiversity Start-Ups.

Despite all focusing on biodiversity, the biodiversity start-ups in our sample specialize in different aspects of biodiversity. As noted in the State of Nature Tech Report (2023) by Nature4Climate (N4C), MRV Collective, and Serena, the implementation, acceleration, and growth of nature-based solutions (NbS) deliver for nature, climate, and people in areas like food and agriculture, land and forest, ocean, water conservation and management, biodiversity and nature restoration, biodiversity credits, and green supply chain traceability and land-tilting management. We follow these general categories for our analysis. Figure 1 presents the distribution of biodiversity start-ups and their funding across five biodiversity sectors. See Table 1 for definitions and examples of these five categories. Panel A categorizes biodiversity start-ups

[6] Our study uses the August 2024 version of PitchBook VC datasets. There is a static variable indicating whether a company (e.g., start-up) has a Twitter URL, and if so, what that URL is. We started our classification based on this static Twitter URL variable. The categorization of start-ups into groups of either "having a Twitter account" or "not having a Twitter account" was a one-time assignment, with no start-ups changing groups or switching their group membership over time. Therefore, the group composition remains consistent over time. The same classification method is applied to the matched generic start-ups.

and their financing into marine, agriculture, animal, forest, and what we call "multi-functional." The multi-functional category has the largest number of start-ups (167) and has received the highest total financing across deals ($7.33 billion). Among the specific biodiversity sectors, forest biodiversity start-ups account for the largest share of funding, receiving 33.7% of total biodiversity financing, much higher than their fraction of counts (162, or 25.7%). The smallest categories, agriculture and animal biodiversity, represent 24% of the start-ups but receive only 13% of total biodiversity funding.

Furthermore, we classify biodiversity start-ups based on whether they *directly* preserve biodiversity or address biodiversity loss *indirectly*. For instance, the company, BeeOdiversity, focuses directly on regenerating and preserving bee populations. In contrast, other start-ups, such as Internet of Elephants, emphasize raising public awareness of biodiversity through gaming and social media, which we assess as indirect. Panel B of Figure 1 presents start-ups and financing based on these two categories. Of the 630 biodiversity start-ups in our sample, 53.8% contribute to biodiversity conservation indirectly, and these start-ups receive 55.2% ($9.42 billion) of total biodiversity financing.

Figure 2 presents a time series of the number of biodiversity start-ups founded by year. The number of newly founded biodiversity start-ups has accelerated since 2017, peaking between 2019 and 2021 with approximately 60 start-ups established per year. Before 2017, fewer than 40 biodiversity start-ups were founded annually worldwide. Of course, the number of biodiversity start-ups founded in 2023 (or even 2022) may be underreported due to our reliance on PitchBook VC data collected in August 2024 and possible reporting delays. The same reason may apply to the total count and value of deals in the last few years of our sample period.[7] Figure 3 complements Figure 2 by presenting the annual trends in biodiversity start-up financing deals. Recall from Table 2 that a typical biodiversity or generic start-up secures a little over two deals during this period of analysis. Panel A of Figure 3 shows the number of financing deals for biodiversity start-ups each year. Before 2018, the annual number of deals remained below 100, but it began to rise significantly in 2018. Panel B illustrates the total amount raised annually, mirroring the trend in Panel A. Fundraising activity increased steadily from 2018, peaking in 2021 following the

[7] See the discussion on PitchBook Report Methodologies for the lag time concerns in "Deal timing and inclusion" and "Deal count estimation" explanations.

adoption of the Kunming Declaration in the same year. Figure 3 suggests that biodiversity financing is still in its early stages and has only gained traction in recent years.

To place biodiversity financing in a broader context, Figure 4 compares financing trends between biodiversity start-ups and generic start-ups drawn from the PitchBook universe. Specifically, Panels A and B contrast the number of deals and total financing raised for biodiversity start-ups (red line), for our matched generic sample of start-ups (light dashed black line), and for all Pitchbook start-ups (dark dashed black line, right hand scale), respectively. While financing activity for start-ups in general has shown steady growth, biodiversity start-ups have only seen substantial increases in the total deal count since 2018 and 2019. This comparison highlights that biodiversity start-ups account for a very small share of overall start-up and venture capital financing; the right-hand scale confirms that the peak year of 2021 for all deals in Pitchbook reaches 90,000 and the total venture financing is over $1.8 trillion. Panel C compares the average deal size for biodiversity and generic start-ups. Unsurprisingly, the average deal size for biodiversity start-ups appears to fluctuate around $10 million—only about one-third of the typical deal size for start-ups in the broader PitchBook universe.

To formally examine differences between biodiversity and generic start-ups in terms of financing and other company characteristics, we use our matched sample from Table 2 to conduct logistic regressions, with results presented in Table 3. We include industry fixed effects to control for sector-specific impacts and cluster the standard errors at the industry level, following similar approaches in Cole et al. (2023), Barber, Morse, and Yasuda (2021), Abadie et al. (2022), and Breuer and Dehaan (2024). Clustering the standard errors at the industry level accounts for potential within-sector dependencies in funding conditions, investor sentiment, and technological trends, given biodiversity start-ups span capital-intensive science-driven sectors (e.g., restoration, biotech) as well as awareness-raising services (e.g., environmental consulting and campaign).

Model (1) of Table 3 regresses *Biodiversity*, a binary indicator that equals one if a start-up is biodiversity-related and zero otherwise, on multiple control variables listed in Panel A of Table 2. The results indicate that biodiversity start-ups are strongly positively associated with financing from impact investors. Specifically, a 10 percentage-point increase in the share of deals financed by impact investors is associated with a 14.1% (i.e., $exp(1.316\times0.1)-1$) higher likelihood of a start-up being biodiversity-related. Due to the success of our matching design, biodiversity and generic start-ups reassuringly do not exhibit significant differences in size, age, share of early-stage deals, or profitability. We also find no significant difference in the proportion of blended deals involving public capital VC sources. This is likely because public capital, such as funding from government-sponsored accelerators and incubators, predominantly targets early-stage financing, and our matched biodiversity and generic start-ups have the same average age.

Model (2) of Table 3 further explores financing differences across biodiversity sectors by comparing biodiversity start-ups within specific biodiversity sectors to their matched generic counterparts. Specifically, this model that spans the next five columns uses generic start-ups as the baseline group in a multinomial logistic regression and then categorizes independently agriculture, animal, forest, marine and multi-function biodiversity deals. The results indicate that start-ups in all but two biodiversity sectors—namely, the animal and agriculture biodiversity sectors—are significantly associated with a higher share of deals financed by impact investors. Among them, start-ups in the forest biodiversity sector appear to exhibit the strongest correlation with impact-investing deals, while start-ups in marine and multi-functional biodiversity sectors share similar coefficient estimates.

Model (3) extends the multinomial logistic regression approach but by distinguishing between biodiversity start-ups that directly and indirectly protect biodiversity, as defined above. The results reinforce the findings from Models (1) and (2), demonstrating that both categories of biodiversity start-ups receive a higher share of impact-investing deals. This underscores the critical role of impact investors in financing biodiversity start-ups.

3.2. Taxonomy and Descriptives of Biodiversity-linked VC Investors.

Compared to biodiversity start-ups, the investors that finance them are even less well-known and understood. Indeed, who are the VC investors that finance biodiversity start-ups? What are their investment preferences? This sub-section addresses these questions.

Venture capital (VC) and private equity (PE) funds constitute an important group of investors financing biodiversity start-ups. PitchBook lists these funds and their investment preferences, enabling us to benchmark the priorities of biodiversity-focused funds against those of all venture funds financing start-ups in the Pitchbook universe. Panel A of Figure 5 reveals that biodiversity-linked investing funds are less likely to invest independently. Over 80% prefer minority stakes and syndication, compared to only about 50% of all PitchBook venture funds favoring minority stakes and about 40% prioritizing syndication. Critically, Panel A underscores that these biodiversity-investing funds are more likely to be “values-driven” investors focused on impact, while about 10%

prioritize ESG (Environmental, Social, Governance) investments or stakes in MWBEs (Minority and Women-Owned Business Enterprises). These proportions (red bars) are markedly higher than those observed in the broader PitchBook fund universe (blue bars).

Biodiversity investors extend beyond traditional funds. Table 4 ranks the top 25 investors in biodiversity start-ups by the number of deals they participate in, revealing a diverse mix of accelerator/incubators, government entities, sovereign wealth funds, and others. The VC firm, Climate Capital, is the leader at 16 deals constituting cumulatively $327 million in total investments over our sample period. The next most active investors are VC fund SOSV, a government accelerator Innovate UK, and two US-based government agencies from the Department of Agriculture and National Science Foundation.

Panel B of Figure 5 compares the prevalence of top investor types in biodiversity start-ups (red bars) to their representation among all Pitchbook start-up investors (blue bars). Venture capital funds account for over 35% of biodiversity investors, followed by individual angel investors at approximately 14% and accelerators/incubators at 10%. The panel further highlights the outsized role of public and impact investors - accelerator/incubators comprise 10% of biodiversity investors, while government agencies represent about 4%. These shares are significantly higher than their proportions in the general investor universe. Impact investors, constituting approximately 5% of biodiversity start-up backers, are nearly absent from PitchBook's broader investor database. Given PitchBook's categorization methodology and investor preferences, therefore, we classify an investor as an "impact investor" if they are explicitly designated as such by PitchBook or manage at least one fund explicitly seeking impact investments, ESG investments, or MWBE investments. The definition mirrors that in prior literature (e.g., Baber, Morse, & Yasuda, 2021; Geczy et al., 2021; Jeffers, Lyu, & Posenau, 2024; Cole et al., 2023), which characterizes impact investors as entities pursuing measurable social or environmental impact alongside financial returns.

3.3. Matching Patterns between Biodiversity Start-Ups and Investors.

The previous sections on the taxonomy of biodiversity start-ups and biodiversity investors suggest that impact investors and public capital play a disproportionately influential role in financing biodiversity start-ups. In this section, we examine the matching between investors and biodiversity start-ups more formally. Since a start-up can engage in multiple financing deals, and investors can choose whether to participate in each deal, our analysis is conducted at the deal level, focusing on transactions between start-ups and participating investors.

Before turning to an econometric analysis, we first illustrate the nature of biodiversity start-up financing deals through two representative examples from PitchBook. These cases highlight the heterogeneity of deal structures and funding sources. *Dendra*, an environmental technology company specializing in large-scale ecosystem restoration, has received funding from a diverse mix of sources, including public funding and impact investors. Its early-stage development was supported by a £5,000 (approximately $0.007 million) grant from Innovate UK in 2015, followed by a £1.95 million (approximately $2.75 million) seed round in 2018 led by private and impact investors such as SystemiQ and Kezar Ventures LLC, and later in 2024 a $15.7 million Series B round involving both traditional venture capital and impact-oriented investors including One Small Planet Foundation and Understorey Ventures. In contrast, *Nossa!*, a start-up producing sustainably sourced Brazilian açaí products intended to promote the preservation of the Amazon rainforest, has relied exclusively on private and traditional venture financing, progressing from angel rounds totaling under €300,000 in 2015/2016 to a €1.03 million venture round in 2019 led by IRD Invest (approximately $0.33 million and $1.17 million). These examples illustrate that biodiversity start-up financing can range from public–private and impact-integrated deals to more conventional venture-backed structures. Detailed deal synopses for these transactions are provided in Appendix A.3**.**

Panel A of Figure 6 compares the prevalence and financial scale of impact investing deals for biodiversity start-ups versus all generic start-ups. We find that about 15% of the deals supporting biodiversity start-ups involve impact investors (red bar), accounting for 10% of the total financing amount. In contrast, in PitchBook's broader deal universe (blue bar), only 5% of deals involve impact investors, representing approximately 3% of total financing. Similarly, Panel B compares the prevalence and financial scale of blended deals involving public capital for biodiversity start-ups (red bars) versus generic Pitchbook start-ups (blue bars). Blended deals constitute approximately 47% of the transactions for biodiversity start-ups, compared to about 36% for generic start-ups. In terms of financial volume, they represent 30% of the total financing for biodiversity start-ups, whereas for generic start-ups, the corresponding share is only around 15%.

We next conduct an empirical analysis to assess whether biodiversity start-ups attract greater participation from impact investors and public investors relative to matched generic start-ups. We estimate across 2,483 deals involving biodiversity and generic star-ups the logistic regression:

$$Impact_i\ (Blended_i) = \ \alpha\ Biodiversity_i + \boldsymbol{\beta X_i} + \boldsymbol{\varepsilon_i},$$

where $Impact_i$ ($Blended_i$) is a binary indicator equal to one if deal i includes at least one impact investor (or at least one public investor) and zero otherwise. $Biodiversity_i$, is a binary variable equal to one if the start-up is biodiversity-related, or zero otherwise. $\boldsymbol{X_i}$ represents a set of deal-level characteristics. If biodiversity start-ups are more likely to attract impact or public investors, we expect the coefficient α to be positive. The deal-year–level regressions also allow us to include both year and industry fixed effects to absorb unobserved temporal and sector-specific trends.

Table 5 presents the estimation results, with standard errors clustered at the industry level.[8] The first three columns examine impact investor participation, and the last three, public investor participation in blended deals. Across all specifications, biodiversity start-ups are significantly more likely to secure funding from impact investors compared to matched generic start-ups. The coefficient in Model (1) of 0.790 implies an odds ratio of 2.20 (i.e., *exp*(0.790)), which means that, holding other factors constant, biodiversity start-ups are a little over twice as likely to receive funding from impact investors, as we saw in Panel A of Figure 6. Models (2) and (3) introduce additional controls, including start-up and deal characteristics such as employee size, age, early-stage status, direct biodiversity preservation efforts, and profitability. Including these controls slightly increases the odds ratio (coefficient of 0.811 implies 2.25 times the odds ratio), and our inferences are not materially altered.

The last three columns of Table 5 analyse public capital participation or blended deals. The coefficients on the biodiversity indicator are significant at the 5% level, though their magnitudes are smaller relative to impact investor participation. Model (4) shows that biodiversity start-ups have 1.26 times the odds (or a 26% greater likelihood, in relative terms) of securing public investor participation than generic start-ups. Models (5) and (6) add further covariates, but the results remain almost intact. These differential odds are muted relative to that for impact investors, as we noted in Figure 6. Collectively, Table 5 confirms that biodiversity start-ups are significantly more likely to attract both impact and public investors.

[8] Standard errors are clustered at the industry level for Table 5 and Table 6, since investors benchmark deal terms within sectors and residual shocks are plausibly correlated at this level. This choice is consistent with our design, which exploits within-industry variation between biodiversity and non-biodiversity start-ups, conditional on industry fixed effects. Firm-level clustering is less reliable because some start-ups, especially young start-ups, have only one or two deals. As a robustness check, however, we also clustered at the firm level. Albeit weaker statistical significance, the results are qualitatively similar.

Next, we investigate the deal sizes of biodiversity start-ups, including those financed by impact and public investors, and the generic start-ups for the sample of 2,483 deals. The regression specification is as follows:

$$Log(Deal\ Size_i) = \alpha\ Biodiversity_i + \beta \boldsymbol{X_i} + \boldsymbol{\varepsilon_i}.$$

The dependent variable is the logarithm of deal size (in millions of dollars) as in Table 2. In addition to analysing all deals, we separately examine subsets of impact deals (only 396 of the 2,483 deals) and blended deals (only 1,094 deals).

Table 6 reports the regression results, with standard errors clustered at the industry level. Across all specifications, the coefficient on the biodiversity indicator is significantly negative, indicating that biodiversity start-ups receive significantly smaller deal sizes. Model (1) estimates a coefficient of -0.548, suggesting that, on average, biodiversity start-ups secure approximately 55% less financing than their matched generic counterpart start-ups. This finding aligns with the summary statistics presented in Table 2. Model (2), which controls for additional covariates, yields equivalent results. Ideally, we would control for the capital needs of biodiversity and matched generic start-ups, but such detailed project-level information is rarely available in opaque private markets. Nevertheless, our matching procedure—based on region, industry, founding year, and initial employee size—ensures that we compare firms with broadly similar capital requirements, allowing observed funding differences to be interpreted as a potential financing gap.[9]

Models (3) and (4) replicate the specification of Model (2) but focus only on subsets of 369 impact deals and 1094 blended deals, respectively. The estimates confirm that, even within these narrower categories, biodiversity start-ups raise less funding than their generic counterparts. However, the gap in deal size is narrower for impact deals compared to the full sample. The coefficient of -0.377 implies only 38% less financing in millions of dollars raised. This finding implies that impact investors help bridge the financing gap for biodiversity start-ups.

Model (5) restores the analysis for the full sample of all deals but extends Model (2) by including two additional interactive indicator variables—one for impact deals and one for blended deals—alongside other deal characteristics. The coefficient on biodiversity remains unchanged,

[9] In an untabulated test, we further leverage our taxonomy of biodiversity start-ups—distinguishing between direct, capital-intensive ventures (e.g., ecosystem restoration or species conservation) and indirect, less capital-intensive ventures (e.g., awareness platforms or biodiversity databases)—and compare their deal size and fundraising. We do not find a statistically significant difference between the two groups, even though direct ventures likely have higher financing needs, which is consistent with the presence of underfunding among biodiversity start-ups that directly contribute to biodiversity protection and restoration.

reinforcing the conclusion that biodiversity start-ups raise significantly less capital than generic start-ups. The impact deal indicator is positive and statistically significant at the 5% level, suggesting that impact investor participation is associated with a 31% increase in deal size. This reflects impact investors' collaborative approach, which often involves syndication and minority stakes to mitigate risks. In contrast, the coefficient on the blended deal indicator is significantly negative, suggesting that deals involving public capital tend to be smaller. This is consistent with the nature of public capital, which often supports early-stage ventures through grants, seed funding, and in-kind support such as office space and incubator programs. Consequently, deals with public capital involvement tend to be smaller than those fully financed by private investors.

Finally, Model (6) explores whether impact or public investors help biodiversity start-ups raise larger deal sizes. We introduce two interaction terms between the biodiversity indicator and the impact/blended deal indicators. The coefficient on the biodiversity indicator remains significantly negative, indicating that biodiversity start-ups continue to face a financing gap. However, the interaction term between biodiversity and impact deals is positive and statistically significant at the 10% level, which implies impact investor participation helps increase fundraising for biodiversity start-ups and is consistent with Oehmke and Opp (2025)'s prediction. We do not find such evidence for public capital participation.

The pivotal role of impact investors and public-sector backers in financing biodiversity start-ups aligns with their distinct investment preferences. Cole et al. (2023) demonstrate that impact investors exhibit greater risk tolerance and patience, favoring nascent and emerging industries. Complementing this, Barber et al. (2021) show that such investors are willing to accept lower financial returns relative to traditional private-market counterparts in exchange for measurable non-pecuniary impact. Biodiversity start-ups, operating at the intersection of innovation and sustainability, naturally fall within the mandate of these investors, benefiting from their patient, risk-tolerant capital. Flammer et al. (2025a) illustrate how concessionary capital—such as public or philanthropic funding in blended finance structures—can subsidize private investments. The blended deal approach mitigates uncertainty for private actors by supporting fact-finding pilot programs or proof-of-concept initiatives, thereby de-risking early-stage ventures for private capital.

Both impact investors and public backers align with the category of values-driven investors, as defined by Starks (2023), and are "minds-alike" to the biodiversity start-ups on ecological and sustainability values. Our study contributes empirical insights into the role of such investors in the underexplored domain of biodiversity finance. Starks (2023) emphasizes the growing importance of sustainability in private markets and notes a critical research gap relative to public markets. By examining biodiversity enterprises, our work addresses this gap, advancing understanding of how values-driven capital shapes sustainable investing in private-market ecosystems.

3.4 Does Social Media Enhance Financing for Biodiversity Start-Ups?

We previously posited that social media activity—particularly on the Twitter platform—may help mitigate the financial challenges faced by biodiversity start-ups. This hypothesis is supported by both previous research and anecdotal evidence.[10] A recent study by Wang, Wu, and Hitt (2024) further supports the idea that social media can facilitate venture financing by highlighting that Twitter usage can help start-ups secure funding and enhance the visibility of underrepresented entrepreneurs, including women and individuals lacking traditional social capital. Given the anecdotal and academic evidence, this section examines the impact of Twitter engagement on biodiversity start-ups and their financing outcomes.

As Panel C of Table 2 shows, biodiversity start-ups exhibit substantial variation in their use of Twitter. In our sample, 37.9% (i.e., 229) of our 605 biodiversity start-ups have active Twitter accounts. Even among those with an account, engagement levels differ significantly, as measured by the number of posted tweets. Start-ups in the lowest quartile have fewer than 36 total tweets, while those in the highest quartile exceed 578 tweets. Given this variation, our analysis proposes to examine both the extensive margin (whether having a Twitter account impacts fundraising) and the intensive margin (whether posting more tweets, conditional on having a Twitter account, influences fundraising).

To assess the extensive margin, we estimate the following regression models for our sample of 605 biodiversity start-ups and the additional 605 matched generic start-ups:

$$Log(Total\ Deal\ Size_i) = \alpha Twitter_i + \beta \boldsymbol{X_i} + \boldsymbol{\varepsilon_i} \ ,$$

$$Total\ Number\ of\ Deals_i = \alpha\ Twitter_i + \beta \boldsymbol{X_i} + \boldsymbol{\varepsilon_i} \ ,$$

where the dependent variable is the natural logarithm of total deal size and total number of deals, respectively, and $Twitter$ is a binary indicator variable equal to one if the biodiversity start-up has

[10] Anecdotally, please see online articles such as "What are the most effective ways to use Twitter for deal sourcing?" from LinkedIn, and "Seven deal sourcing strategies for investors" from Affinity. Cao, Fang, and Lei (2021) show that firms also use Twitter to publicize adverse news about peers.

an active Twitter account. The coefficient α captures the extensive margin effect of having a Twitter account on fundraising and is expected to be positive.

However, estimating the regressions solely for biodiversity start-ups does not reveal the incremental effect of social media activity that is unique to biodiversity-linked start-ups, because Twitter engagement may generally facilitate financing for start-ups of any type (Wang, Wu, and Hitt, 2024). To benchmark our results, we therefore re-estimate the regressions using a sample of matched generic start-ups. Finally, we estimate a pooled specification that includes both biodiversity and matched generic start-ups, in which we interact the *Twitter* indicator with the *Biodiversity* indicator to isolate *the differential effect of* Twitter presence for biodiversity start-ups.

Table 7 presents the regression results. Models (1) – (4) estimate the effects of having a Twitter account on the (log) total fundraising of biodiversity start-ups: Model (1) is estimated without control variables, while the other three include them, with the latter two focusing specifically on impact and blended deals. We also include country fixed effects in Models (2) – (4), as start-ups in certain countries (e.g., China) may have limited access to Twitter. Model (1) estimates α of 0.358, significant at the 5% level, implying that having a Twitter account increases total funds raised by biodiversity start-ups by 36%, translating to an increase of \$3.49 million on a base average of around \$9.76 million (from Table 2). Model (2), which controls for additional company characteristics and country fixed effects, yields an even larger coefficient of 0.487, suggesting that a Twitter account is associated with more funds raised by \$4.75 million for biodiversity start-ups. Models (3) and (4) replace the dependent variable with (log) total impact deal size and (log) total blended deal size, respectively, setting the dependent variable to zero for biodiversity-linked start-ups never financed by impact investors or public capital. Model (3) reports a coefficient of 0.199, significant at the 10% level, indicating that having a Twitter account increases total funds raised through impact deals by 19.9%. Model (4) reports an effect of similar magnitude for blended deals, though it is not statistically significant at conventional levels. Overall, these results suggest that Twitter presence is associated with a boost in capital raising for biodiversity start-ups, consistent with our prior discussion.

Moreover, the comparison of Model (2) in Table 7 with Models (3) and (4) reveals that the positive association between Twitter usage and fundraising for biodiversity start-ups is not predominantly driven by impact investing or blended financing deals. Indeed, the results indicate that transactions *without* involvement from impact investors or public-sector backers are the primary contributors to this effect. This finding may reflect the fact that values investors—including impact investors and public backers—possess greater confidence in the long-term sustainability goals of these ventures (or they simply share the same values or beliefs in sustainability). Their prior experience may have equipped them with deeper insights into these start-ups' business models and specialized expertise in evaluating such investments, reducing their reliance on external signals, like those from social media, for deal sourcing. By contrast, Twitter appears to bridge information gaps for "minds-unalike" *value* investors, who may lack prior exposure to biodiversity ventures. Specifically, the platform mitigates information asymmetry by enhancing visibility, transparency, and quality signaling. These dynamics align with Wang, Wu, and Hitt (2024), who demonstrate that start-ups' Twitter activity improves access to information and engage previously unfamiliar investors, thereby leading to more financing deals.

To provide a benchmark for interpreting the results for biodiversity start-ups, Model (5) repeats the same regression as Model (2) but for the 605 matched generic start-ups. The results indicate that having a Twitter account also positively affects the total fundraising of generic start-ups, though the magnitude is slightly smaller: the coefficient of 0.454 implies an approximate 45.4% increase in total deal size, compared with 48.7% for biodiversity start-ups. These effects are similar. Model (6) pools biodiversity and generic start-ups and includes an interaction term between *Biodiversity* and *Twitter* to formally test whether Twitter presence provides incremental fundraising benefits to biodiversity ventures. The interaction coefficient is positive (0.197) but statistically insignificant, confirming that while Twitter engagement supports fundraising overall, its marginal effect for biodiversity start-ups is not significantly different from that for generic start-ups when measured in terms of total deal size.

Next, we examine whether having a Twitter account leads to more deals for biodiversity start-ups. Following Cohn, Liu, and Wardlaw (2022), we use a Poisson regression with the same covariates in Models (1) – (6) of Table 7 for Models (7) – (12). Model (7) estimates an α of 0.479, which implies a 61.45%, or $exp(0.479) - 1$, increase in the expected number of financing deals for biodiversity start-ups with a Twitter account. When focusing on impact and blended deals, the effects are even stronger. Model (9) shows a coefficient of 0.629, indicating that a Twitter account is associated with an 87.57% increase in the expected number of impact deals. Similarly, Model (10) estimates a coefficient of 0.518, significant at the 1% level, suggesting a 67.87% increase in the expected number of blended deals. These statistically and economically significant results highlight that having a Twitter account increases deal flow for biodiversity start-ups.

Like the analysis of total fundraising, Model (11) benchmarks the effect of having a Twitter account on the number of financing deals for biodiversity start-ups by repeating the regression of Model (8) for the 605 matched generic start-ups. The results showed a significant positive association of Twitter engagement with the number of deals for generic start-ups, confirming that social media visibility is associated with increased deal activity in general. Model (12) then formally compares the effects of Twitter engagement between biodiversity and generic start-ups by including an interaction term between Biodiversity and Twitter. Here, the coefficient on this interaction is 0.186, statistically significant at the 5% level, indicating that Twitter presence has a disproportionally stronger association with the number of deals for biodiversity start-ups than for their generic counterparts, even though the total fundraising amount does not differ significantly from that of comparable generic start-ups.

Beyond the extensive margin, we next examine the intensive margin - whether more posted tweets further enhance fundraising for biodiversity start-ups with a Twitter account, and whether this effect is incremental relative to matched generic start-ups. To do so, we modify our regression specification as follows:

$$Log(Total\ Deal\ Size_i) = \alpha Log\ (\#Tweets_i) + \beta \boldsymbol{X_i} + \boldsymbol{\varepsilon_i},$$

$$Total\ Deal\ Number_i = \alpha\ Log\ (\#Tweets_i) + \beta \boldsymbol{X_i} + \boldsymbol{\varepsilon_i},$$

where the independent variable now measures the (log) number of posted tweets. We remain agnostic regarding the expected sign of this coefficient: increased tweeting activity may enhance visibility and attract additional funding, but it may also have no marginal effect if the market primarily responds to the mere presence of a Twitter account rather than the intensity of posting.

Table 8 presents the results in the same format as Table 7. Models (1) to (6) examine the effects of Twitter posting intensity on (log) total fundraising. The sample size is smaller—229 biodiversity start-ups and 235 matched generic start-ups—reflecting that only start-ups with an existing Twitter account during our sample period are included in these regressions. Models (1) and (2) indicate that more posted tweets increase the biodiversity-linked start-up's total fundraising. A 1% increase in the number of tweets is associated with more total funds raised by approximately 0.23%. Models (3) and (4) examine impact and blended deals separately. Both models provide evidence that more frequent tweeting increases fundraising in these types of deals. Model (3) estimates a statistically significant coefficient of 0.084, implying that a 1% increase in tweets is associated with more impact deal funding by 0.084%. Model (4) reports a coefficient of 0.156, suggesting that a 1% increase in tweets is associated with more blended deal funding by 0.156%. Turning to the benchmark sample of matched generic start-ups, nevertheless, Model (5) shows that more posted tweets are also associated with increased total fundraising. Model (6), which pools biodiversity and generic start-ups and includes the interaction term, indicates that the marginal effect of tweeting for biodiversity start-ups is not significantly different from that for generic start-ups.

The remaining columns of Table 8 for Models (7) to (12), examine the link between Twitter posting intensity with deal counts. The results suggest that a greater number of posted tweets is associated with a larger number of financing deals for biodiversity start-ups, and regardless of whether the deals are financed by impact investors or public capital. A 1% increase in tweets is associated with a 0.157% increase in the total number of deals for biodiversity start-ups. The effect appears specific to biodiversity start-ups - Model (11) shows no significant relationship between the number of tweets and deal counts for generic start-ups. Model (12), which formally compares the effects between biodiversity and generic start-ups, confirms this pattern. The coefficient on the interaction term between Biodiversity and Ln(#tweets) is 0.093, significant at the 1% level, indicating that more frequent tweeting is associated with more deals for biodiversity start-ups relative to comparable generic start-ups.

Timing may matter in deal activity. The results to now have pooled all deals for biodiversity- and generic start-ups across time. We next leverage temporal variation in tweeting activity and the dynamics of financing outcomes. Specifically, we regress (log) deal size in year *t* on (log) tweets posted in year *t-1*, controlling for company and deal characteristics. Particularly, we control for company fixed effects. Using annual deal-level fundraising and tweeting activity with company fixed precisely captures within-firm time-series variation and offers an as-if event study analysis; but we continue to caution readers about over-interpreting any of these as causal effects. We include a COVID-period indicator (2020–2021) to account for the heightened use of Twitter during pandemic lockdowns and cluster the standard errors at the company level.

Table 9 presents the results. Model (1) focuses on biodiversity start-ups and shows that greater Twitter posting intensity increases individual deal size. A 1% increase in tweets is associated with a 0.11% increase in deal size, which translates to approximately \$3,507 per tweet (i.e., 0.11% × \$3.188 million, the average deal size from Panel A of Table 2). Consistent with our earlier analysis, Model (2) benchmarks the results using the matched generic start-ups. In this case, we do not find evidence that greater posting intensity is associated with greater fundraising for generic start-ups. Model (3), which formally compares the effects of posting intensity between biodiversity and generic start-ups, confirms a differential impact but the effect is statistically weak. Consistent with Table 8, Model (3) indicates that more frequent tweeting is associated with incremental value for biodiversity start-ups with better financing outcomes relative to comparable generic start-ups. Finally, Models (4) and (5) examine impact and blended deals, respectively, but find no evidence that higher posting intensity is associated with the size of these specific deal types.

Overall, our findings convey a consistent message: both the presence of a Twitter account and greater posting intensity are linked to the financing of biodiversity start-ups. While the effects on total fundraising amounts are broadly comparable between biodiversity-linked and generic start-ups, the association with deal frequency is more pronounced for biodiversity start-ups. In other words, more intense social media activity disproportionately benefits biodiversity start-ups by being associated with more financing deals relative to their generic counterparts.

3.5 An Identification Experiment on Social Media and Biodiversity-Linked Financing.

Twitter initially imposed a restrictive 140-character limit per tweet. In 2017, Twitter relaxed this restriction, increasing the character limit to 280.[11] This expansion allowed longer text, enabling branded URLs, more structured tweets, and complete sentences in posts. As *Forbes* suggested, this change facilitated richer content and promotion, leading to increased Twitter activity.[12] We hypothesize that this exogenous shock to Twitter's engagement, a decision made for reasons unrelated to Twitter activity involving VC financing, could positively impact funding outcomes. If confirmed, these findings would also reinforce our earlier conclusions about the role of Twitter usage for biodiversity start-up financing outcomes.[13]

To test this hypothesis, we estimate for 1,311 deals involving biodiversity-linked start-ups the following regression:

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[11] See "Twitter Tests Lengthening the 140-Character Tweet" by Kathleen Chaykowski, *Forbes*, September 26, 2017. Also, see "Twitter officially expands its character count to 280 starting today" by Sarah Perez, *TechCrunch*, November 7, 2017.

[12] Figure A.1 in Appendix A.4 plots the average tweet length per month for biodiversity startups and the matched sample of non-biodiversity startups from January 2013 to December 2023 and shows a discrete jump in tweet length following this policy change.

[13] We acknowledge that the decision to open a Twitter account is endogenous and may reflect unobserved start-up characteristics—such as founder proactivity, marketing orientation, or investor networks. As such, our results should be interpreted with this caveat in mind.

$$Log\left(Deal\ Size_{i,t}\right) = \alpha_1 Twitter_i \times Post_t + \alpha_2 Twitter_i + \alpha_3 Post_t + \beta \boldsymbol{X_{i,t}} + \boldsymbol{\varepsilon_{i,t}}$$

where $Post_t$ is an indicator variable that equals one if a deal occurs after 2017. The coefficient α_1 of the interaction term $Twitter_i \times Post_t$ captures the incremental effect of Twitter usage following the relaxation of the character limit.[14] As in our previous analysis, we examine all deals involving biodiversity start-ups with Twitter accounts and we separately analyze deals financed by at least one impact investor or public investor (blended deals).

Table 10 presents the regression results. Models (1) and (2) indicate that, on average, deal sizes increased following the positive shock, suggesting that Twitter usage helps biodiversity start-ups by enhancing deal size. However, we do not find strong evidence that the character limit expansion significantly affected the size of impact deals and blended deals, as shown in Models (4) and (6). Consistent with our findings in Tables 8 and 9, this result suggests that impact investors are less sensitive to biodiversity start-ups' Twitter activity than private investors.

To formally assess the parallel trends assumption underlying our difference-in-differences (DID) design, we augment the regressions of Table 10 and estimate a leads-and-lags specification in which we interact the Twitter indicator with financing year dummies, using 2017—the year of Twitter's character limit expansion—as the omitted reference year. To enhance statistical power and account for major disruptions to firm activity during the COVID-19 lockdown period, we group the post-treatment years into three bins: 2018–2019 (immediately after the expansion), 2020–2021 (COVID-affected years), and 2022–2023 (post-pandemic years). This approach also facilitates a clear visual and statistical check of pre-trends versus post-treatment effects.

The results in Table 11 support the parallel trends assumption. Coefficients for the pre-2017 years ($\leq$ 2014, 2015, and 2016) are small and statistically insignificant, indicating no differential pre-trend in fundraising between biodiversity start-ups with and without a Twitter account prior to the character limit expansion. In contrast, coefficients for 2018 and later years are positive and statistically significant, consistent with a post-treatment effect in which Twitter engagement is associated with larger deal sizes. The largest effects appear in the immediate post-treatment period (2018–2019) and again in the post-pandemic period (2022–2023), suggesting that the visibility gains from Twitter are most pronounced in periods of market recovery and active fundraising.

[14] See an earlier footnote in Section 2.2, which discusses Panel C of Table 2, regarding the fixed memberships of start-ups in groups with and without Twitter accounts. The group memberships stay constant over time.

Overall, these results reinforce the credibility of our DID approach by satisfying the parallel trends condition and providing dynamic evidence of treatment effects.

3.6. The Biodiversity Start-Up's Founders

Although a systematic study of biodiversity start-up founders lies beyond the scope of this paper, we provide a brief descriptive overview to highlight the diverse educational and professional backgrounds of the entrepreneurs driving this sector.[15] Founders of biodiversity start-ups often combine scientific expertise with business and technology experience, reflecting the interdisciplinary nature of biodiversity innovation. For example, the co-founder and CEO of *Archireef* holds a Ph.D. in biological sciences and leads efforts to restore degraded coral reef ecosystems using 3D-printed terracotta reef tiles. The scientific advisor at *Sundew* is a molecular biologist with nearly 20 years of experience in microbial strain development and now develops fermentation-based bioproducts for controlling aquatic pests and invasive species. Similarly, the founder of *Rhizocore Technologies* leverages a background in biochemistry and forestry to create locally adapted mycorrhizal fungi to enhance forest regeneration and woodland biodiversity.

This entrepreneurial ecosystem also reflects gender and professional diversity and a wide variety of national origins. Leaders at *Pina Earth* combine scientific expertise with market applications, developing AI-based forest carbon certification tools that make local forest climate protection measurable and tradeable. The founder of *Spoor* merges engineering and forest management experience with NGO and sustainability work to advance AI-enabled bird monitoring for wind farms, bridging renewable energy and biodiversity protection. Collectively, these founders come from academia, environmental NGOs, technology start-ups, and international corporations, demonstrating that biodiversity entrepreneurship is fueled by interdisciplinary expertise and the intersection of scientific innovation and commercial execution.

4. Conclusions and Future Work.

Our findings highlight the emergence and growing prominence of biodiversity start-ups in the venture capital and sustainable investing landscape. Leveraging a novel machine learning approach with a large language model, we systematically identify 630 biodiversity start-ups in the PitchBook venture capital datasets from 2010 to 2023, and examine their financing deals, investors,

[15] We are grateful to our discussant, Qifei Zhu, and the Editor for encouraging us to pursue this further analysis on the founders. A much deeper investigation is worthy.

startup-investor matching patterns, and social media usage. Biodiversity start-ups, despite their critical ecological contributions, are associated with notably smaller total and average deal sizes relative to comparably matched non-biodiversity start-ups. Nonetheless, biodiversity start-ups have a unique financing structure - they rely more on impact investors and blended finance that involves public-sector partners, and they attract a broader coalition of investors including those who prefer minority stakes and syndication, as well as venture capital firms. This suggests a hybrid model of support that combines ecological stewardship with profit-seeking motives.

The heterogeneity of biodiversity start-ups underscores the multifaceted nature of their business activities. Our algorithm categorizes biodiversity start-ups by their functional focus (marine, forest, agricultural, animal, or multi-functional) and by whether they have direct or indirect effects on biodiversity protection and restoration. Multi-functional biodiversity ventures account for the largest share of both overall funding and total start-up counts, while forest biodiversity ties with marine biodiversity in the count of start-ups but exceeds the latter in total funds raised. Start-ups taking indirect approaches to biodiversity protection constitute just over half of the identified ventures and receive slightly more than half of total funds raised.

Lastly, our analysis indicates that Twitter usage is associated with more favorable fundraising outcomes for biodiversity start-ups. Entities with Twitter accounts raise larger total deal sizes and secure a greater number of deals compared to those without accounts. More frequent tweeting appears to offer a modest additional benefit. Social media usage is linked to attracting funding from “minds-unalike” *value* investors for biodiversity start-ups, complementing the involvement of “minds-alike” *values* investors, such as impact-focused and public-sector backers. Our results indicate that social media can mitigate information asymmetries and can expand the investor base in the biodiversity entrepreneurship landscape. While biodiversity start-ups benefit significantly from the presence of impact and public-sector investors, social media activity can be effective in attracting more *value* (for-profit) investors who may not share an explicit environmental mission. By increasing visibility and signaling credibility, social media can bridge the gap between biodiversity ventures pursuing ecological objectives and a broader pool of capital.

From a policy perspective, our findings underscore the significance of impact investors and public-sector actors with their interventions in promoting biodiversity innovation. Programs encouraging blended financing arrangements may complement private sector investments, thereby supporting ventures that advance broader ecological goals while contending with inherent scale and risk challenges. Our analysis also highlights promising avenues for future research, including a deeper examination of investor coalitions, the long-term performance and survival of biodiversity start-ups, and the broader societal impact of their nature-positive innovations. As sustainability and nature resilience awareness grow more pronounced, understanding these mechanisms will be increasingly vital for both financial and environmental decision-makers.

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Data Availability Statement

The final lists of biodiversity-linked and generic start-ups examined in the study has been shared with the journal's editorial office with the final submission. We have also shared a complete code package. The original data from Pitchbook and Crunchbase is proprietary. As a result, we have only included pseudo-data set that illustrates the format of the files read by the code, so that users can understand and check the functionality of the code. We include log files that were generated when the code was run on the actual data, and produced the results included in the paper.

Table 1. Examples of Biodiversity Start-Ups by Focus.

This table displays examples of different biodiversity startups by their area of focus, classified by a large language model (LLM) with human fine-tuning. *Marine Biodiversity*: focuses on marine ecosystems, including the conservation, restoration, aquaculture, and monitoring of marine species, coral reefs, fisheries, oceans, and other marine environments. *Forest Biodiversity*: focuses on forest ecosystems, such as reforestation, afforestation, forest monitoring, forest-related carbon credits, and biodiversity linked to forest habitats. *Agriculture Biodiversity*: focuses on sustainable farming, regenerative agriculture, and biodiversity-friendly farming practices, agroforestry, as well as inputs (like biofertilizers) and technologies that promote sustainable farming. *Animal Biodiversity*: focuses on wild animals (terrestrial or freshwater), tracking and monitoring animal species, protecting animal habitats, and offering products or services that protect or support animal biodiversity. *Multifunctional Biodiversity*: any other startups that do not fit into the above categories. Pane A shows examples from Crunchbase, and Panel B demonstrates examples from PitchBook.

Panel A. Crunchbase Examples

Focus	Example Company	Crunchbase Description	Crunchbase Categories (Industries)	Homepage URL
Marine Biodiversity	GreenWave	"GreenWave supports a new generation of ocean farmers and innovators working to restore ecosystems, mitigate climate change."	GreenTech, Marine Technology, Science and Engineering, Sustainability	https://www.greenwave.org/
Forest Biodiversity	CCNW (Conservation Contracts NorthWest)	"CCNW is a specialist contracting and consultancy company specializing in forest conservation, landscape management & ecology."	Business Information Systems, Consulting, Environmental Consulting, Information Technology, Professional Services	https://www.ccnw.info/woodland-management/
Agriculture Biodiversity	TraitGenetics	"TraitGenetics is specialised in the development and analysis of molecular markers for biodiversity and plant breeding research."	Biotechnology, Professional Services, Science and Engineering	https://www.traitgenetics.com/
Animal Biodiversity	Re:wild (Global Wildlife Conservation)	"Global Wildlife Conservation conserves the diversity of life on Earth by safeguarding wildlands and supporting guardians."	Environmental Consulting, Professional Services	https://www.globalwildlife.org/ https://www.rewild.org/
Multifunctional Biodiversity	iNaturalist	"iNaturalist is a social network with mapping and shares biodiversity information that connects people to nature via technology."	Education, Environmental Consulting, Life Science, Social Network, Biotechnology, Internet Services, Professional Services, Science and Engineering	https://www.inaturalist.org/

Table 1. Examples of Biodiversity Start-Ups by Focus. (Cont.)

Panel B. PitchBook Examples				
Focus	**Example Company**	**PitchBook Description**	**PitchBook Industries**	**Homepage URL**
Marine Biodiversity	rrreefs	"Operator of an environmental company intended to provide restoring reef ecosystem services. The company rebuilds damaged coral reefs using their three-dimensional printing technology, creates new underwater attractions for ecotourism, and raises awareness of coastlines, enabling conservation organizations to sustainably restore and protect marine environments."	Business Products and Services (B2B), Commercial Services, Environmental Services (B2B)	https://www.rrreefs.com/
Forest Biodiversity	Land Life	"Provider of reforestation services intended to restore hectares of degraded land and plant trees at scale. The company's services make use of data and technology such as drones, artificial intelligence, and monitoring applications to grow trees efficiently, enabling corporations to have a sustainable and transparent way to take climate action and compensate for carbon emissions."	Materials and Resources, Forestry, Forestry Development/Harvesting	https://landlifecompany.com/
Agriculture Biodiversity	BeeOdiversity	"Provider of environmental and biodiversity services intended to promote preservation, ensure pollution reduction, and the setting up sustainable agriculture. The company engages in the regeneration and preservation of bees and offers an environmental monitoring tool that measures pollutants and the state of biodiversity based on the cleverness of bees and data interpretation software, enabling industries to reduce industrial and agricultural pollution to maintain equilibrium in the ecosystem."	Business Products and Services (B2B), Commercial Services, Environmental Services (B2B)	https://beeodiversity.com/
Animal Biodiversity	WildLife Partners	"Operator of a wildlife conservation company intended to promote wildlife and its protection. The company engages in the preservation and protection of wildlife animals as well as offers service, expertise, and credibility to breed exotic wildlife, enabling conservationists to save endangered species of animals and plants from all over the world."	Business Products and Services (B2B), Commercial Services, Environmental Services (B2B)	https://wildlifepartners.com/
Multifunctional Biodiversity	Dendra Systems	"Operator of an environmental technology company intended to address the restoration of natural ecosystems globally. The company's technology addresses the challenge of degraded land across the globe created from years of imbalance between the rate of ecosystem destruction and ecosystem restoration, enabling enterprises to gain access to an integrated approach to data analytics and automation services to meet ecosystem restoration and reporting requirements."	Business Products and Services (B2B), Commercial Services, Environmental Services (B2B)	https://www.dendra.io/

Table 2. Summary Statistics of Biodiversity Start-Ups and Financing Deals.

Panel A presents company-level summary statistics for biodiversity start-ups and their matched generic counterparts. Propensity score matching is used to select the best-matched generic start-ups based on company age and size (measured by the latest available number of employees), ensuring that the matched start-ups were founded in the same region and operate in the same industry as biodiversity start-ups. When a start-up's founding year is unavailable, the year of its first financing is used as a proxy. *Ln(Employment)* represents the natural logarithm of the average number of employees across all deals. *Age* is the number of years between the last financing date and the founding date. *Early* is the proportion of deals classified as early-stage financing by PitchBook. *Positive Profit* is the proportion of deals in which the start-up has disclosed a positive EBITDA, as recorded by PitchBook. *Impact* and *Blended* indicate the fraction of deals partially financed by impact investors and public capital, respectively. *Total Deal Size* is the total amount of capital raised by a start-up (in million USD), while *Total Num of Deals* represents the total number of financing deals secured. *Avg Deal Size* is the ratio of *Total Deal Size* to *Total Num of Deals*. The final "Difference" column reports the mean difference test between the two groups of start-ups. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel B This panel presents deal-level summary statistics for biodiversity start-ups and their matched generic counterparts. *Biodiversity* is a binary variable equal to 1 if the start-up is classified as biodiversity-related. *Impact* and *Blended* are binary variables indicating whether a deal is partially financed by impact investors or public capital, respectively. *Ln(Employment)* represents the natural logarithm of the number of employees. *Age* is the number of years between the deal date and the founding date. *Early* is a binary variable equal to 1 if the deal is classified as early-stage financing by PitchBook. *Direct* is a binary variable equal to 1 if the start-up is biodiversity-related and directly addresses biodiversity loss. *Positive Profit* is a binary variable equal to 1 if the start-up has disclosed a positive EBITDA, as recorded by PitchBook, during the financing deal.

Panel C reports summary statistics of Twitter Engagement by biodiversity start-ups and their matched generic counterparts. *Twitter* is a binary indicator variable equal to one if a startup has an active Twitter account. *#Tweets* is the total number of Tweets posted on the Twitter account by Dec 2024. The final "Difference" column reports the mean difference test between the two groups of start-ups. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Matched Biodiversity & Generic Startups

	Matched Biodiversity Startups						Matched Generic Startups						
	Count	Mean	SD	25th	Median	75th	Count	Mean	SD	25th	Median	75th	Difference
Ln(Employment)	605	2.942	1.087	2.398	2.741	3.281	605	2.843	0.946	2.464	2.639	3.384	0.099*
Age	605	7.944	11.777	2.000	5.000	10.000	605	6.899	10.823	2.000	4.000	8.000	1.045
Early	605	0.601	0.449	0.000	0.857	1.000	605	0.601	0.446	0.000	0.857	1.000	-0.000
Positive Profit	605	0.035	0.163	0.000	0.000	0.000	605	0.028	0.146	0.000	0.000	0.000	0.007
Impact	605	0.169	0.307	0.000	0.000	0.250	605	0.080	0.228	0.000	0.000	0.000	0.090***
Blended	605	0.323	0.396	0.000	0.000	0.667	605	0.302	0.400	0.000	0.000	0.600	0.022
Total Deal Size	605	9.758	37.877	0.000	0.385	4.293	605	22.472	158.637	0.000	0.600	4.024	-12.714*
Total Num of Deals	605	2.392	2.039	1.000	2.000	3.000	605	2.167	1.671	1.000	2.000	3.000	0.225**
Avg Deal Size	605	3.188	11.558	0.000	0.200	1.883	605	6.623	34.467	0.000	0.309	2.031	-3.435**

Table 2. Summary Statistics of Biodiversity Start-Ups and Financing Deals. (Cont.)

Panel B. Matched Biodiversity & Generic Startups: Financing Deals

	Count	Mean	SD	25th	Median	75th
Biodiversity	2,483	0.528	0.499	0	1	1
Impact	2,483	0.159	0.366	0	0	0
Blended	2,483	0.441	0.497	0	0	1
Ln(Employment)	2,483	2.776	1.121	2.2	2.64	3.04
Age	2,483	5.326	7.490	1	3	7
Early	2,483	0.703	0.457	0	1	1
Direct	2,483	0.234	0.424	0	0	0
Positive Profit	2,483	0.029	0.167	0	0	0

Panel C. Matched Biodiversity & Generic Startups: Twitter Engagement

	Matched Biodiversity Startups						Matched Generic Startups						
	Count	Mean	SD	25th	Median	75th	Count	Mean	SD	25th	Median	75th	Difference
Twitter	605	.379	.485	0	0	1	605	.388	.488	0	0	1	-0.010
#Tweets	229	301	298	36	166	578	235	309	303	38	170	620	-7.927

Table 3. Binomial and Multinomial Logistic Regression Comparing Biodiversity and Non-Biodiversity Start-Ups.

This table presents multinomial logistic regression results comparing biodiversity start-ups with matched non-biodiversity generic start-ups. The reference group consists of matched non-biodiversity generic start-ups. Model (1) compares biodiversity start-ups to their matched counterparts. Model (2) extends the analysis by differentiating start-ups across various biodiversity sectors (e.g., marine biodiversity) relative to matched non-biodiversity start-ups. Model (3) distinguishes between start-ups that directly and indirectly preserve biodiversity. All start-up characteristics are defined as in Panel A. of Table 2. Standard errors are clustered at the industry level. *, **, and *** denote significance levels of 0.10, 0.05, and 0.01, respectively.

	(1)			(2)			(3)	
	Biodiversity	Agriculture	Animal	Forest	Marine	Multifunctional	Direct	Indirect
Impact	1.316***	0.792	0.518	2.058***	1.204***	1.085**	1.385***	1.246***
	(0.425)	(0.680)	(0.946)	(0.321)	(0.452)	(0.438)	(0.460)	(0.429)
Blended	0.130	0.243	0.231	-0.105	0.430***	-0.129	-0.025	0.256*
	(0.111)	(0.223)	(0.609)	(0.186)	(0.112)	(0.170)	(0.163)	(0.144)
Ln(Employment)	0.110	0.206	-0.133	0.206	-0.046	0.236	0.159	0.064
	(0.134)	(0.187)	(0.164)	(0.179)	(0.124)	(0.148)	(0.138)	(0.133)
Age	0.009	-0.007	0.018	0.011	0.014	0.007	0.007	0.012
	(0.010)	(0.006)	(0.016)	(0.008)	(0.012)	(0.011)	(0.006)	(0.013)
Early	0.048	0.342	-0.554	-0.151	0.303	0.115	0.187	-0.060
	(0.192)	(0.319)	(0.571)	(0.583)	(0.397)	(0.151)	(0.226)	(0.235)
Positive Profit	0.106	-0.155	1.288	-0.850	-0.280	0.575*	0.399	-0.345
	(0.262)	(0.968)	(0.834)	(0.873)	(0.368)	(0.296)	(0.364)	(0.368)
Obs.	1210			1210			1210	
Pseudo R-squared	0.025			0.063			0.057	
Industry FE	Yes			Yes			Yes	

Table 4. Top 25 Investors in Biodiversity Start-Ups.

This table lists the top 25 investors in biodiversity start-ups, ranked by the number of deals financed. The first column presents the investor name, followed by the primary investor type. The third and fourth columns report the number of deals financed and the total deal size (in million USD), respectively. The final four columns indicate whether the investor is classified as an impact investor, utilizes public capital, prefers minority stakes, and participates in syndication.

Investor Name	Primary Type	#Deals	Total Deal Size	Impact	Public	Prefers minority stake	Will syndicate
Climate Capital	Venture Capital	16	327.185	0	0		
SOSV	Venture Capital	14	36.271	0	1	1	1
Innovate UK	Accelerator/Incubator	14	4.061	1	1	1	1
United States Department of Agriculture	Government	14	4.124	1	1		
National Science Foundation	Government	12	3.704	0	1		
Invest Nova Scotia	Venture Capital	12	1.555	0	1	1	1
European Innovation Council Fund	Venture Capital	11	21.188	0	1		
Antler	Venture Capital	11	15.267	1	1	1	1
Finnish Fund for Industrial Cooperation	Limited Partner	10	155.328	1	1	1	1
ImpactAssets	Impact Investing	10	71.090	1	0	1	1
Horizon 2020 SME Instrument	Government	9	5.619	1	1		
Pale blue dot	Venture Capital	8	27.374	1	0	1	1
Sustainable Ocean Alliance	Accelerator/Incubator	8	9.618	0	1		
Ocean Impact Organisation	Accelerator/Incubator	8	0.212	1	1		
Creative Destruction Lab	Accelerator/Incubator	8	-	1	1		
Boost VC	Venture Capital	7	228.320	0	1	1	1
Bpifrance	Sovereign Wealth Fund	7	37.991	1	1	1	1
Y Combinator	Accelerator/Incubator	7	11.995	0	1	1	1
Lowercarbon Capital	Venture Capital	7	135.848	1	0	1	1
MassChallenge	Accelerator/Incubator	7	0.218	1	1		
Techstars	Accelerator/Incubator	7	3.700	1	1	1	1
Aqua-Spark	Venture Capital	7	33.719	1	0	1	1
Plug and Play Tech Center	Accelerator/Incubator	7	7.079	0	1	1	1
Gaingels	Venture Capital	6	259.700	1	0	1	1
National Institute of Allergy and Infectious Diseases	Government	6	10.045	1	1		

Table 5. Biodiversity Start-Ups and the Likelihood of Impact and Public Financing.

This table presents logistic regression results examining whether biodiversity start-ups are more likely to receive financing from impact or public investors. The dependent variable in Columns (1)–(3) is an indicator for whether a deal includes at least one impact investor, while the dependent variable in Columns (4)–(6) indicates whether a deal involves at least one public investor. The sample consists of deals financing biodiversity start-ups and matched non-biodiversity generic start-ups. All deal-level characteristics are defined in Panel B. of Table 2. All specifications include industry and year fixed effects. Standard errors are clustered at the industry level. *, **, and *** denote significance levels of 0.10, 0.05, and 0.01, respectively.

	At least one impact investor			At least one public investor		
	(1)	(2)	(3)	(4)	(5)	(6)
Biodiversity	0.790***	0.815**	0.811**	0.236***	0.302**	0.301**
	(0.249)	(0.342)	(0.340)	(0.090)	(0.133)	(0.133)
Ln(Employment)		0.018	0.031		-0.138*	-0.134
		(0.022)	(0.024)		(0.082)	(0.088)
Age		-0.022	-0.019		0.011	0.011
		(0.018)	(0.017)		(0.011)	(0.011)
Early		-0.245	-0.256		1.750***	1.746***
		(0.256)	(0.259)		(0.119)	(0.125)
Direct		-0.037	-0.023		-0.146	-0.143
		(0.186)	(0.181)		(0.196)	(0.197)
Positive Profit			-0.739*			-0.169
			(0.385)			(0.307)
Obs.	2483	2483	2483	2483	2483	2483
Pseudo R-squared	0.085	0.087	0.088	0.031	0.123	0.123
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 6. Determinants of Start-Up Deal Size: Biodiversity, Impact, and Public Investors. This table presents regression results examining the factors influencing start-up deal size, with a focus on whether biodiversity start-ups secure smaller deals compared to matched non-biodiversity start-ups and the impact of investor type on deal size. The dependent variable is the log of deal size (in million USD) for biodiversity and matched non-biodiversity start-ups. All other deal characteristics are defined in Panel B. of Table 2. Columns (1), (2), (5), and (6) analyze all deals, while Columns (3) and (4) focus on deals that include partial financing from impact investors and public capital, respectively. All specifications include year and industry fixed effects. Standard errors are clustered at the industry level. *, **, and *** denote significance levels of 0.10, 0.05, and 0.01, respectively.

	All Deals	All Deals	Impact Deals	Blended Deals	All Deals	All Deals
	(1)	(2)	(3)	(4)	(5)	(6)
Biodiversity	-0.548***	-0.580***	-0.377*	-0.556***	-0.586***	-0.608**
	(0.092)	(0.120)	(0.164)	(0.143)	(0.122)	(0.166)
Impact					0.313**	0.112
					(0.090)	(0.078)
Blended					-0.378**	-0.352
					(0.112)	(0.192)
Biodiversity × Impact						0.307*
						(0.156)
Biodiversity × Blended						-0.040
						(0.196)
Ln(Employment)		0.377***	0.515***	0.472***	0.366***	0.365***
		(0.053)	(0.049)	(0.103)	(0.048)	(0.048)
Age		-0.004	0.003	-0.010*	-0.003	-0.003
		(0.003)	(0.021)	(0.005)	(0.004)	(0.004)
Early		-1.218***	-0.920*	-1.121***	-1.071***	-1.069***
		(0.120)	(0.420)	(0.226)	(0.118)	(0.119)
Direct		0.092	-0.029	0.056	0.080	0.071
		(0.125)	(0.077)	(0.201)	(0.123)	(0.123)
Positive Profit		-0.148	-0.692***	0.384	-0.129	-0.113
		(0.099)	(0.100)	(0.235)	(0.083)	(0.085)
Obs.	2483	2483	396	1094	2483	2483
R-squared	0.054	0.183	0.223	0.149	0.192	0.193
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 7. Twitter Engagement and Biodiversity Start-Up Fundraising: Extensive Margin.

This table examines the relationship between Twitter engagement and the start-up's fundraising outcomes. The key independent variable indicates whether a biodiversity start-up has an active Twitter account. The dependent variables include the log of total deal size (Columns 1–6) and total number of deals (Columns 7–12). Columns 1-4 (7-10) exclusively study biodiversity start-ups; Column 5 (11) study matched generic start-ups as a benchmark; Column 6 (12) include both groups of start-ups to study the incremental value of Twitter engagement to biodiversity start-ups. The Poisson model is used for the total number of deals, following Cohn, Liu, and Wardlaw (2022). Results are stratified by deal type: all deals, impact deals, and blended deals, with impact and blended deal metrics set to zero for start-ups lacking impact or public financing. Coefficients and standard errors of the *Direct* variable for matched generic start-ups in Columns 5 and 11 are suppressed because the variable is uniformly zero, as the direct/indirect taxonomy applies only to biodiversity start-ups. Standard errors are clustered at the industry level. *, **, and *** denote significance levels of 0.10, 0.05, and 0.01, respectively.

	Total Deal Size						Total Deal Number					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Biodiversity-linked Startups Only						Biodiversity-linked Startups Only					
	Full Sample	Full Sample	Impact Deals Only	Blended Deals Only	Matched Sample Only	All Deals	Full Sample	Full Sample	Impact Deals Only	Blended Deals Only	Matched Sample Only	All Deals
Twitter	0.358**	0.487**	0.199*	0.155	0.454**	0.405**	0.479***	0.440***	0.629***	0.518***	0.270***	0.292***
	(0.140)	(0.178)	(0.103)	(0.115)	(0.205)	(0.185)	(0.060)	(0.070)	(0.180)	(0.089)	(0.074)	(0.073)
Ln (Employment)		0.534***	0.197***	0.278***	0.540***	0.510***		0.004	0.166	-0.089	-0.015	-0.011
		(0.116)	(0.045)	(0.076)	(0.091)	(0.059)		(0.044)	(0.137)	(0.099)	(0.071)	(0.043)
Age		-0.011*	-0.005**	-0.004	-0.010	-0.009***		-0.005	-0.027**	0.002	0.001	-0.001
		(0.006)	(0.002)	(0.003)	(0.007)	(0.003)		(0.004)	(0.011)	(0.006)	(0.002)	(0.002)
Direct		0.073	-0.041	0.133		0.081		-0.071	0.119	-0.121		-0.059
		(0.095)	(0.070)	(0.101)		(0.106)		(0.064)	(0.149)	(0.171)		(0.068)
Early		-0.581***	0.042	-0.196	-0.787***	-0.690***		0.044	-0.105	0.873***	-0.142**	-0.033
		(0.204)	(0.115)	(0.127)	(0.164)	(0.153)		(0.140)	(0.178)	(0.210)	(0.058)	(0.084)
Positive Profit		0.483*	-0.245	-0.119	-0.300	0.153		0.074	-3.756	-0.317	-0.396	-0.145
		(0.255)	(0.159)	(0.168)	(0.573)	(0.271)		(0.148)	(2.854)	(0.443)	(0.325)	(0.197)
Biodiversity						-0.190*						0.090
						(0.106)						(0.107)
Biodiversity×Twitter						0.197						0.186**
						(0.251)						(0.088)
Obs.	605	605	605	605	605	1210	605	605	605	605	605	1210
R-squared	0.011	0.226	0.117	0.131	0.236	0.204	0.030	0.059	0.134	0.129	0.053	0.049
Country FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 8. Twitter Engagement and Biodiversity Start-Up Fundraising: Intensive Margin.

This table examines the relationship between Twitter engagement and the start-up's fundraising outcomes. The key independent variable indicates the log number of tweets posted on a biodiversity start-up's Twitter account. The dependent variables include the log of total deal size (Columns 1–6) and total number of deals (Columns 7–12). Columns 1-4 (7-10) exclusively study biodiversity start-ups; Column 5 (11) study matched generic start-ups as a benchmark; Column 6 (12) include both groups of start-ups to study the incremental value of Twitter engagement to biodiversity start-ups. The Poisson model is used for the total number of deals, following Cohn, Liu, and Wardlaw (2022). Results are stratified by deal type: all deals, impact deals, and blended deals, with impact and blended deal metrics set to zero for start-ups lacking impact or public financing. Coefficients and standard errors of the *Direct* variable for matched generic start-ups in Columns 5 and 11 are suppressed because the variable is uniformly zero, as the direct/indirect taxonomy applies only to biodiversity start-ups. Standard errors are clustered at the industry level. *, **, and *** denote significance levels of 0.10, 0.05, and 0.01, respectively.

	Total Deal Size						Total Deal Number					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Biodiversity-linked Startups Only						Biodiversity-linked Startups Only					
	Full Sample	Full Sample	Impact Deals Only	Blended Deals Only	Matched Sample Only	All Deals	Full Sample	Full Sample	Impact Deals Only	Blended Deals Only	Matched Sample Only	All Deals
Ln(#tweets)	0.148***	0.230***	0.084*	0.156***	0.092*	0.083**	0.102***	0.157***	0.136***	0.182***	-0.001	0.041*
	(0.045)	(0.055)	(0.041)	(0.038)	(0.053)	(0.040)	(0.027)	(0.026)	(0.032)	(0.046)	(0.026)	(0.023)
Ln (Employment)		0.520***	0.345**	0.346***	0.611***	0.597***		-0.098**	0.093	-0.223**	0.095	0.009
		(0.183)	(0.136)	(0.121)	(0.145)	(0.104)		(0.047)	(0.102)	(0.098)	(0.079)	(0.063)
Age		-0.036*	-0.018	-0.020	-0.005	-0.014		-0.012	-0.045*	0.000	-0.001	-0.004
		(0.019)	(0.011)	(0.013)	(0.007)	(0.010)		(0.009)	(0.025)	(0.011)	(0.002)	(0.003)
Direct		-0.227	-0.192	0.035		-0.252		-0.166	0.013	-0.233		-0.173
		(0.225)	(0.159)	(0.186)		(0.248)		(0.131)	(0.195)	(0.235)		(0.132)
Early		-0.361	0.277*	-0.161	-0.290	-0.319		0.200	0.188	1.347***	-0.019	0.144
		(0.220)	(0.146)	(0.172)	(0.364)	(0.240)		(0.133)	(0.343)	(0.216)	(0.111)	(0.088)
Positive Profit		-1.418***	-0.646*	-0.503	0.724	-0.080		-1.547***	-8.410	-1.472***	-0.189	-0.814**
		(0.369)	(0.335)	(0.368)	(1.359)	(0.633)		(0.421)	(7.517)	(0.508)	(0.390)	(0.344)
Biodiversity						-0.239						-0.134
						(0.377)						(0.163)
Biodiversity×Ln(#tweets)						0.088						0.093***
						(0.065)						(0.025)
Obs.	229	229	229	229	235	464	229	229	229	229	235	464
R-squared	0.029	0.285	0.164	0.192	0.252	0.231	0.021	0.108	0.077	0.159	0.065	0.066
Country FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 9. The Relationship Between Twitter Activity and Biodiversity Start-Up Deal Size.

This table presents regression results analyzing the effect of Twitter activity on the size of financing deals at the deal-year level. The key independent variable, Ln(#Tweets), represents the natural logarithm of the number of tweets posted by a biodiversity start-up in year *t-1*, while the dependent variable is the natural logarithm of deal size in year *t*. *Covid* is an indicator variable equal to one for the pandemic lockdown periods, i.e., the year 2020 and 2021. Model (1) and (2) report the results for all financing deals by biodiversity and matched generic start-ups, respectively; Model (3) pools all financing deals and study the incremental value of Twitter activities to biodiversity start-ups; Models (4) and (5) study the biodiversity start-up's impact deals and blended deals, respectively. An impact deal is a deal financed by at least one impact investor; a blended deal is a deal financed by at least one public investor. Coefficients and standard errors for the *Positive Profit* indicator for impact deals in Column 4 are suppressed as no impact deal in the sample reports positive profit yet. All specifications include company fixed effects. Standard errors are clustered at the company level. *, **, and *** denote significance levels of 0.10, 0.05, and 0.01, respectively.

	(1) Biodiversity-linked Deals Only	(2) Generic Start-up Deals Only	(3) All Deals	(4) Biodiversity-linked Impact Deals	(5) Biodiversity-linked Blended Deals
Ln(#tweets)	0.110*	0.043	0.003	0.112	0.128
	(0.057)	(0.086)	(0.078)	(0.084)	(0.113)
Ln(#tweets) ×Biodiversity			0.155*		
			(0.092)		
Ln(Employment)	0.275	-0.069	0.100	0.714***	0.129
	(0.176)	(0.161)	(0.117)	(0.252)	(0.266)
Age	0.130**	0.055	0.101***	-0.088	0.120*
	(0.050)	(0.049)	(0.035)	(0.133)	(0.070)
Positive Profit	-0.257	-0.782*	-0.624		-0.639
	(0.672)	(0.449)	(0.435)		(1.023)
Early	-0.692**	-0.838***	-0.714***	-1.415**	-0.862
	(0.295)	(0.287)	(0.204)	(0.595)	(0.574)
Covid	-0.143	-0.389	-0.250*	-0.496*	-0.067
	(0.152)	(0.276)	(0.142)	(0.283)	(0.260)
Obs.	640	542	1182	153	342
R-squared	0.462	0.488	0.483	0.715	0.370
Company FE	Yes	Yes	Yes	Yes	Yes

Table 10. The Effect of Twitter's Character Limit Increase on Biodiversity Start-Up Financing.

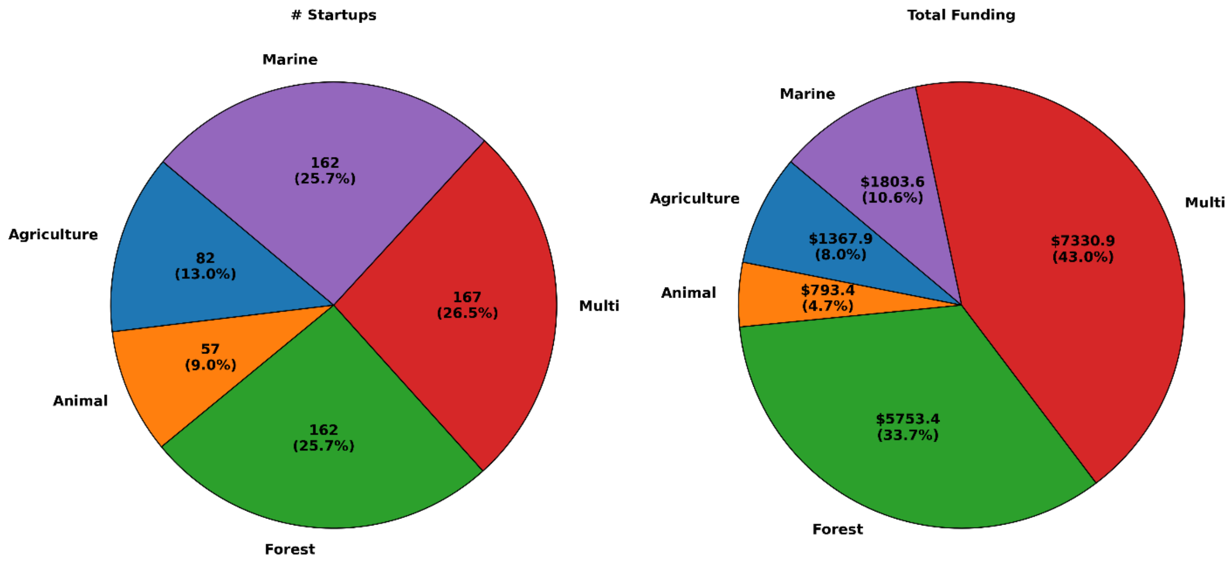
This table examines the impact of Twitter's character limit expansion from 140 to 280 characters on November 7, 2017, on the financing outcomes of biodiversity start-ups. The increased character limit is expected to enhance communication between start-ups and investors, strengthening the positive effects of Twitter usage on financing outcomes. The sample includes all financing deals involving biodiversity start-ups. The dependent variable is the natural logarithm of deal size. *Twitter* is a binary variable indicating whether a biodiversity start-up has a Twitter account, and *Post* is a binary variable equal to 1 for deals occurring after 2017. Columns (1) and (2) analyse all deals, Columns (3) and (4) focus on impact deals (financed by at least one impact investor), and Columns (5) and (6) examine blended deals (financed by at least one public investor). Standard errors are clustered at the company level. *, **, and *** denote significance levels of 0.10, 0.05, and 0.01, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	All deals		Impact Deals		Blended Deals	
Twitter × Post	0.922**	0.847**	-0.537	-0.647	1.032*	0.905
	(0.383)	(0.373)	(0.452)	(0.644)	(0.607)	(0.623)
Obs.	1311	1311	267	267	617	617
R-squared	0.533	0.543	0.704	0.756	0.484	0.492
Controls	No	Yes	No	Yes	No	Yes
Company FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

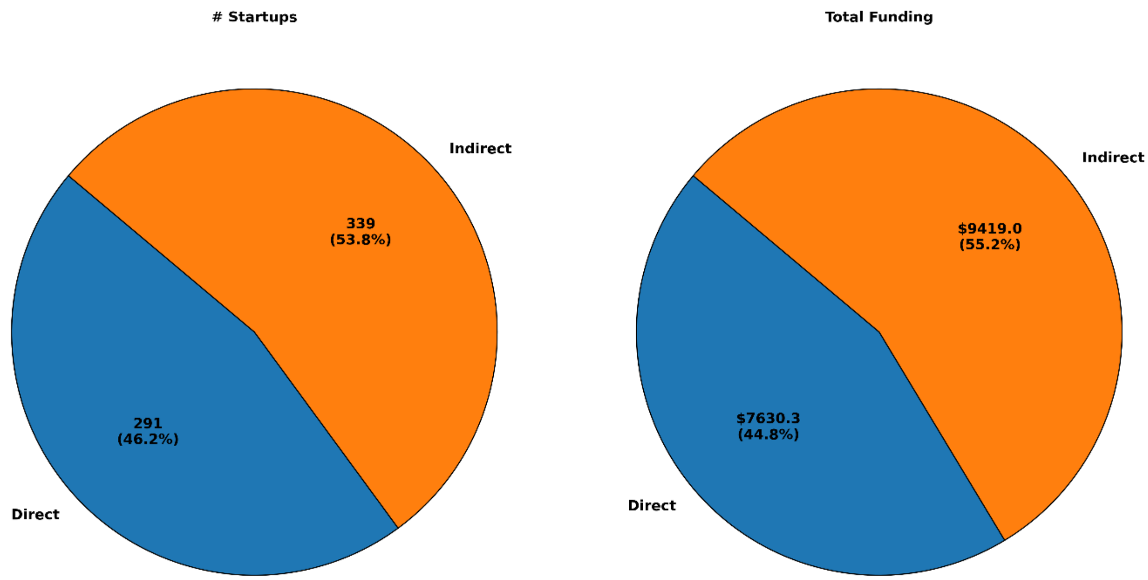
Table 11. Parallel Trends Test: Financing Outcomes Before and After Twitter's Character Limit Expansion.

This table assesses the parallel trends assumption underlying the difference-in-differences analysis of Twitter's character limit expansion from 140 to 280 characters on November 7, 2017. The sample includes all financing deals involving biodiversity start-ups. The dependent variable is the natural logarithm of deal size. Twitter is a binary variable equal to 1 if the biodiversity start-up has a Twitter account. Each row reports the interaction between Twitter and a financing year indicator, with 2017 omitted as the reference year. To enhance statistical power and account for major disruptions to firm activity during the COVID-19 lockdown period, we group the post-shock years into three bins: 2018–2019 (immediately after the character limit expansion), 2020–2021 (COVID-affected years), and 2022–2023 (post-pandemic period). Coefficients for 2018 and later years are positive and statistically significant, consistent with a post-treatment effect. Coefficients for pre-2017 years are small and statistically insignificant, supporting the parallel trends assumption. Columns (1) and (2) report results without and with control variables, respectively. All regressions include company and year fixed effects. Standard errors are clustered at the company level. *, **, and *** denote significance levels of 0.10, 0.05, and 0.01, respectively.

	(1) All Deals	(2) All Deals
Twitter × I(Year ≤ 2014)	0.208	0.042
	(0.659)	(0.697)
Twitter × I(Year = 2015)	-0.493	-0.681
	(0.829)	(0.849)
Twitter × I(Year = 2016)	1.084	1.005
	(0.693)	(0.678)
Twitter × I(Years 2018–2019)	1.294**	1.107*
	(0.574)	(0.579)
Twitter × I(Years 2020–2021)	0.866*	0.791
	(0.521)	(0.511)
Twitter × I(Years 2022–2023)	1.288**	1.008*
	(0.558)	(0.555)
Obs.	1311	1311
R-squared	0.537	0.546
Controls	No	Yes
Company FE	Yes	Yes
Year FE	Yes	Yes



Panel A.



Panel B.

Figure 1. Distribution of Biodiversity Start-Ups by Types.

Panel A presents the distribution of biodiversity-related start-ups and their total fundraising across different sectors. Panel B presents the distribution of biodiversity-related start-ups, and their total fundraising based on whether they directly preserve biodiversity or not. The total funding is in millions of US dollars.

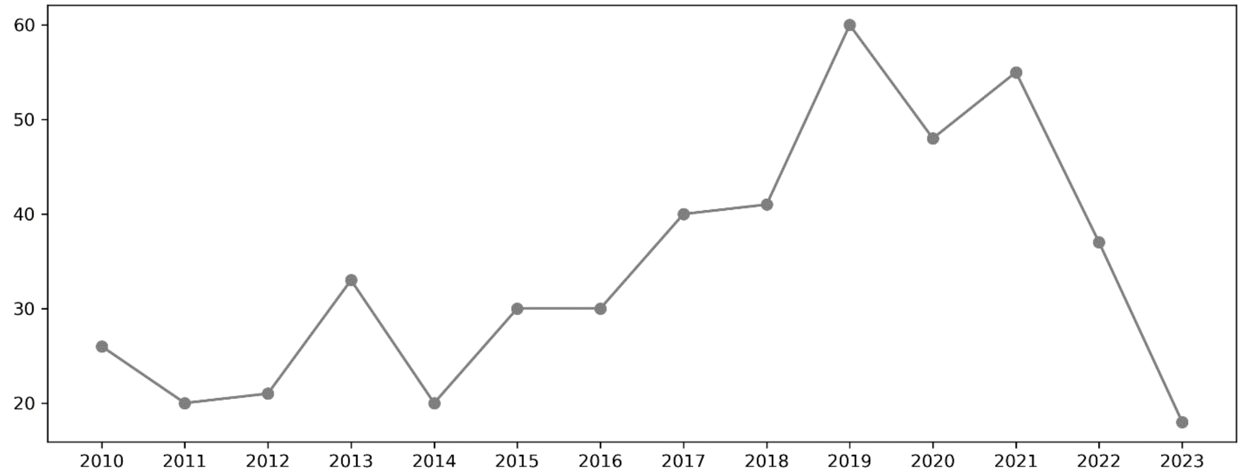
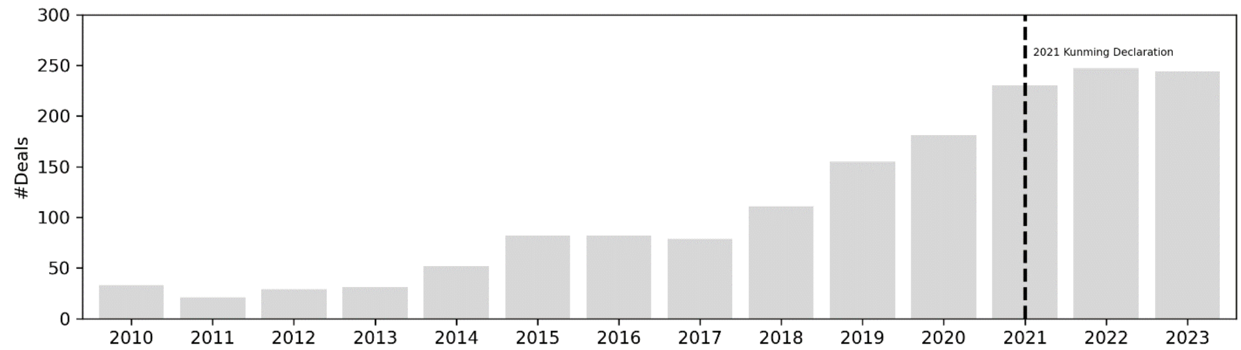
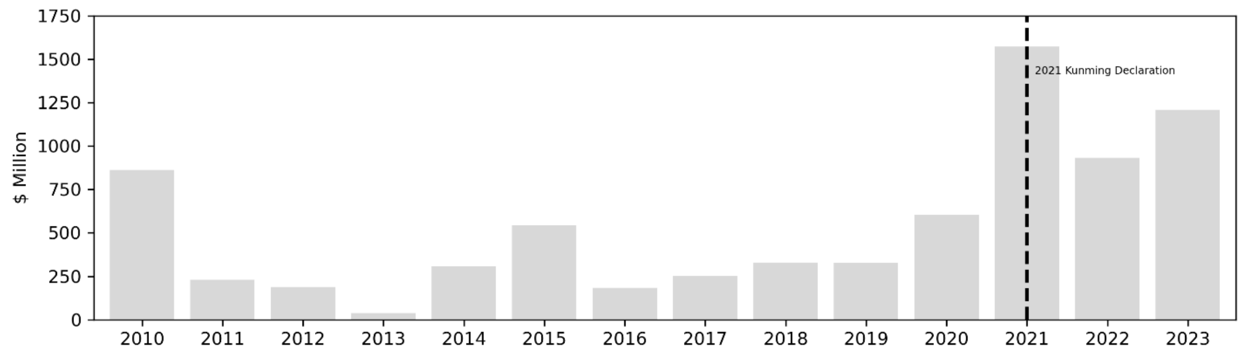


Figure 2. Annual Number of Biodiversity Start-Ups Founded.

This figure presents the number of biodiversity-related start-ups founded each year. Note that since the data comes from the August 2024 PitchBook VC dataset, the number of start-ups founded in 2023 may be underreported due to time lags in data collection and reporting.



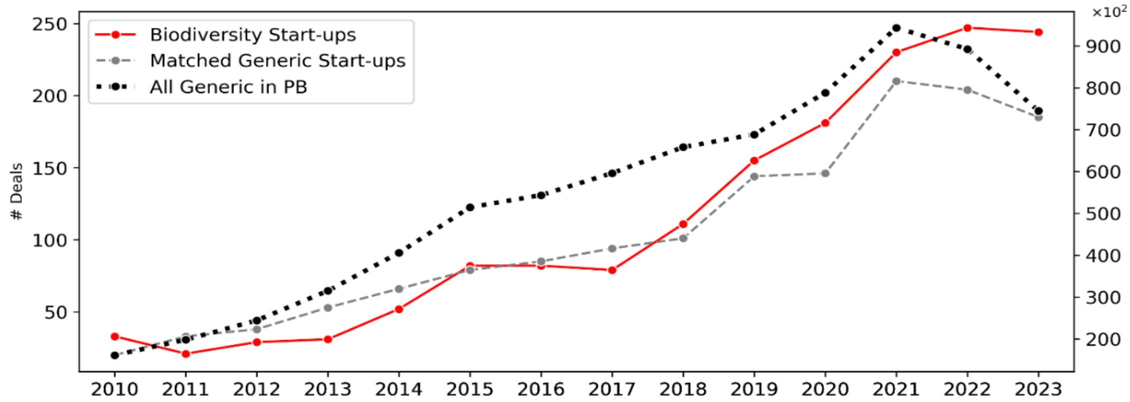
Panel A.



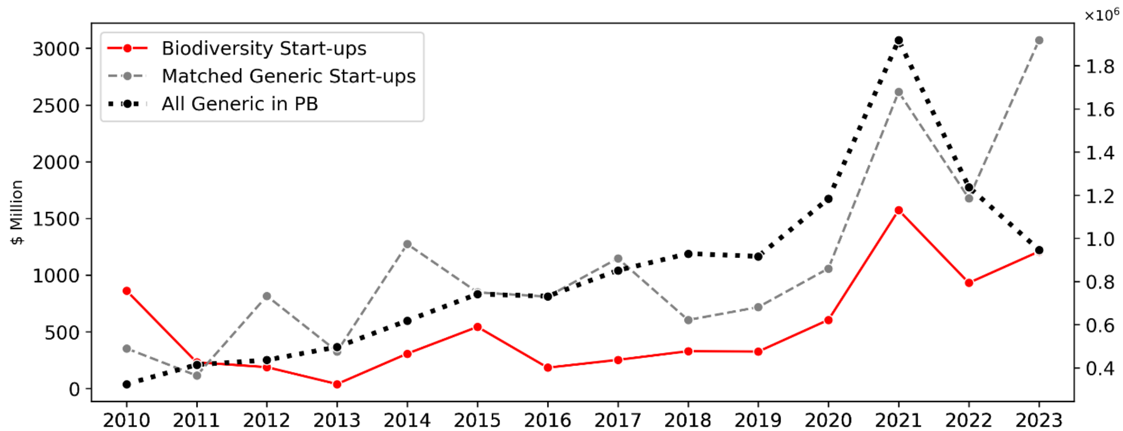
Panel B.

Figure 3. Annual Trends in Biodiversity Start-Up Financing

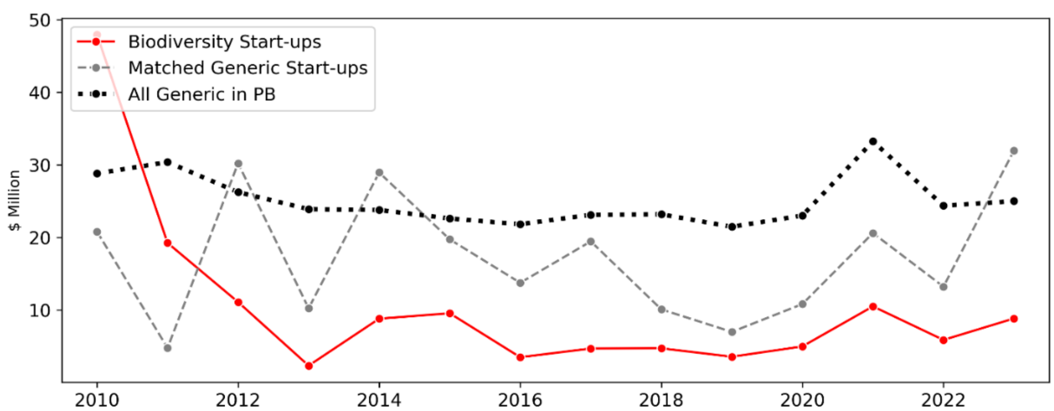
This figure illustrates the yearly trends in biodiversity start-up financing. Panel A shows the number of financing deals per year, while Panel B reports the total value of financing deals raised annually. The dashed line marks the Kunming Declaration in 2021.



Panel A.



Panel B.



Panel C.

Figure 4. Financing Trends of Biodiversity Start-Ups Compared to Generic and All Start-Ups

This figure compares the financing activity of 605 biodiversity startups, 605 matched generic startups, and all 294,738 startups in the PitchBook VC data universe. Panel A presents the annual number of financing deals, Panel B reports the total fundraising amount (in millions of USD), and Panel C shows the average deal size (in millions of USD). The red solid line represents biodiversity startups, the gray dashed line represents matched generic startups, and the black dotted line represents all startups in PitchBook. In Panels A and B, values for the red and gray lines correspond to the vertical axis on the left-hand side, while the black dotted line is scaled to the vertical axis on the right-hand side. For example, $900 \times 10^2 = 90{,}000$, and $1.8 \times 10^6 = 1{,}800{,}000$. In Panel C, a single vertical axis is sufficient.

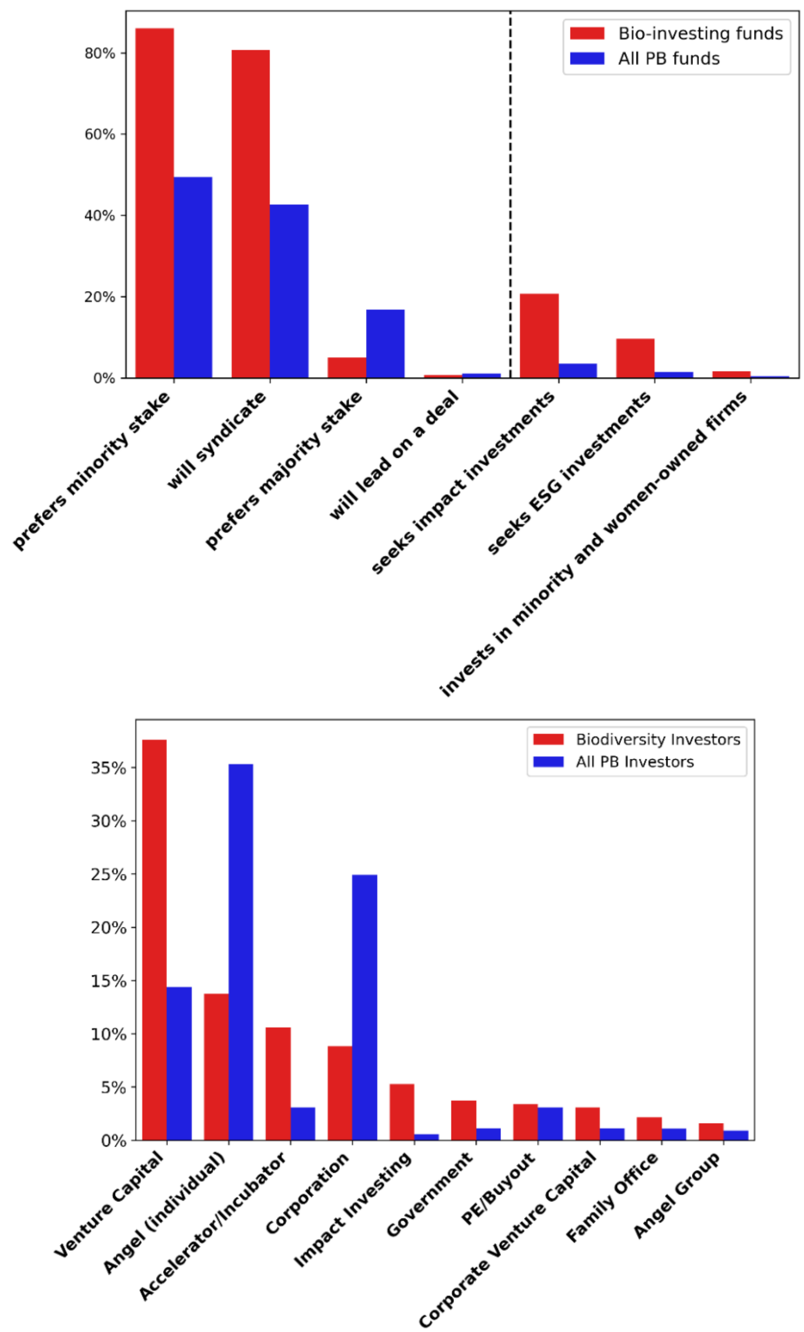
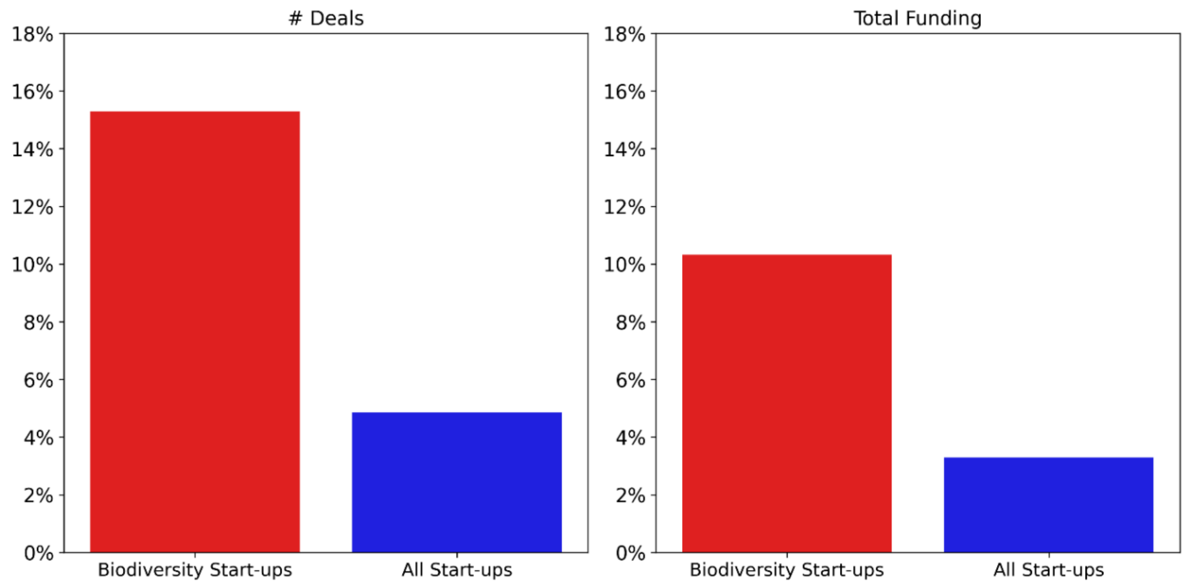
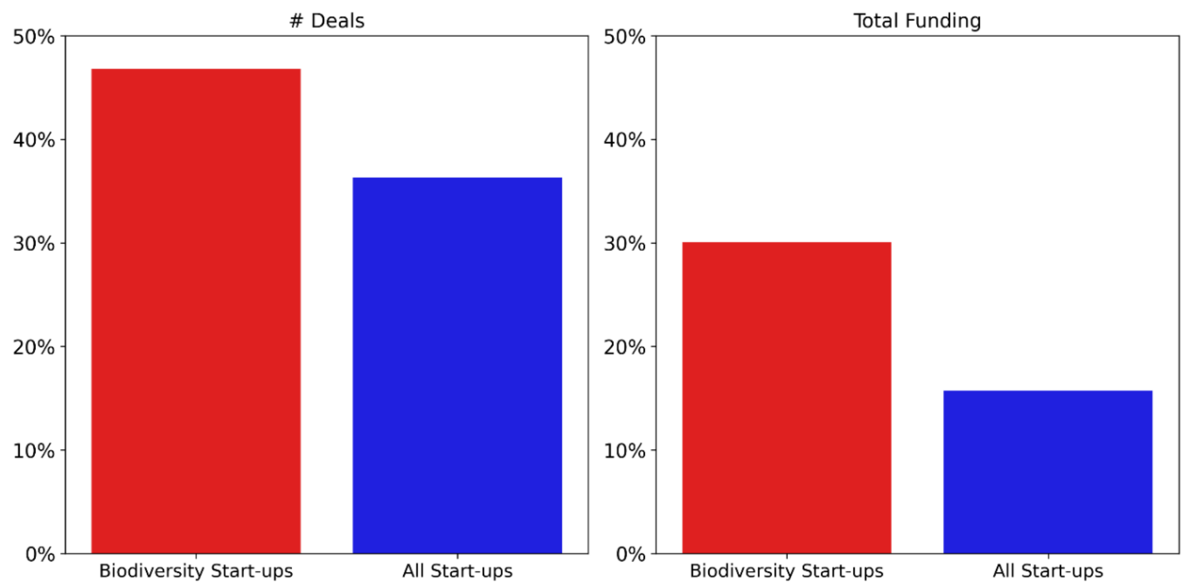


Figure 5. Fund and Investor Characteristics in Biodiversity Start-Up Financing

This figure compares the characteristics of funds and investors involved in biodiversity start-up financing to those in the broader PitchBook universe. Panel A displays the percentage of funds with specific investment preferences among 416 funds investing in biodiversity start-ups versus all 98,028 funds in PitchBook. Panel B presents the distribution of investor types among 2,246 investors backing biodiversity start-ups compared to the 234,846 investors in the PitchBook universe.



Panel A.



Panel B.

Figure 6. Impact and Public Investor Participation in Biodiversity Start-Up Financing

This figure compares the involvement of impact and public investors in biodiversity start-up financing relative to the broader PitchBook universe. Panel A examines impact investors, with the left figure showing the percentage of deals involving at least one impact investor and the right figure presenting the share of total fundraising from such deals. Panel B focuses on public investors (capital), with the left figure displaying the percentage of deals that include at least one public investor and the right figure showing the share of total fundraising from these deals. Comparisons are made between 1,956 deals financing biodiversity start-ups and 1,006,272 deals in the PitchBook universe. We classify an investor as an "impact investor" if they are explicitly designated as such by PitchBook or if they manage at least one fund explicitly targeting impact investing, ESG (Environmental, Social, and Governance) criteria, or MWBE (Minority and Women-Owned Business Enterprises). Our definition of "public capital (investors)" in blended finance deals adopts the framework of Flammer, Giroux, and Heal (2025a), encompassing both public-sector institutions (e.g., government agencies, economic development agencies, sovereign wealth funds, public-funded accelerators/incubators, and public pension funds) and non-profit sources (e.g., not-for-profit venture capital, foundations, universities, and endowments).

Appendix

A.1 Our Pre-registered Hypotheses and Final Empirical Approach.

In our pre-registered proposal submitted in August 2024 to the *Review of Finance* for this Call for Research Proposals: Special Issue on Biodiversity and Natural Resource Finance, we proposed our empirical tests based on the following three hypotheses.

The first of our three proposed hypotheses was that biodiversity start-ups are underfinanced compared to climate start-ups and other non-climate, non-biodiversity-linked ventures. As noted in the introduction, this was the core motivation for our study, acknowledging the financing gap highlighted in the 2020 *Nature Conservancy* report and the additional hurdles in attracting investment for conservation and biodiversity-loss mitigation projects.

Our second hypothesis proposed that active engagement on social media can help biodiversity start-ups raise capital on better terms. To examine this, we developed two supplementary hypotheses. The first, focused on *extrinsic value*, asked whether Twitter engagement enhances investor attraction to biodiversity ventures compared with traditional new businesses—specifically, whether using Twitter improves the likelihood, level, or frequency of successful fundraising. The second, focused on *intrinsic value*, compared the impact of Twitter engagement between biodiversity and climate-related start-ups (such as those in carbon capture or green energy). We remained agnostic about the results, as both biodiversity and climate start-ups pursue social impact objectives and represent nontraditional ventures.

Our third hypothesis considered whether different investor types matter differently for biodiversity-linked venture financing. This prompted two supplementary hypotheses addressing potential channels of investor engagement. Channel #1 focused on whether in-person networking (particularly when facing social constraints such as those imposed by the COVID-19 pandemic) is a better tool than social media to remedy funding disparities. Channel #2 focused on information asymmetry, regarding whether and how social media affects biodiversity venture financing.

After the August 2024 proposal, we refined our pre-registered hypotheses based on the feedback and suggestions from the managing editor, program co-chairs, scientific committee members, our discussant, and the audience at the October 2024 Research Workshop: Biodiversity Finance & Natural Resource Finance. Our original analysis and tests primarily focus on biodiversity start-ups and their funding activities, leveraging social media. Following the input from the October 2024 workshop, we expanded our focus to include the VC investors themselves, their composition, and the motivations behind their investment in biodiversity-linked ventures. And we broadened our analysis to the new title of the study, biodiversity entrepreneurship, which includes not only the ventures but also the VC investors. We also now use comparable non-biodiversity generic start-ups as the control group. Finally, we have redesigned our social media analysis. The empirical details and results are reported in the following two sections, and they constitute four parts: (1) a taxonomy and descriptives of biodiversity start-ups (including their financing deals); (2) a taxonomy and descriptives of biodiversity-linked venture investors; (3) the matching patterns between biodiversity start-ups and their investors; and (4) biodiversity start-up social media activities and the financing outcomes.

It is important to first document the taxonomy and descriptive analysis of the biodiversity start-ups, their financing deals, and their investors. The matching pattern between biodiversity start-ups and investors is also noteworthy. Among the investors and financing methods for biodiversity ventures, we are especially interested in: (i) *values investors* (versus *value investors*), as defined in Starks (2023), or *impact investors*, as in Barber, Morse, and Yasuda (2021), Geczy et al. (2021), Jeffers, Lyu, and Posenau (2024), and Cole et al. (2023), and (ii) *blended financing*, as in Flammer, Giroux, and Heal (2025a, 2025b). We retain our focus on the role of social media in reducing information symmetry as in Wang, Wu, and Hitt (2024) and wonder if it can help to bridge the gap between biodiversity start-ups and those "minds-unalike" *value investors* to improve the fundraising outcomes from them. Lastly, to mitigate concerns about the overlapping effects of two shocks, we only use the 2017 Twitter character limit increase in our identification experiment. [1]

[1] To facilitate identification, we initially proposed two quasi-natural experiments. The first was Twitter's character limit increase from 140 to 280 in 2017. The second was Elon Musk's 2022 acquisition and privatization of Twitter. We conjectured that the first would improve Twitter's usefulness, while the second would hinder it. Based on feedback, we removed the second shock (2022) to avoid overlapping effects with the 2017 change and COVID-19 years since 2020.

A.2. Fine-tuning the LLM to identify biodiversity start-ups from PitchBook.

Our training sample of biodiversity start-ups comes from Crunchbase. We begin by applying textual analysis to start-up business descriptions in Crunchbase, using biodiversity keywords from Giglio et al. (2023). Following this initial identification, each candidate start-up undergoes manual verification through a review of its corporate website and gains consensus among multiple research assistants. This process yields 173 confirmed biodiversity start-ups.

We supplement the positive sample of biodiversity start-ups with two groups of non-biodiversity-related start-ups (negative labels). First, we extract sustainability-focused start-ups from Crunchbase's sustainability category, excluding those explicitly tied to biodiversity. Due to the imbalance between sustainability and biodiversity start-up counts, we employ propensity score matching to select 173 sustainability start-ups that mirror the biodiversity sample in textual description length and industry focus (e.g., Natural Resources, Biotechnology, Data & Analytics). This group highlights distinctions between general sustainability efforts (e.g., carbon capture) and biodiversity-specific activities (e.g., habitat restoration). Second, we randomly sample 173 generic start-ups from Crunchbase, unrelated to either sustainability or biodiversity. Combining these groups with the positive sample produces a balanced and hybrid training dataset of 519 start-ups.

To identify biodiversity start-ups from PitchBook, we employed the LLaMA 3.1 model fine-tuned using the Low-Rank Adaptation (LoRA) technique with a rank parameter of 16. The manually annotated dataset of biodiversity start-up descriptions from Crunchbase served as the training corpus, with 9-fold Stratified K-Fold cross-validation ensuring robustness and preventing overfitting. Each fold trained the model on a subset of the dataset, while another subset was used for validation.

The fine-tuning process utilized 4-bit quantization for efficient memory usage and faster training times. The maximum sequence length was set to 15,360 tokens, and training employed a batch size of 2 per device with gradient accumulation steps set to 4, effectively simulating a larger batch size. The learning rate was initialized at $2e^{-4}$ using the AdamW optimizer with 8-bit precision, weight decay of 0.01, and a linear learning rate scheduler. Each fold was trained for one epoch, leveraging mixed precision (FP16 or BF16 depending on hardware support).

A key feature of our implementation was the use of the Alpaca-style prompt template, which formatted training data as instruction-response pairs, enhancing the model's alignment to the classification task. The training pipeline also incorporated gradient checkpointing to manage long sequences without exhausting GPU memory.

The fine-tuning achieved a final validation accuracy exceeding 96% across the folds, with a test accuracy of approximately 96.15%. After achieving this threshold, the fine-tuned model was applied to unlabelled start-up data from PitchBook, classifying companies based on their business descriptions.

This systematic approach provided a robust framework for identifying biodiversity start-ups, combining manual annotations, state-of-the-art language models, and efficient fine-tuning techniques.

A.3. Example Financing Deals of Biodiversity Start-ups from PitchBook

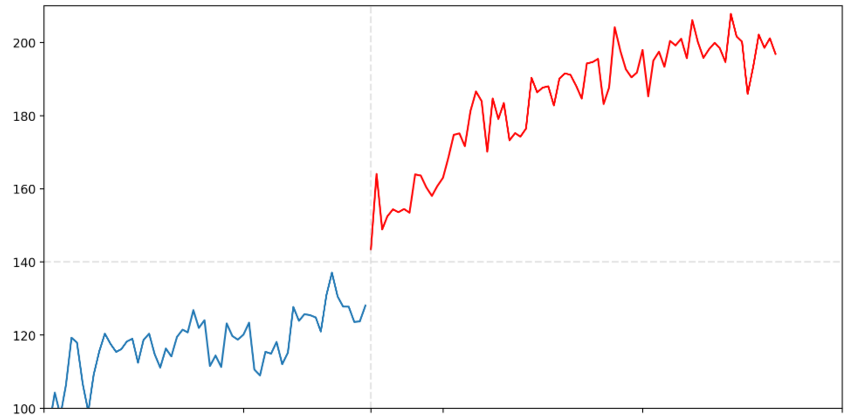
Dendra Systems: *"Operator of an environmental technology company intended to address the restoration of natural ecosystems globally. The company's technology addresses the challenge of degraded land across the globe created from years of imbalance between the rate of ecosystem destruction and ecosystem restoration, enabling enterprises to gain access to an integrated approach to data analytics and automation services to meet ecosystem restoration and reporting requirements."* Specific financing details include:

- The company received £5,000 (approximately $0.007 million) of grant funding from Innovate UK on May 1, 2015
- The company raised £1.95 million (approximately $2.75 million) of seed funding from Parrot Drones, SystemiQ and Kezar Ventures LLC on April 17, 2018, putting the company's pre-money valuation at £8.06 million (approximately $11.37 million). VentureSouq, and other undisclosed investors also participated in the round.
- The company raised $15.7 million of Series B venture funding in a deal led by Zouk Capital on May 8, 2024, putting the company's pre-money valuation at $80 million. Aramco Ventures, Airbus Ventures, Helium-3 Ventures, Greenlight Ventures NZ, One Small Planet Foundation, and Understorey Ventures also participated in the round. The funds will be used for expansion into new geographical markets and the continuous enhancement of its pioneering AI-enabled ecology platform.

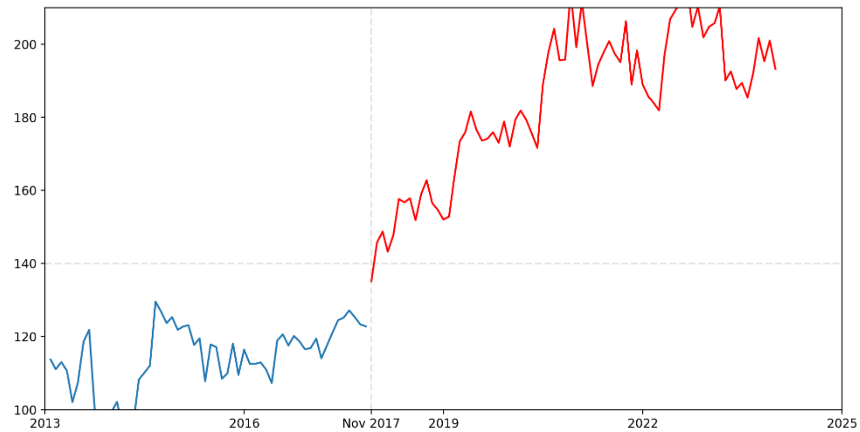
Nossa!: *"Producer of healthy and authentic Brazilian açai products intended to promote the preservation of the Amazon rainforest. The company offers natural and certified organic acai pulp, sorbet, smoothies, and drinks, enabling restaurants to provide their customers with a unique and nutritious taste experience."* Specific financing details include:

- The company raised €167,500 (approximately $0.19 million) of angel funding from undisclosed investors on May 19, 2015, putting the company's pre-money valuation at EUR 750,000.
- The company raised €122,925 (approximately $0.14 million) of angel funding from undisclosed investors on May 30, 2016, putting the company's pre-money valuation at EUR 1.18 million.
- The company raised €1.03 million (approximately $1.17 million) of venture funding from IRD Invest and other undisclosed investors on March 20, 2019, putting the company's pre-money valuation at €3.7 million (approximately $4.20 million).

A.4 Maximum Character Limit Increase and Tweet Length



Panel A. Biodiversity Startups



Panel B. Non-biodiversity Startups

Figure A.1 Tweet Lengths of Biodiversity and Non-biodiversity Startups

This figure plots the average tweet length per month for biodiversity startups (Panel A) and a matched sample of non-biodiversity startups (Panel B) from January 2013 to December 2023. Each data point represents the mean length of tweets posted by startups in a given month. The vertical dashed line marks November 2017, when Twitter increased the maximum character limit from 140 to 280. Both panels show a discrete jump in tweet length following this policy change. Two-sample mean comparison tests confirm that tweet length after November 2017 is significantly greater than before, at the 1% level for both biodiversity and non-biodiversity startups.