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Does biodiversity matter for firm value?

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ABSTRACT

This paper investigates the relationship between firms' impact on biodiversity and its firm value and the economic and financial mechanisms underlying this link, filling a gap concerning the financial materiality of biodiversity loss. By analysing a global panel of 1,848 publicly listed companies across 49 countries from 2018 to 2022, this study highlights how the Corporate Biodiversity Footprint (CBF) influences not only firms' market valuations (Tobin's Q, Market-to-Book) but also their operating profitability as measured by Return on Assets (ROA). At the same time, the CBF affects firms' cash generation capacity both decreasing the level and increasing the volatility of operating cash flows. Further heterogeneity analyses reveal that the effect of CBF on firm value is particularly strong for large firms, firms producing tangible goods, firms headquartered in megadiverse countries, and countries with a high level of biodiversity conservation. The erosion of ROA is especially evident in countries already severely affected by biodiversity loss. The results have important implications for investors, banks, corporate managers, and policymakers to improve risk pricing, forward-looking corporate governance, and realign corporate strategies and capital allocation with global biodiversity targets.

1. Introduction

For decades, the decline of biodiversity has quietly progressed in the background. Only recently has it begun to capture the full attention of scholars, professionals, and policymakers. Biodiversity, the vast network of living organisms and the ecosystems they sustain, is not merely a natural asset; it is tightly interwoven with economic life. It supports nearly half of global GDP (World Economic Forum, 2022), and most firms depend on it directly or indirectly through their supply chains (Katic et al., 2023). When biodiversity declines, the natural inputs that feed production systems become scarcer, placing entire sectors under pressure, such as agriculture, forestry, medicine, and tourism. At the same time, the activities of firms often accelerate this decline, triggering losses in productivity, legal controversies, and reputational damage.

Today, biodiversity is vanishing unprecedentedly in human history (Dasgupta, 2021). Its erosion is increasingly framed as a systemic risk (Karolyi & Tobin-de la Puente, 2023), prompting international regulators and organisations to respond. Initiatives like the Kunming-Montreal Global Biodiversity Framework and the Taskforce on Nature-Related Financial Disclosure (TNFD) also released recommendations and guidelines to support businesses and financial institutions in evaluating, reporting, and responding to their nature-related dependencies, impacts, risks, and opportunities. In 2024, biodiversity loss is listed in the World Economic Forum's

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Global Risk Report as one of the top 5 risks in terms of likelihood and impact for the next ten years.[1]

While the academic community has developed a rich body of research on climate risks, the economic consequences of biodiversity loss remain far less understood. Early studies suggest markets are beginning to price these risks (Ma et al., 2024; Garel et al., 2024; Coqueret et al., 2025; Giglio et al., 2023). Exposure to biodiversity-related risks can compromise productivity, inflate compliance costs, heighten cash flow volatility, and damage corporate reputations, undermining the firm's operational and financial stability (Yang & Li, 2025; Li et al., 2025; Cosma et al., 2025). These dynamics raise the cost of capital and can push market valuations downward (Krueger et al., 2020; Bolton & Kacperczyk, 2021).

Following the sustainable preferences equilibrium model (Pástor et al., 2021), firms with negative biodiversity profiles may experience sustained demand-driven discounts in both equity and debt markets, as well as an increased cost of capital (Zerbib, 2019; Baker et al., 2022). These factors can lead to unexpected financial burdens or strategic limitations, ultimately contributing to downward revisions in firm value (Liang & Renneboog, 2017; Krueger et al., 2020). Firms facing these risks often hold higher precautionary cash reserves, which can divert capital from productive investments and reduce overall capital efficiency (Ahmad & Karpuz, 2024). Conversely, firms that invest in safeguarding biodiversity often gain stakeholder trust, which can translate into higher market value (Bassen et al., 2024).

This paper aims to extend the nascent literature on biodiversity finance by testing whether the impact of a company's activities on biodiversity affects its firm value and exploring economic and financial mechanisms underlying this link, filling a gap concerning its financial materiality. Investors, banks, and rating agencies need evidence to correctly price biodiversity-related exposures and avoid "biodiversity stranded assets." Corporate managers and Boards must also assess long-term risks and consider them in capital allocation, disclosure practices, and strategies.

As a measure of biodiversity impact, we use the Corporate Biodiversity Footprint (CBF), a science-based measure constructed by Iceberg Data Lab, which measures the absolute biodiversity loss caused by a company's annual activities. This measure quantifies biodiversity loss by looking at not only the direct impacts of firms but also the impacts of their value chains.

To evaluate the effect of CBF on firm value, we apply a fixed effects panel model on a sample including annual observations from 2018 to 2022 for 1,848 publicly listed companies with available data on both Iceberg Data Lab and LSEG Data & Analytics (Refinitiv).

Our results corroborate and extend previous evidence (e.g. Garel et al., 2024), highlighting the adverse effect of corporate biodiversity footprint on the firms' market-based valuations, measured through Tobin's Q and Market-to-Book ratios, and on their underlying fundamentals. Specifically, we show that CBF reduces firms' operating profitability (ROA) and affects their cash generation capacity both decreasing the level and increasing the volatility of operating cash flows.

Moreover, our study breaks down a firm's CBF by type of environmental channels (GHG, water, air, soil), by direct or indirect impact (Scope 1, 2, 3), and explores heterogeneity effects by industry, country, and firm size. Our results reveal that the relationship between biodiversity loss and firm value is particularly pronounced for large firms, firms producing tangible goods, and firms headquartered in megadiverse countries. At the same time, the erosion of ROA is especially evident in countries already severely affected by biodiversity loss.

These findings clarify how biodiversity becomes a tangible determinant of firm performance and confirm the economic relevance of transition risk, consistent with discounted cash flow theory and the implications derived from the Pástor et al. (2021) model on ESG risks.

The structure of the paper is as follows. Section 2 reviews the relevant literature and formulates the research hypothesis. Section 3 outlines the methodological approach. Section 4 presents the empirical findings, while Section 5 offers concluding remarks and discusses the implications of the results.

2. Literature review

In recent years, academic finance has begun to incorporate biodiversity loss as a new dimension of environmental risk. While climate risk has received massive attention (Krueger et al., 2020; Bolton & Kacperczyk, 2021), biodiversity is emerging as a systemic factor that can alter the assessment of traditional financial risks.

The impact of climate risk (physical or transition) on credit variables such as default risk, cost of debt, and capital allocation efficiency has been well demonstrated by many studies (Feng et al., 2024; Xu et al., 2024; Trinh et al., 2024; Safiullah et al., 2024).

The recent financial literature on biodiversity builds on these empirical results. To understand how biodiversity loss impacts corporate value, we consider previous studies that examine the impact of biodiversity on the main determinants of firm value.

Consistent with the Discounted Cash Flow (DCF) theory (Richardson, 2006; Fama & French, 2006), a reduction of operating cash flow, an increase of its volatility or an increase in the cost of capital/debt may reduce firm value. A first group of studies documents a direct effect of biodiversity risk on idiosyncratic and systemic risk (default, bankruptcy) and on the ability of firms to generate stable cash flows over time. Adamolekun (2024) documents a positive relationship between biodiversity risk and the probability of default, highlighting the importance of considering ecological factors in financial risk assessments. Li et al. (2025) show that firms with higher exposure to biodiversity risk are less efficient in production due to increased external financing needs and higher cost of capital. Carvalho et al. (2023) provide the first global mapping of biodiversity dependencies, highlighting how operational vulnerability is concentrated in the agri-food, chemical, and construction sectors. These dependencies result in a structural vulnerability of corporate

[1] https://www.weforum.org/publications/global-risks-report-2024/.

operations, which is often exacerbated by the lack of firm-level strategies specifically aimed at mitigating nature-related risks. Therefore, expected operating cash flows become increasingly unstable and less predictable over time. Giglio et al. (2023) propose a theoretical framework in which natural risks, including biodiversity risks, increase the expected volatility of returns and modify the perceived systemic risk. Biodiversity is a factor priced by the market, even if undervalued, similar to market risk or climate risk in ESG asset pricing models. Companies with a high impact on biodiversity (i.e., high exposure) must offer higher expected returns, they have a higher cost of capital, and this translates into a lower valuation.

Some studies strictly concern financial markets, showing that biodiversity risk is progressively translating into required risk premiums that affect the cost of capital in DCF models, thus lowering the present value of future cash flows for biodiversity-intensive firms. Bassen et al. (2024) show that weak biodiversity governance is associated with an increased probability of stock crashes. Garel et al. (2024) confirm the start of a "risk pricing" process. After 2021, investors have started to require a risk premium upon the prospect and uncertainty of future regulation to preserve biodiversity. Coqueret et al. (2025) introduce the concept of "biodiversity premium", showing that investors require an additional return to hold stocks of high-impact companies, suggesting an expansion of ESG asset pricing models. Ma et al. (2024) found that physical risk significantly affects stock returns, but the impact of transition risk

Table 1
Sample distribution and representativeness.

PANEL A: Sectorial distribution

Main sector	Freq.	%	Main sector	Freq.	%
Asset Management	198	2.14	Internet & Data	205	2.22
Automotive & Logistics	149	1.61	Leisure	215	2.33
Bank	700	7.58	Materials	160	1.73
Beverages	170	1.84	Media	64	0.69
Building products	45	0.49	Metals & Mining	336	3.64
Chemicals	580	6.28	Oil & Gas	17	0.18
Construction & Real Estate	775	8.39	Paper and Forest	85	0.92
Defense	25	0.27	Pharmaceutical	530	5.74
Education	20	0.22	Power	145	1.57
Electrical Equipment	76	0.82	Retail and Wholesale	135	1.46
Electronics	816	8.83	Services	115	1.24
Energy	77	0.83	Software	365	3.95
Financial Services	577	6.24	Telecommunications	195	2.11
Food	630	6.82	Textiles	120	1.30
Healthcare	339	3.67	Thrifts & Mortgage Finance	20	0.22
Hotel and accommodation	40	0.43	Tobacco	15	0.16
Household goods	256	2.77	Transportation	110	1.19
Industrial Equipment	396	4.29	Waste	19	0.21
Insurance	500	5.41	Water	20	0.22
			Total	9,240	100

PANEL B: Country distribution

Country	Freq.	%	Country	Freq.	%	Country	Freq.	%
Australia	265	2.87	Hungary	10	0.11	Portugal	20	0.22
Austria	45	0.49	Indonesia	100	1.08	Qatar	10	0.11
Belgium	30	0.32	India	435	4.71	Saudi Arabia	35	0.38
Bermuda	55	0.60	Ireland	65	0.76	Singapore	105	1.14
Brazil	50	0.54	Israel	130	1.41	South Africa	85	0.92
Canada	175	1.89	Italy	70	0.76	South Korea	355	3.84
Cayman	215	2.33	Japan	1,130	12.23	Spain	75	0.81
Chile	25	0.27	Luxembourg	45	0.49	Sweden	135	1.46
China	1,695	18.34	Malaysia	80	0.87	Switzerland	165	1.79
Colombia	15	0.16	Mexico	50	0.54	Thailand	120	1.30
Czechia	10	0.11	Netherlands	115	1.24	Turkey	195	2.11
Denmark	70	0.76	Norway	60	0.65	Taiwan	315	3.41
Finland	60	0.65	New Zealand	40	0.43	UAE	25	0.27
France	135	1.46	Panama	10	0.11	UK	390	4.22
Germany	220	2.38	Peru	10	0.11	USA	1,615	17.48
Greece	20	0.22	Philippines	40	0.43			
Hong Kong	100	1.08	Poland	20	0.22			
						Total	9,240	100

PANEL C: Sample representativeness

Year	Market capitalization of sampled firms (bn $)	Total market capitalization (bn $)	%
2018	26,419	66,522	39.72
2019	33,732	76,011	44.38
2020	40,952	90,280	45.36
2021	46,868	105,327	44.50
2022	36,670	88,993	41.21

Note(s): In Panel C, information concerning the total market capitalization (bn $) is collected from the World Bank.

has yet to materialise. Stock portfolios from regions with larger nature reserves, non-state-owned enterprises, and a high GDP exhibit a higher sensitivity to biodiversity.

At the same time, according to the agency theory (Jensen, 1986; Gompers et al., 2003), sub-optimal management decisions (overinvestment, liquidity excess, accounting distortions and managerial myopia) may reduce the firm value. Some previous studies argue that the damage caused by firms to biodiversity creates regulatory and reputational uncertainty that translates into budget constraints and defensive behaviours by management (precautionary liquidity, debt structure and defensive governance). Ahmad and Karpuz (2024) show that firms with greater exposure to biodiversity risk accumulate more precautionary liquidity, especially in contexts of future regulatory uncertainty. Yang and Li (2025) document an effect on debt maturity mismatch: firms exposed to biodiversity risks use more short-term debt to finance long-term investments, meaning liquidity risk, credit frictions and low trust by lenders. Du et al. (2025) highlight how managers tend to adopt opportunistic behaviours (selling shares) in the presence of biodiversity risk pressures, suggesting implications for corporate governance and investor confidence. Zhao et al. (2025) find a negative relationship between "managerial myopia" (the excessive focus on short-term financial results) and biodiversity-related performance and, in line with Du et al. (2025), highlight that internal governance is often inadequate in absorbing and converting biodiversity risk signals into effective strategies.

The previous literature, therefore, provides a theoretical and empirical basis for considering biodiversity loss as a relevant determinant of firm value and formulates the research hypothesis:

H1: *The firm's impact on biodiversity is negatively related to the firm's value.*

3. Data and methodology

3.1. Sample description

To test our hypothesis, we identified a group of listed companies for which the information required by the empirical assessment was complete, especially concerning firms' biodiversity impact. In line with this, we selected all firms for which Iceberg Data Lab provides the Corporate Biodiversity Footprint throughout the coverage period, i.e. 2018–2022. Then, we checked their inclusion in LSEG Data & Analytics (formerly Refinitiv Eikon), from which we collected all economic and financial information necessary to build control variables at the firm level. The final sample comprises 1,848 publicly listed companies from 49 countries operating in 38 industries. The distribution of observations across countries and industries is provided in Table 1 (Panels A and B, respectively).

Since the sample selection strategy is contingent on data availability from the Iceberg Data Lab, we assessed the sample's representativeness by comparing the market capitalisation of the firms in our sample with the total market capitalisation of the countries under examination. Panel C of Table 1 shows that the representativeness of our sample equals or exceeds 40 % over the observation period. A sample covering 40 % of the market capitalisation is in line with the standards adopted in recent literature (Garel et al., 2024).

3.2. Empirical model

To test our research hypothesis and thus to study whether the impact of firms on biodiversity affects their value, we estimate the following regression model:

$$FirmValue_{i,t} = \beta_{CBF} * CBF_{i,(t-1,t-2)} + \sum_{j=1}^{9} X'_{i,t-1} * \theta_j + \gamma_t + \tau_c + \mu_s + \varepsilon_{i,t}$$

We employ two measures of firm value, that is, Tobin's Q and Market-to-Book (MB, hereafter) (Florio & Leoni, 2017; Mollick & Haidar, 2024). Tobin's Q, first proposed by Tobin (1969), is the market capitalisation ratio to the replacement cost of its total assets, whereas MB is computed as the total market value of equity divided by the total book value of equity. These market-oriented measures tend to be forward-looking. Consistent with Krüger (2015), and different from Garel et al. (2024), we choose Tobin's Q and MB to capture investors' long-term valuation of firm fundamentals and intangible assets. Both measures are considered in logarithm form (Xie et al., 2022).

Our primary explanatory variable is the Corporate Biodiversity Footprint (CBF, hereafter) developed by Iceberg Data Lab. This metric estimates the annual impact of the activities of corporations, financial institutions, real estate and sovereign entities on global and local biodiversity. The CBF methodology uses the Mean Species Abundance (MSA) metric to quantify the impact on biodiversity. MSA is a biodiversity metric that expresses the average relative abundance of native species in an ecosystem compared to their abundance in an ecosystem undisturbed by human activities and pressures. The variable *CBF* is expressed in the unit of measure Km^2. MSA and identifies the negative impact generated by activity on biodiversity in terms of square kilometres of "artificialized" or "denatured" land (Garel et al., 2024). For example, -1 Km^2.MSA corresponds to the biodiversity value $1Km^2$ of tropical pristine forest undisturbed by human activities (Iceberg Data Lab, 2023). In terms of operationalisation, in line with Garel et al. (2024), we multiply the CBF score by -1 so that higher values indicate a more negative impact on biodiversity and implement it in its natural logarithm form due to strong skewness. In addition, we estimate the lagged effect of the CBF score on firm value using a time lag of 1 year and 2 years. This allows us to alleviate reverse causality and test for a lagged effect of CBF on firm value.

In our model, X' is a vector of control variables (at the firm and country level). More specifically, similarly to Li et al. (2018) and Buchanan et al. (2018), we include: i) *PPE*, computed as the natural logarithm of the ratio of property, plant and equipment to total revenue; ii) *CAPEX*, i.e. the natural logarithm of the ratio of capital expenditures on total revenue; iii) *Rev_growth*, i.e. the annual

growth rate of total revenue; iv) *Leverage*, computed as the natural logarithm of the ratio of total debt to total equity; v) *Cash*, i.e. the natural logarithm of cash and other short-term assets divided by total assets; vi) *R&D_int*, that measures R&D intensity and which equals annual research and development expense divided by total assets; vii) *E_score*, a score ranging between 0 and 100 that measures companies' environmental performance; viii) *Size* is measured through companies' total assets; ix) *GDP_growth* measures the annual growth rate of GDP per capita. Except for *Rev_growth* and *GDP_growth*, all other control variables are lagged by one year. Lagging firm-specific characteristics help us avoid endogeneity problems related to the simultaneity of balance sheet variables (Altunbas et al., 2022).

Following Garel et al. (2024), the model includes a set of year (γ_t), country (τ_c) and industry (μ_s) fixed effects. Some baseline estimations include fixed effects at the industry-year level ($\mu_s \times \gamma_t$). Standard errors are clustered at the firm level.

The definitions of all variables implemented in this paper are included in Table A1 (Appendix), while Table 2 provides descriptive statistics.

4. Empirical results

4.1. Correlations and univariate analysis

Table A2 (Appendix) reports the pairwise correlations of the variables implemented in the main model. It shows that CBF negatively correlates with Tobin's Q and MB (p-value < 0.01), revealing that a lower firm value characterises firms with a more negative impact on biodiversity. Furthermore, the correlations of firm-level control variables with Tobin's Q and MB align with the results of previous studies analysing the determinants of firms' value (e.g. Li et al., 2018; Buchanan et al., 2018).

We also carried out mean and median difference tests between high and low CBF sub-samples to further test the presence and strength of a causal relationship between biodiversity impact and firm value. In particular, we divided the sampled firms into CBF terciles each year and for each industry and compared the mean and median Tobin's Q and MB for the low (T1) and high (T3) terciles (Hasan et al., 2021). Subsequently, we replicated the analysis by dividing the firms into CBF terciles each year and for each country. The results of these univariate analyses are reported in Table A3 (Appendix), which suggests that firms with lower CBF (i.e. with a smaller impact on biodiversity) have significantly higher Tobin's Q and MB compared to high CBF counterparts.

Finally, we tested whether CBF is useful in forecasting Tobin's Q and MB through Granger-causality hypothesis tests. Specifically, this test allows us to understand whether one variable *X* (CBF in our case) can be meaningfully described as an independent variable of a variable *Y* (Tobin's Q and MB in our case), whether the relation is uni- or bi-directional, or whether no relation exists (Granger, 1969). By considering the 1-year lag length, results of Granger-causality tests suggest a predictive causal relationship from CBF to Tobin's Q and from CBF to MB (*p-value* < 0.01), but no relation exists in the opposite direction (Table A4, Appendix). This evidence supports our hypothesis (HP1) and partially rules out possible reverse causality issues.

4.2. Baseline empirical results

Tables 3 and 4 report the results of panel fixed effects regression models investigating the effect of CBF on Tobin's Q and MB, respectively.

Consistent with our H1, the results show a negative and statistically significant effect of 1-year and 2-year lag of CBF on firm value. The initial robustness of the results is corroborated using various combinations of country, time and industry fixed effects, always showing that the negative impact generated by activity on biodiversity erodes firm value. More in detail, for a 1 % increase in CBF, the

Table 2
Descriptive statistics.

	N. obs.	Mean	Median	St. Dev.	Min	Max
Tobin's Q	8,825	−0.104	0.009	1.468	−8.959	4.916
MB	8,716	0.991	0.889	1.100	−5.999	7.169
CBF	9,240	4.509	5.061	3.116	−9.657	12.375
CBF_land	9,237	3.595	4.156	3.555	−12.182	12.355
CBF_ghg	9,238	1.902	2.113	2.614	−10.404	9.576
CBF_air	7,420	1.079	1.429	2.754	−11.673	8.974
CBF_water	9,233	1.164	1.874	4.082	−14.172	11.194
CBF_s1	9,222	−0.144	0.193	3.736	−13.423	9.468
CBF_s2	8,822	−3.546	−2.347	4.664	−30.439	5.694
CBF_s3	9,237	4.248	4.897	3.367	−11.314	12.355
PPE	8,071	0.344	0.236	0.385	−0.319	6.914
CAPEX	7,982	0.085	0.046	0.161	−0.054	6.378
Rev_Growth	8,134	1.280	1.063	9.270	−6.892	819.573
Leverage	8,775	0.561	0.449	0.512	0	6.048
Cash	7,702	0.150	0.115	0.125	0	0.681
R&D_int	8,887	0.015	0	0.033	0	0.483
E_score	7,757	49.761	52.585	27.552	0	98.995
Size	8,887	54.388	7.955	201.444	0.009	4206.860
GDP_growth	8,925	2.494	2.559	3.858	−17.668	15.836

Table 3
Baseline results: The effect of CBF on Tobin's Q.

	(1)	(2)	(3)	(4)	(5)	(6)
		1-year lag			2-year lag	
CBF	−0.037***	−0.086***	−0.086***	−0.037***	−0.087***	−0.088***
	(0.009)	(0.011)	(0.011)	(0.009)	(0.011)	(0.011)
PPE	−0.276***	−0.190***	−0.190***	−0.238***	−0.167**	−0.167**
	(0.078)	(0.073)	(0.072)	(0.075)	(0.073)	(0.073)
CAPEX	0.351*	0.453**	0.468**	0.339*	0.485**	0.491**
	(0.184)	(0.182)	(0.183)	(0.195)	(0.192)	(0.491)
Rev_Growth	0.048	0.048	0.040	0.042	0.040	0.034
	(0.063)	(0.067)	(0.065)	(0.063)	(0.064)	(0.062)
Leverage	−0.681***	−0.569***	−0.571***	−0.650***	−0.534***	−0.536***
	(0.064)	(0.058)	(0.058)	(0.067)	(0.059)	(0.059)
Cash	2.353***	2.127***	2.139***	2.549***	2.306***	2.312***
	(0.248)	(0.229)	(0.233)	(0.254)	(0.233)	(0.236)
R&D_int	3.787***	2.360***	2.372***	3.829***	2.212***	2.234***
	(0.831)	(0.829)	(0.842)	(0.887)	(0.855)	(0.864)
E_score	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Size	−0.005***	−0.004***	−0.004***	−0.005***	−0.004***	−0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
GDP_growth	0.000	0.002	0.000	0.002	0.004	0.002
	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)
Year FE	Yes	Yes	No	Yes	Yes	No
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	No	Yes	No
Industry x Year FE	No	No	Yes	No	No	Yes
Observations	4,772	4,772	4,772	3,725	3,725	3,725
R^2	0.510	0.590	0.595	0.507	0.591	0.595
Adjusted R^2	0.504	0.582	0.577	0.499	0.580	0.576

Note(s): Fixed-effects regression results for the dependent variable *Tobin's Q*. In Models 1–3, the 1-year lag of the independent variable *CBF* is implemented, while Models 4–6 consider the 2-year lag. All variables are defined in Table A1 (Appendix). Standard errors in parentheses are clustered at the firm level.
*$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

negative effect on Tobin's Q ranges between −0.04 % and −0.09 % depending on the lag length of CBF and the set of fixed effects considered (Table 3). Regarding economic significance, one standard deviation (3.116) increase in CBF reduces Tobin's Q, ranging from 8.5 % to 19.13 % of its standard deviation (1.468). Similar effects are observable for MB: for a 1 % increase in CBF, the negative effect on MB ranges from −0.41 % to −0.089 % (Table 4). Consequently, a one standard deviation increase in CBF reduces firms' MB by 11.6 to 25 % of its standard deviation of 1.100. This evidence reveals the intense attention paid by financial markets and investors to the impact of firms' activities on biodiversity: investors are pricing firms' CBF, thus reducing their market value. The results are consistent, in principle, with previous studies by Matsumura et al. (2014), Choi and Luo (2021) and Perdichizzi et al. (2024) about the negative relationship between firms' environmental impact and their market value. The impact of control variables on firm value is totally in line, in terms of sign and significance, with the existing literature (Li et al., 2018).

4.3. Additional analysis

4.3.1. Environmental impact channels

To provide more insights into the effects of CBF on firm value, we deepen the analysis by decomposing CBF into its four environmental channels: Land Use through occupation or transformation of land (*CBF_land*), Climate Change through GHG emissions (*CBF_ghg*), Air Pollution through nitrogen and sulfur oxides emissions (*CBF_air*), and Water Pollution through ecotoxic compounds release (*CBF_water*), to test their effect on Tobin's Q and MB separately (Table 5):

The results in Table 5, which include time, firm and industry fixed effects, show that all four components of CBF have a negative and statistically significant influence on Tobin's Q (Panel A) and MB (Panel B). Looking at the magnitude of the coefficients, however, we can draw conclusions about which component has a more substantial impact on firm value. Overall, we found that *CBF_ghg* and *CBF_air* components have a stronger impact on Tobin's Q and MB than the *CBF_land* and *CBF_water* components. Specifically, a 1 % increase in *CBF_land*, *CBF_ghg*, *CBF_air* and *CBF_water* leads to reductions in Tobin's Q of approximately −0.06 %, −0.13 %, −0.11 % and −0.07 %, respectively. Similarly, the negative effects on MB are −0.06 %, −0.12 %, −0.10 % and −0.06 % for a 1 % increase in *CBF_land*, *CBF_ghg*, *CBF_air* and *CBF_water*, respectively. The reasons for the difference could be attributable to the more or less accentuated perception by the market and different levels of awareness: a company's greenhouse gas emissions and air pollution are "global" issues,

Table 4
Baseline results: effect of CBF on MB.

	(1)	(2)	(3)	(4)	(5)	(6)
		1-year lag			2-year lag	
CBF	−0.043***	−0.088***	−0.089***	−0.041***	−0.088***	−0.089***
	(0.009)	(0.012)	(0.012)	(0.009)	(0.012)	(0.012)
PPE	−0.395***	−0.298***	−0.296***	−0.342***	−0.261***	−0.260***
	(0.070)	(0.068)	(0.067)	(0.070)	(0.068)	(0.068)
CAPEX	0.218	0.340**	0.345**	0.159	0.317*	0.317*
	(0.174)	(0.166)	(0.166)	(0.181)	(0.174)	(0.178)
Rev_Growth	0.059	0.058	0.052	0.049	0.046	0.043
	(0.060)	(0.062)	(0.060)	(0.057)	(0.056)	(0.055)
Leverage	0.204***	0.313***	0.314***	0.240***	0.352***	0.352***
	(0.065)	(0.059)	(0.061)	(0.068)	(0.061)	(0.062)
Cash	2.298***	2.069***	2.088***	2.464***	2.229***	2.242***
	(0.243)	(0.222)	(0.226)	(0.249)	(0.226)	(0.230)
R&D_int	3.675***	2.344***	2.332***	3.736***	2.263**	2.259**
	(0.878)	(0.864)	(0.875)	(0.949)	(0.907)	(0.915)
E_score	−0.001	−0.001	−0.001	−0.001	−0.002	−0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Size	−0.002***	−0.002***	−0.002**	−0.002***	−0.002***	−0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
GDP_growth	−0.001	0.001	0.000	0.000	0.003	0.002
	(0.004)	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)
Year FE	Yes	Yes	No	Yes	Yes	No
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	No	Yes	No
Industry x Year FE	No	No	Yes	No	No	Yes
Observations	4,746	4,746	4,746	3,702	3,702	3,702
R^2	0.387	0.479	0.485	0.387	0.482	0.487
Adjusted R^2	0.380	0.469	0.462	0.377	0.469	0.463

Note(s): Fixed-effects regression results for the dependent variable *MB*. Models 1–3 implement the 1-year lag of the independent variable CBF, while Models 4–6 consider the 2-year lag. All variables are defined in Table A1 (Appendix). Standard errors in parentheses are clustered at the firm level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

systemic problems affecting everyone, are the subject of many regulations, and there is widespread awareness of this among investors. Pollution linked to the emission of harmful substances into the air has a widespread impact: it can move far away from the source of the pollution and, therefore, have an impact on a larger scale compared to the more localized effects of land use, which affects as a whole the location of the company, or water pollution which may be perceived as a problem of a specific region.

4.3.2. Direct and indirect impacts

In addition, our analysis decomposes firm impacts on biodiversity into Scope 1 (*CBF_s1*), 2 (*CBF_s2*) and 3 (*CBF_s3*) to provide a more granular and complete picture of biodiversity loss's direct and indirect impacts on firm value (Table 6).

The results in Table 6 show that companies' direct and indirect biodiversity impacts on biodiversity loss negatively and statistically significantly affect Tobin's Q (Panel A) and MB (Panel B). More in detail, a 1 % increase in *CBF_s1*, *CBF_s2*, and *CBF_s3* leads to reductions in Tobin's Q of approximately −0.06 %, −0.03 % and −0.07 %, respectively. Similarly, the negative effects on MB are −0.07 %, −0.03 %, and −0.08 % for a 1 % increase in *CBF_s1*, *CBF_s2*, and *CBF_s3*, respectively. However, Scope 3 impacts appear to be the most significant, presenting higher coefficients. These results indicate that firms' impact on Biodiversity Loss is strongly linked to their supply chains (Boldrini et al., 2023). The impact of bank and financial companies on biodiversity should also be assessed not so much by looking at their direct impacts, which are negligible, but by looking at loans, financing and investments (Pasiouras et al., 2024; Chiaramonte et al., 2024).

4.3.3. The biodiversity-profitability nexus

Following our investigation of the effect of firms' CBF on their market-based valuation, we further explore its implications for firms' internal value creation capacity. In particular, we analyse the impact of CBF on firms' operating profitability from an economic perspective, using the return on assets (ROA) as our main measure (Li et al., 2018). This choice is theoretically grounded in value-based planning models (Varaiya et al., 1987), which posit that firm value ultimately derives from the ability to generate returns above the cost of capital, and that market valuations reflect expectations about the firm's long-term profitability. Consistently, empirical evidence shows that profitability is a key driver of firm value alongside growth (Varaiya et al., 1987) and that more profitable firms command higher market valuations (Novy-Marx, 2013). Although several studies treat firm value and profitability as two manifestations of the same construct, namely, financial performance (Aydoğmuş et al., 2022; Li et al., 2018), their behaviour is not always fully

Table 5
The effect of CBF on Tobin's Q and MB by type of environmental channel.

Panel A. Dependent variable: Tobin's Q								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	1-year lag	2-year lag	1-year lag	2-year lag	1-year lag	2-year lag	1-year lag	2-year lag
CBF_land	−0.056***	−0.058***						
	(0.009)	(0.009)						
CBF_ghg			−0.126***	−0.127***				
			(0.012)	(0.012)				
CBF_air					−0.108***	−0.103***		
					(0.013)	(0.013)		
CBF_water							−0.069***	−0.068***
							(0.008)	(0.008)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,772	3,725	4,771	3,725	3,734	2,610	4,768	3,722
R^2	0.584	0.584	0.602	0.603	0.597	0.603	0.596	0.595
Adjusted R^2	0.575	0.574	0.594	0.593	0.586	0.589	0.588	0.585
Panel B. Dependent variable: MB								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	1-year lag	2-year lag	1-year lag	2-year lag	1-year lag	2-year lag	1-year lag	2-year lag
CBF_land	−0.063***	−0.064***						
	(0.010)	(0.011)						
CBF_ghg			−0.121***	−0.120***				
			(0.013)	(0.013)				
CBF_air					−0.102***	−0.097***		
					(0.013)	(0.013)		
CBF_water							−0.064***	−0.063***
							(0.008)	(0.008)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,746	3,702	4,745	3,702	3,711	2,593	4,742	3,699
R^2	0.473	0.476	0.490	0.493	0.486	0.496	0.481	0.483
Adjusted R^2	0.462	0.463	0.480	0.480	0.473	0.477	0.471	0.470

Note(s): Fixed-effects regression results for the dependent variables *Tobin's Q* (Panel A) and *MB* (Panel B). CBF is decomposed into its four components, namely Land Use, GHG Emissions, Air Pollution, and Water Pollution. In Models 1, 3 and 5, the 1-year lag of the independent variables *CBF_land*, *CBF_ghg*, *CBF_air*, and *CBF_water* is implemented, while Models 2, 4 and 6 consider the 2-year lag. Control variables include *PPE*, *CAPEX*, *Rev_Growth*, *Leverage*, *Cash*, *R&D_int*, E_*score*, *Size*, and *GDP_Growth*. All variables are defined in Table A1 (Appendix). Standard errors in parentheses are clustered at the firm level.
*$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

overlapping (see, e.g., Cui & Mak, 2002), thus justifying the need to analyse them separately. Therefore, analysing the effect of the CBF on profitability helps us uncover how biodiversity-related exposures may affect firm value.

Thereafter, to gain deeper insights on how CBF may influence corporate performance and disentangle the economic mechanisms underlying the overall effect, we further decompose ROA according to the DuPont equation in: i) *Profit_margin*, computed as pretax income to sales, and ii) *Asset_turnover*, computed as sales to total assets (Table 7).

The results in Table 7 (Models 1–2) indicate that a higher CBF is associated with a lower ROA. Therefore, compared to prior research, our findings not only reaffirm the detrimental effect of CBF on firms' market value (e.g., Garel et al., 2024), but also reveal a worsening of operating performance. In this regard, interesting are the results from the DuPont decomposition of ROA (Models 3–6, Table 7). This decomposition highlights that CBF has a significant negative effect on *Profit_margin*, which more than offsets its positive effect on *Asset_turnover*. Specifically, the coefficients associated with CBF are −0.077 and −0.085 in Models 3–4 (where *Profit_margin* is the dependent variable), while a positive coefficient of 0.066 emerges in Models 5–6 (where *Asset_turnover* is the dependent variable). These results explain why the overall effect of CBF on ROA remains slightly negative. Firms with higher CBF may face greater exposure to biodiversity-related transition risks, mainly caused by the transition to a green economy, market shifts, or changes in technology and regulations. These dynamics can accelerate the depreciation of certain assets beyond their normal aging process, leading to premature write-downs or devaluations, commonly referred to as stranded assets. As a consequence, the total asset base diminishes, while sales could remain relatively stable in the short term, which would mechanically increase the asset turnover ratio. Therefore, the positive association with asset turnover is likely to reflect the shrinking value of the asset base due to biodiversity-related devaluation, rather

Table 6
The effect of CBF on Tobin's Q by scope of emissions.

Panel A. Dependent variable: Tobin's Q						
	(1)	(2)	(3)	(4)	(5)	(6)
	1-year lag	2-year lag	1-year lag	2-year lag	1-year lag	2-year lag
CBF_s1	−0.064***	−0.063***				
	(0.009)	(0.009)				
CBF_s2			−0.027***	−0.028***		
			(0.005)	(0.005)		
CBF_s3					−0.072***	−0.074***
					(0.010)	(0.010)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,769	3,723	4,559	3,527	4,772	3,725
R^2	0.587	0.586	0.584	0.585	0.587	0.589
Adjusted R^2	0.578	0.575	0.576	0.574	0.579	0.578
Panel B. Dependent variable: MB						
	(1)	(2)	(3)	(4)	(5)	(6)
	1-year lag	2-year lag	1-year lag	2-year lag	1-year lag	2-year lag
CBF_s1	−0.067***	−0.065***				
	(0.010)	(0.010)				
CBF_s2			−0.026***	−0.025***		
			(0.005)	(0.005)		
CBF_s3					−0.075***	−0.076***
					(0.011)	(0.011)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,766	3,720	4,555	3,525	4,769	3,722
R^2	0.192	0.211	0.186	0.221	0.195	0.214
Adjusted R^2	0.176	0.191	0.170	0.201	0.179	0.194

Note(s): Fixed-effects regression results for the dependent variables *Tobin's Q* (Panel A) and *MB* (Panel B). CBF is decomposed in Scope 1-, Scope 2- and Scope 3-related biodiversity loss. In Models 1, 3 and 5, the 1-year lag of the independent variables *CBF_s1*, *CBF_s2*, and *CBF_s3* is implemented, while Models 2, 4 and 6 consider the 2-year lag. Control variables include *PPE*, *CAPEX*, *Rev_Growth*, *Leverage*, *Cash*, *R&D_int*, E_*score*, *Size*, and *GDP_Growth*. All variables are defined in Table A1 (Appendix). Standard errors in parentheses are clustered at the firm level.
*$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

than genuine efficiency gains. Yet this effect is not sufficient to offset the deterioration in profitability. Lower margins, driven by rising operational and compliance costs such as higher input prices, reduced pricing power, and expenditures for fines, compensation, or remediation, combine with reduced asset efficiency, ultimately leading to weaker operating performance for firms with higher CBF.

4.3.4. Channel analysis: The role of operating cash flow and its volatility

Building on the previous analysis, we now shift to a financial perspective, focusing on operating cash flow and its volatility to provide complementary insights into how biodiversity risks affect firms' effective cash generation and financial resilience.

Consistent with the Discount Cash Flow (DCF) framework (Fama & French, 2006) and investment-based valuation models (Zhang, 2006; Lyandres et al., 2008), both the level and volatility of operating cash flow are key determinants of firm value. Operating cash flow represents the cash inflows and outflows directly related to the company's core business and reflects the ability to generate sufficient cash to sustain and grow operations without relying on external financing. Higher cash flow increases valuation through improved profitability and capital access. Higher cash flow volatility reflects greater information uncertainty, which leads investors to demand a risk premium, thereby reducing firm valuation metrics like Tobin's Q and MB.

We conduct a two-stage analysis to explore the possible mediating role of operating cash flow and cash flow volatility in the relationship between CBF and firm value (Nikbakht, 2024; Feng et al., 2024). CBF can impact both the level and volatility of operating cash flow in several ways, primarily due to the environmental risks, regulatory changes, and the costs associated with biodiversity-related initiatives (Feng et al., 2024; Safiullah et al., 2024).

For instance, a firm's dependence on natural resources may expose it to fluctuating production costs due to environmental degradation or scarcity. In addition, regulatory pressures, alongside norms and cultural expectations from stakeholders regarding environmental concerns, may lead to unexpected operating costs due to compliance needs and reputational effects on customer demand, as well as demand-side shocks due to shifts in consumer preferences. Finally, a shortfall in operating cash flow may impair a

Table 7
The effect of CBF on ROA and its DuPont components.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable	ROA		Profit_margin		Asset_turnover	
	1-year lag	2-year lag	1-year lag	2-year lag	1-year lag	2-year lag
CBF	−0.003*	−0.004**	−0.077***	−0.085***	0.066***	0.066***
	(0.002)	(0.002)	(0.012)	(0.013)	(0.013)	(0.013)
PPE	−0.027***	−0.027***	0.291	0.336	−0.606***	−0.626***
	(0.006)	(0.006)	(0.266)	(0.324)	(0.190)	(0.227)
CAPEX	−0.053***	−0.047***	0.440	0.290	−0.445	−0.454
	(0.016)	(0.017)	(0.546)	(0.639)	(0.332)	(0.377)
Rev_Growth	0.026***	0.028***	0.066*	0.071	0.143***	0.139**
	(0.006)	(0.007)	(0.040)	(0.044)	(0.055)	(0.057)
Leverage	−0.041***	−0.041***	−0.313***	−0.296***	−0.059	−0.033
	(0.005)	(0.005)	(0.057)	(0.061)	(0.047)	(0.047)
Cash	0.128***	0.129***	1.590***	1.632***	0.212	0.210
	(0.038)	(0.038)	(0.245)	(0.264)	(0.205)	(0.210)
R&D_int	−0.575***	−0.533***	0.161	0.104	−0.952	−0.767
	(0.153)	(0.146)	(0.860)	(0.901)	(0.591)	(0.570)
E_score	0.000***	0.000***	0.001	0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Size	−0.000***	−0.000***	0.000	0.000	−0.003***	−0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
GDP_growth	0.001***	0.001**	0.004	0.007	0.010**	0.008
	(0.001)	(0.001)	(0.006)	(0.006)	(0.005)	(0.005)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,769	3,722	4,312	3,349	4,710	3,676
R^2	0.195	0.214	0.277	0.278	0.527	0.526
Adjusted R^2	0.179	0.194	0.261	0.258	0.517	0.513

Note(s): Fixed-effects regression results for the dependent variables *ROA, Profit_margin,* and *Asset_turnover*. In Models 1, 3, 5 the 1-year lag of the independent variable *CBF* is implemented, while Models 2, 4, 6 consider the 2-year lag. All variables are defined in Table A1 (Appendix). Standard errors in parentheses are clustered at the firm level.
*$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

company's ability to meet its debt obligations (Feng et al., 2024), deteriorating its creditworthiness. All this results in increased risk perception from investors, thereby damaging firm value (Wang & Yang, 2023).

In light of these considerations, we consider as mediators: i) *opCF*, computed as the company's operating cash flow scaled by total assets, and ii) *CF_volatility*, measured as the standard deviation of operating cash flow over a rolling 3-year window, implemented in its natural logarithmic form (Safiullah et al., 2024). Table 8 reports the results of the mediation analyses for *opCF* (Panel A) and *CF_volatility* (Panel B).

Results indicate that the proposed channels are valid, as in the first stage, we demonstrate a negative impact of CBF on *opCF* (Model 1, Table 8, Panel A) and a positive impact of CBF on *CF_volatility* (Models 1–2, Table 8, Panel B). In the second stage, we observe the negative effect of CBF on firm value with a lower effect size compared to our baseline findings (Tables 3 and 4) after controlling for the channel, i.e. *opCF* (Models 3–6, Table 8, Panel A) and *CF_volatility* (Models 3–6, Table 8, Panel B). This evidence demonstrates that the level and volatility of operating cash flow can be mechanisms through which CBF negatively affects firm value. In addition, while the mediating effect of *opCF* weakens and becomes statistically insignificant in 2 years, the mediating effect of *CF_volatility* is strong and persistent, considering a 2-year lagged effect. The short-term mediating effect of *opCF* may stem from the inherent nature of this measure, which is usually subject to short-term fluctuations and managerial interventions, which can rapidly alter its level in the near term, but do not necessarily have long-lasting effects. Finally, our analysis confirms that the level and volatility of operating cash flow have direct effects on firm value: the former exerts a positive influence. In contrast, the latter has a negative impact.

4.4. Robustness tests

4.4.1. Alternative measure of firm value

As a first robustness test, we change our dependent variable. In particular, we use a measure of the total value of the company, i.e. Enterprise Value (*EV*), computed as the market value of equity, debt, and other non-equity claims, minus cash and cash equivalents, scaled by total assets. Results are reported in Table 9.

Models 1–2 in Table 9 show that CBF negatively influences *EV*, fully confirming the baseline results.

Table 8
The effect of CBF on firm value: the channel of CF from operating activities and CF volatility.

Panel A. CF from operating activities as mediator						
	(1)	(2)	(3)	(4)	(5)	(6)
	Dep. Variable: opCF_TA		Dep. variable: Tobin's Q		Dep. variable: MB	
	1-year lag	2-year lag	1-year lag	2-year lag	1-year lag	2-year lag
CBF	−0.003**	−0.003	−0.078***	−0.081***	−0.082***	−0.083***
	(0.002)	(0.002)	(0.011)	(0.011)	(0.011)	(0.011)
opCF_TA			2.788***	2.775***	2.606***	2.632***
			(0.358)	(0.399)	(0.348)	(0.378)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,725	3,688	4,724	3,688	4,698	3,665
R^2	0.193	0.194	0.639	0.638	0.533	0.536
Adjusted R^2	0.176	0.173	0.631	0.628	0.524	0.524
Panel B. CF volatility as mediator						
	(1)	(2)	(3)	(4)	(5)	(6)
	Dep. Variable: CF_volatility		Dep. variable: Tobin's Q		Dep. variable: MB	
	1-year lag	2-year lag	1-year lag	2-year lag	1-year lag	2-year lag
CBF	0.189***	0.186***	−0.071***	−0.071***	−0.071***	−0.070***
	(0.021)	(0.020)	(0.012)	(0.012)	(0.012)	(0.012)
CF_volatility			−0.083***	−0.090***	−0.100***	−0.106***
			(0.018)	(0.019)	(0.017)	(0.019)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,725	3,689	4,721	3,686	4,695	3,663
R^2	0.433	0.442	0.596	0.597	0.491	0.495
Adjusted R^2	0.422	0.428	0.587	0.587	0.481	0.482

Note(s): Fixed-effects regression results for the mediation analysis exploring *opCF_TA* (Panel A) and *CF_volatility* (Panel B) as possible mechanism. In Panel A, Models 1–2 implement *opCF_TA* as dependent variable, Models 3–4 implement *Tobin's Q* as dependent variables, while in Models 5–6 the dependent variable is *MB*. In Panel B, Models 1–2 implement *CF_volatility* as dependent variable, Models 3–4 implement *Tobin's Q* as dependent variables, while in Models 5–6 the dependent variable is *MB*. In both Panel A and B, Models 1, 3 and 5, implement the 1-year lag of the independent variables *CBF*, while Models 2, 4 and 6 consider the 2-year lag. Control variables include *PPE*, *CAPEX*, *Rev_Growth*, *Leverage*, *Cash*, *R&D_int*, E_*score*, *Size*, and *GDP_Growth*. All variables are defined in Table A1 (Appendix). Standard errors in parentheses are clustered at the firm level.
*$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.4.2. Alternative independent variables

As a further test, we also change our main explanatory variable (i.e. CBF) to check whether baseline results also hold when scaling CBF by the volume of companies' activity. To this purpose, we divided the CBF score by firms' sales and re-run the baseline models. Results of this sensitivity test, reported in Table A5 (Appendix), confirm the negative influence of CBF on firm value.

Although Iceberg Data Lab's CBF has a structure and rationale consistent with both financial materiality principles (as in Garel et al., 2024) and environmental accountability frameworks (e.g., TNFD, GRI), and is appropriate for an international sample, our analysis to date has relied on third-party measures. Therefore, we conduct an additional robustness test adopting the 10 K-based Biodiversity Scores developed and publicly released by Giglio et al. (2023)[2] for U.S.-listed companies. We alternatively replace CBF with three biodiversity scores: i) *10 K-based Count Score*, i.e. a binary variable equal to 1 if a 10-K statement contains at least two sentences related to biodiversity, 0 otherwise; ii) *10 K-based Negative Score*, that represents the number of negative biodiversity sentences minus the number of positive sentences in a 10-K statement, and iii) *10 K-based Regulation*, a binary variable equal to 1 if the 10-K statement of a company contains at least two biodiversity risk sentences and at least one of them is a biodiversity regulation risk sentence, 0 otherwise (Table 10).

Results in Table 10 suggest that biodiversity-conscious companies, as well as those that are aware of biodiversity-related risks, exhibit higher value, as measured by Tobin's Q (Panel A) and MB (Panel B). Specifically, the 1-year lagged values of the *10 K-based Count Score* and *10 K-based Negative Score* are significantly associated with Tobin's Q, with coefficients of 0.33 and –0.319, respectively (Models 1 and 3, Table 10, Panel A). Moreover, the 2-year lag of *10 K-based Regulation* shows a positive and statistically significant relationship with both Tobin's Q and Market-to-Book ratio, with coefficients of 0.486 and 0.546, respectively (Model 6, Table 10, Panel A and B). These findings suggest that investors tend to reward firms that demonstrate an awareness of the regulatory implications associated with their impact on biodiversity. The observed differences between the 1-year and 2-year lagged effects of the 10 K-based Biodiversity Scores and between the two firm value metrics are likely driven by variations in sample composition and geographical

[2] 10*K*-based Biodiversity Scores released by Giglio et al. (2023) are available here: https://www.biodiversityrisk.org/.

Table 9
Sensitivity test: alternative dependent variable.

	(1)	(2)
Dep. Variable	EV	
	1-year lag	2-year lag
CBF	−0.241***	−0.215***
	(0.052)	(0.045)
PPE	−0.274*	−0.227
	(0.147)	(0.140)
CAPEX	0.389	0.422
	(0.458)	(0.497)
Rev_Growth	0.233	0.174
	(0.185)	(0.124)
Leverage	−0.153	−0.149
	(0.140)	(0.127)
Cash	6.309***	5.168***
	(1.129)	(0.950)
R&D_int	10.192**	7.595**
	(4.156)	(3.584)
E_score	−0.010***	−0.007**
	(0.003)	(0.003)
Size	−0.001	−0.001
	(0.001)	(0.001)
GDP_growth	0.028**	0.032**
	(0.014)	(0.013)
Year FE	Yes	Yes
Country FE	Yes	Yes
Industry FE	Yes	Yes
Observations	4,711	3,677
R^2	0.304	0.311
Adjusted R^2	0.290	0.293

Note(s): Fixed-effects regression results for the dependent variable *EV*. In Model 1 the 1-year lag of the independent variables *CBF* is implemented, while Models 2 consider the 2-year lag. All variables are defined in Table A1 (Appendix). Standard errors in parentheses are clustered at the firm level.
*$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

coverage (only US Firms) relative to the baseline models. Additionally, these discrepancies may stem from the nature of the measures themselves: while the CBF captures firms' actual impact on biodiversity, the 10 K-based Biodiversity Scores reflect firms' disclosure and communication efforts.

Crucially, the robustness analysis supports the overall consistency of our findings: a firm's impact on biodiversity (captured by the CBF and reflected in 10 K reports) is a significant dimension in shaping firm value. Taken together, these results reinforce the importance of considering both tangible actions and narrative strategies in assessing corporate biodiversity exposure.

4.5. Heterogeneity analysis

Heterogeneity analysis is widely employed to validate the conditional nature of theoretical mechanisms (Lins et al., 2017; Trinh et al., 2024). To test for heterogeneity across firms with different contexts or with specific characteristics, we implement a split-sample approach.

4.5.1. Industries' environmental exposure

As specified by Hoogendoorn et al. (2015), the environmental impact of firms is linked to the circumstances of the industrial sectors they belong to, some of which may depend on the use of natural resources by having to deal with complex and resource-intensive extraction and processing processes. For this reason, firms belonging to such sectors are more closely monitored by stakeholders and regulators and are more active in environmental strategies than less resource-intensive firms (Williamson et al., 2006; Delmas & Toffel, 2004). For example, Graafland et al. (2003) showed that firms in the metals sector are more active in environmental practices than those in financial services and retail. To consider these circumstances, we follow the approach proposed by Hoogendoorn et al. (2015) and split firms according to the "tangibility" of their business sector, distinguishing between products (tangible), tangible services (involving a clear physical or material component during delivery, like passenger transport, restaurants, hotels), and intangible services.

The results in Table 11 show a negative and statistically significant relationship between CBF and firm value (Tobin's Q: Panel A; MB: Panel B), which, however, turns out to be a little weaker when we analyse the MB of the tangible service category. This may be explained by a greater perceived distance from direct effects on biodiversity or, alternatively, by a less elastic demand regarding biodiversity issues. Indeed, services provided by hotels, clinics, gas or electricity suppliers, or transportation companies are considered essential or with no alternative, regardless of any impacts on biodiversity.

Table 10
Sensitivity test: the effect of 10 K-based Scores on Tobin's Q and MB (Giglio et al., 2023).

Panel A. Dependent variable: Tobin's Q						
	(1)	(2)	(3)	(4)	(5)	(6)
	1-year lag	2-year lag	1-year lag	2-year lag	1-year lag	2-year lag
10 K-based Count Score	0.332*	0.287				
	(0.183)	(0.227)				
10 K-based Negative Score			−0.319*	−0.227		
			(0.163)	(0.260)		
10 K-based Regulation Score					0.400	0.486**
					(0.267)	(0.212)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	No	No	No	No	No
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	860	647	860	647	860	647
R^2	0.557	0.558	0.557	0.557	0.557	0.558
Adjusted R^2	0.534	0.527	0.534	0.526	0.533	0.527
Panel B. Dependent variable: MB						
	(1)	(2)	(3)	(4)	(5)	(6)
	1-year lag	2-year lag	1-year lag	2-year lag	1-year lag	2-year lag
10 K-based Count Score	0.348	0.311				
	(0.239)	(0.258)				
10 K-based Negative Score			−0.408	−0.297		
			(0.273)	(0.322)		
10 K-based Regulation Score					0.435	0.546*
					(0.336)	(0.283)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	No	No	No	No	No
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	842	630	842	630	842	630
R^2	0.493	0.500	0.494	0.499	0.493	0.500
Adjusted R^2	0.466	0.465	0.466	0.465	0.466	0.466

Note(s): Fixed-effects regression results for the dependent variable *Tobin's Q* (Panel A) and *MB* (Panel B). CBF is alternatively replaced by 10 K-based Count Score, 10 K-based Negative Score and 10 K-based Regulation Score. In Models 1, 3 and 5, the 1-year lag of 10 K-based Biodiversity Scores is implemented, while Models 2, 4 and 6 consider the 2-year lag. Control variables include *PPE*, *CAPEX*, *Rev_Growth*, *Leverage*, *Cash*, *R&D_int*, E_*score*, *Size*, and *GDP_Growth*. All variables are defined in Table A1 (Appendix). Standard errors in parentheses are clustered at the firm level.
*$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.5.2. *Countries' exposure to biodiversity risk*

Following Garel et al. (2024), we seek to understand whether the effect of CBF on firm value differs between countries. Specifically, we perform a heterogeneity analysis using the Biodiversity Habitat Index (BHI) as a variable that allows us to discriminate between countries with low and high biodiversity risk. In our case, we distinguish between countries with a BHI above the median value (high BHI), i.e., countries that experienced low habitat loss or degradation and, as opposed, countries with a BHI below the median value (low BHI). The second group includes countries that experienced severe problems in terms of biodiversity loss.

The results in Table 12 show that the influence of CBF on firm value is negative and statistically significant equally for countries with high and low biodiversity risk (or low and high BHI), with slightly stronger coefficients in high-BHI countries (Tobin's Q: Panel A – Models 1–4; MB: Panel B – Models 1–4). This pattern suggests that investors penalise firms with larger biodiversity footprints, and that such penalties are particularly pronounced in markets where biodiversity is still relatively abundant (high BHI). In these contexts, investors may anticipate future tightening of environmental regulations, rising costs of biodiversity-related externalities, or growing reputational risks, and thus discount these firms' expected future cash flows, lowering their market valuations. In contrast, in countries where biodiversity has already been severely depleted (low-BHI), the market appears to react less strongly, possibly because the biodiversity-related costs are already capitalised in current prices.

To further investigate the economic mechanisms behind these valuation effects, we also conducted additional analyses on accounting profitability (ROA). These analyses (available upon request) showed that CBF is negatively associated with ROA in low-BHI countries (−0.006**, −0.007**), while the effect is small and statistically insignificant in high-BHI countries. In low-BHI countries, where biodiversity loss has already severely materialised, a higher CBF is likely already translated into higher operational costs, resource scarcity, and lower ecological productivity, which directly erode firms' operating profitability, as reflected in lower ROA. By contrast, in high-BHI countries, where biodiversity is still relatively abundant, biodiversity-related risks are mainly feared and anticipated by investors, but they have not yet shown any effects on firms' operations and profitability. As a result, firms with high CBF are penalised in forward-looking market valuations (Tobin's Q, MB), while their current accounting profitability (ROA) remains largely unaffected.

To further strengthen this result, we divided the sample by whether or not the companies were based in Megadiverse countries, i.e.,

Table 11
The effect of CBF on Tobin's Q: tangible products vs. tangible services vs. intangible services.

Panel A. Dependent variable: Tobin's Q						
	(1)	(2)	(3)	(4)	(5)	(6)
	Tangible products		Tangible services		Intangible services	
	1-year lag	2-year lag	1-year lag	2-year lag	1-year lag	2-year lag
CBF	−0.106***	−0.111***	−0.086***	−0.095***	−0.054***	−0.047***
	(0.018)	(0.018)	(0.032)	(0.034)	(0.017)	(0.017)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,372	1,859	859	674	1,533	1,185
R^2	0.635	0.618	0.624	0.637	0.717	0.715
Adjusted R^2	0.622	0.601	0.586	0.590	0.701	0.694
Panel B. Dependent variable: MB						
	(1)	(2)	(3)	(4)	(5)	(6)
	Tangible products		Tangible services		Intangible services	
	1-year lag	2-year lag	1-year lag	2-year lag	1-year lag	2-year lag
CBF	−0.093***	−0.097***	−0.052	−0.058*	−0.076***	−0.064***
	(0.018)	(0.018)	(0.032)	(0.034)	(0.017)	(0.017)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,364	1,854	849	665	1,524	1,177
R^2	0.519	0.525	0.575	0.584	0.609	0.609
Adjusted R^2	0.502	0.503	0.531	0.530	0.587	0.581

Note(s): Fixed-effects regression results for three subsamples of companies identified according to the tangibility of the product/service they offer: tangible products, tangible services and intangible services. The dependent variable is *Tobin's Q* (Panel A) and *MB* (Panel B). Models 1, 3, and 5 implement the 1-year lag of the independent variables CBF, while Models 2, 4, and 6 consider the 2-year lag. Control variables include *PPE*, *CAPEX*, *Rev_Growth*, *Leverage*, *Cash*, *R&D_int*, E_*score*, *Size*, and *GDP_Growth*. All variables are defined in Table A1 (Appendix). Standard errors in parentheses are clustered at the firm level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

the 17 countries harbouring about 70 per cent of the earth's biodiversity (Skouloudis et al., 2019).

The results are arranged in Table 12 and show that for firms headquartered in Megadiverse countries, the relationship between CBF and firm value is stronger (Tobin's Q: Panel A – Models 5–8; MB: Panel B – Models 5–8). Firms in countries with low biodiversity suffer less from the consequences of nature's deterioration. The reasons could be a lower dependence on natural resources for companies in these countries, a lower legislative and regulatory pressure, a lower sensitivity towards the issue of biodiversity on the part of local stakeholders and a lower weight attributed by international or institutional investors to the loss of biodiversity, as it has a low impact and is local in scope. The results (available upon request) are similar, in principle, when we use ROA as the dependent variable.

4.5.3. Firms' exposure: The role of size

Biodiversity impact tends to escalate with firm size due to the increased exploitation of natural resources, broader supply chains, and numerous productive areas, increasing the risk of interaction with sensitive and vulnerable ecosystems. Furthermore, large firms are subject to greater scrutiny from the media, regulators and ESG investors (Bissoondoyal-Bheenick et al., 2023). This can increase perceived exposure, even when the impact is the same. To test the discriminant role of companies' size, we categorised them as small or large based on whether their size (in terms of total assets) falls below or above the sample median. Results for each subsample are reported in Table 13.

As expected, the negative effect of CBF on firm value is statistically significant only for larger companies, both in terms of Tobin's Q (Models 3 and 4, Table 13) and MB (Models 7 and 8, Table 13). By contrast, no significant effect emerges for smaller firms (Models 1–2 and 5–6, Table 13). In line with Carvalho et al. (2023) and Garel et al. (2024), firm size emerges as a structural driver of biodiversity risk exposure and therefore as a factor able to affect the relationship between CBF and firm value, both across and within industries.

4.6. Addressing endogeneity

4.6.1. 2SLS model

To avoid reverse causality problems, baseline models include the CBF score lagged by 1 or 2 years. To more effectively address potential endogeneity issues, we also implement a two-stage least squares (2SLS) estimation approach. Aligning with previous studies (see Liu et al., 2015; Safiullah et al., 2024), we instrument the CBF score of a specific firm in a given year by using the average CBF score of other firms in the same industry, country and year (*AvgCBF*). The rationale behind using *AvgCBF* is that firms' CBF likely positively correlates with their domestic competitors' CBF due to similar economic activities and potential impact on biodiversity (Safiullah

Table 12
The effect of CBF on firm value: countries' exposure to biodiversity risk.

Panel A. Dependent variable: Tobin's Q								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	High BHI		Low BHI		Megadiverse		Other	
	1-year lag	2-year lag	1-year lag	2-year lag	1-year lag	2-year lag	1-year lag	2-year lag
CBF	−0.097***	−0.098***	−0.073***	−0.076***	−0.123***	−0.123***	−0.049***	−0.047***
	(0.018)	(0.018)	(0.017)	(0.016)	(0.017)	(0.018)	(0.015)	(0.015)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,657	2,020	1,984	1,597	2,327	1,847	2,444	1,877
R^2	0.589	0.588	0.664	0.666	0.577	0.580	0.611	0.607
Adjusted R^2	0.579	0.574	0.651	0.650	0.566	0.567	0.597	0.589
Panel B. Dependent variable: MB								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	High BHI		Low BHI		Megadiverse		Other	
	1-year lag	2-year lag	1-year lag	2-year lag	1-year lag	2-year lag	1-year lag	2-year lag
	−0.100***	−0.098***	−0.066***	−0.070***	−0.106***	−0.104***	−0.059***	−0.058***
	(0.017)	(0.018)	(0.017)	(0.017)	(0.018)	(0.018)	(0.015)	(0.015)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,636	2,001	1,979	1,593	2,307	1,829	2,438	1,872
R^2	0.537	0.541	0.496	0.499	0.469	0.475	0.470	0.470
Adjusted R^2	0.526	0.527	0.476	0.475	0.456	0.458	0.451	0.447

Note(s): Fixed-effects regression results for subsamples of companies identified according to their high/low BHI index (Models 1–4) and according to their belonging to megadiverse countries (Models 5–8). In Panel A the dependent variable is *Tobin's Q*, while in Panel B the dependent variable is *MB*. In Models 1, 3, 5 and 7, the 1-year lag of the independent variables *CBF* is implemented, while Models 2, 4, 6 and 8 consider the 2-year lag. Control variables include *PPE*, *CAPEX*, *Rev_Growth*, *Leverage*, *Cash*, *R&D_int*, E_*score*, *Size*, and *GDP_Growth*. All variables are defined in Table A1 (Appendix). Standard errors in parentheses are clustered at the firm level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

et al., 2024; Kabir et al., 2020), as well as due to standard practices in the country where the firm is headquartered. However, *AvgCBF* is unlikely to influence individual firm value directly (Liu et al., 2015).

The results of the 2SLS model are reported in Table 14.

In particular, the first-stage estimations (Models 1a and 2a, Table 14) indicate that *AvgCBF* is positively associated with CBF and can be considered a valid instrument since the Kleibergen-Paap LM statistic[3] is statistically significant at the 1 % level. At the same time, the Kleibergen-Paap F-statistic (>10 % maximal IV, Stock and Yogo, 2002) and the Anderson-Rubin Wald test (*p-value* < 0.05) suggest that the implemented instruments are not weak. Moreover, the models do not suffer from overidentification problems, as the number of instruments and instrumented variable is the same. The second-stage estimations indicate that CBF negatively influence firms' value in terms of Tobin's Q and MB (Model 1b and 2b, Table 14), thus confirming our baseline findings.

4.6.2. GMM and LSDVC models

In addition, we also implement an iterated generalised method of moments (GMM) model, a technique that allows us to deal with multiple sources of endogeneity, including omitted variables, reverse causality and simultaneity (Arellano & Bond, 1991; Hansen et al., 1996; Blundell and Bond, 1998). This empirical method consists of a dynamic panel data estimation that can tackle endogeneity concerns by implementing internal instrument (Yang & Masron, 2024). In our setting, we assume that CBF and all control variables are potentially endogenous, while year dummies are exogenous instrumental variables (Liu et al., 2015). As instrumental variables, we also considered the second, third or fourth lags of the dependent and control variables and implemented Windmeijer's (2005) finite-sample standard error correction. The results of the iterated GMM models are shown in Table 15.

Consistent with our baseline findings, GMM models suggest that CBF negatively influences Tobin's Q (Model 1, Table 15) and MB (Model 4, Table 15). The GMM estimations satisfy all necessary conditions: the AR1 test rejects the null hypothesis of no first-order serial correlation (*p-value* < 0.05), the AR2 test accepts the null hypothesis of no second-order serial correlation (*p-value* > 0.05), and the Hansen J-test fails to reject the hypothesis of instruments' homogeneity.

However, given the short period of our dataset (5 years), GMM models may not perform optimally. To ensure the robustness of our baseline findings in a dynamic panel setting, we complement GMM with the Least Squares Dummy Variable Correction (LSDVC) method. LSDVC applies a recursive bias correction to the dynamic fixed-effects estimator and has been shown to outperform GMM in

[3] The 2SLS estimations include robust standard errors. As a consequence, the Kleibergen-Paap LM statistic and the Kleibergen-Paap F-statistic are automatically provided in place of the better-known Anderson LM statistic and the Cragg-Donald F-statistic, respectively.

Table 13
The effect of CBF on firm value: small vs. large companies.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent variable: Tobin's Q				Dependent variable: MB			
	Small companies		Large companies		Small companies		Large companies	
	1-year lag	2-year lag	1-year lag	2-year lag	1-year lag	2-year lag	1-year lag	2-year lag
CBF	−0.010	−0.014	−0.033**	−0.032**	−0.013	−0.014	−0.048***	−0.044***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.015)	(0.015)	(0.016)	(0.016)
PPE	−0.316***	−0.332***	−0.058	−0.023	−0.355***	−0.351***	−0.231***	−0.190**
	(0.096)	(0.109)	(0.089)	(0.083)	(0.099)	(0.111)	(0.088)	(0.083)
CAPEX	0.406*	0.617**	0.408**	0.336**	0.273	0.385	0.371*	0.288
	(0.231)	(0.251)	(0.191)	(0.164)	(0.210)	(0.249)	(0.224)	(0.198)
Rev_Growth	0.088*	0.075	0.038	0.023	0.110**	0.092*	0.040	0.024
	(0.052)	(0.053)	(0.062)	(0.054)	(0.050)	(0.048)	(0.060)	(0.050)
Leverage	−0.215***	−0.210***	−0.526***	−0.492***	0.633***	0.651***	0.361***	0.392***
	(0.045)	(0.047)	(0.072)	(0.073)	(0.069)	(0.073)	(0.079)	(0.082)
Cash	1.022***	1.104***	2.397***	2.566***	0.983***	1.021***	2.536***	2.675***
	(0.239)	(0.250)	(0.408)	(0.419)	(0.250)	(0.260)	(0.390)	(0.398)
R&D_int	1.018	0.811	3.380**	3.451***	1.573*	1.488	2.086	2.269*
	(0.763)	(0.819)	(1.309)	(1.329)	(0.882)	(0.963)	(1.368)	(1.374)
E_score	0.001	0.001	0.003***	0.003**	0.001	0.001	0.003**	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Size	−0.204***	−0.212***	−0.004***	−0.003***	−0.184***	−0.202***	−0.001*	−0.001*
	(0.014)	(0.015)	(0.001)	(0.001)	(0.019)	(0.016)	(0.001)	(0.001)
GDP_growth	0.008*	0.009*	0.005	0.006	0.008*	0.009*	0.000	0.002
	(0.004)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,286	1,778	2,485	1,947	2,273	1,767	2,472	1,935
R^2	0.596	0.605	0.612	0.617	0.543	0.555	0.517	0.525
Adjusted R^2	0.580	0.585	0.598	0.599	0.524	0.532	0.499	0.503

Note(s): Fixed-effects regression results for two subsamples of companies identified according to their *Size*: small and large companies. In Models 1–4 the dependent variable is *Tobin's Q*, while in Models 5–8 the dependent variable is *MB*. In Models 1, 3, 5 and 7, the 1-year lag of the independent variables *CBF* is implemented, while Models 2, 4, 6 and 8 consider the 2-year lag. All variables are defined in Table A1 (Appendix). Standard errors in parentheses are clustered at the firm level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

short panels (Tanin et al., 2024; Bruno, 2005). Unlike GMM, LSDVC provides more reliable estimates in small samples, avoids weak instruments, finite sample bias, and the risk of overfitting. Results, based on the Arellano-Bond (AB) and Blundell-Bond (BB) estimators and with a bias correction up to order O(1/NT^2), are provided in Table 15 and fully confirm our baseline results (Models 2–3 and 5–6, Table 15).

4.6.3. Firm fixed effects and entropy balancing method

We acknowledge that in our main analysis, there may be some unobserved firm-specific characteristics not captured by our control variables. To mitigate potential omitted variable bias, we rerun the baseline specifications with firm fixed effects to verify the stability of our findings. Results are reported in Table 16 for the dependent variables Tobin's Q and MB (Models 1 and 3, respectively) and corroborate our main findings.

Finally, following Hasan et al. (2021), we also re-run our baseline model after implementing the entropy balancing method, able to deal with random and systematic inequalities between firms with high and low impact on biodiversity (Xu et al., 2024). In particular, we divide the firm-year observations into treatment (high CBF) and control (low CBF) groups based on the yearly median value of CBF. Entropy balancing re-weights the observations of the control group to balance the mean, variance, and skewness of variables across treatment and control units. Then, we re-estimate regressions using entropy-balanced observations, whose results are reported in Models 2 and 4 of Table 16 for Tobin's Q and MB, respectively. Again, CBF's negative and statistically significant effect on firms' value is confirmed.

5. Discussion and conclusions

Our paper responds to the growing call for greater involvement of banking and finance scholars in tackling biodiversity loss (Karolyi & Tobin-de la Puente, 2023) and empirical evidence on the financial materiality of firms' impact on biodiversity. Using fixed-effects regression models on a global panel of 1,848 publicly listed firms from 49 countries between 2018 and 2022, we show that firms' biodiversity impact, as measured by the Corporate Biodiversity Footprint (CBF), negatively affects firm value, as proxied by Tobin's Q and Market-to-Book ratio. These findings are robust across multiple specifications, including endogeneity and reverse causality tests.

By decomposing the effect across the environmental channels underlying the CBF (land use, greenhouse gas emissions, air

Table 14
Addressing endogeneity: instrumental 2SLS regressions.

	(1a)	(1b)	(2a)	(2b)
	First stage	Second stage	First stage	Second stage
Dep. variable	CBF	Tobin Q	CBF	MB
CBF		−0.306***		−0.282***
		(0.056)		(0.053)
Avg_CBF	0.224***		0.224***	
	(0.030)		(0.030)	
PPE	−0.256***	−0.183***	−0.253***	−0.318***
	(0.093)	(0.049)	(0.094)	(0.052)
CAPEX	−1.117***	−0.042	−1.121***	0.013
	(0.225)	(0.137)	(0.226)	(0.137)
Rev_Growth	−0.283***	−0.009	−0.284***	0.019
	(0.046)	(0.069)	(0.046)	(0.073)
Leverage	0.325***	−0.467***	0.347***	−0.373***
	(0.079)	(0.047)	(0.084)	(0.048)
Cash	−1.586***	1.898***	−1.569***	1.774***
	(0.316)	(0.192)	(0.319)	(0.180)
R&D_int	−1.684**	1.975***	−1.507*	1.981***
	(0.804)	(0.553)	(0.808)	(0.570)
E_score	0.022***	0.003**	0.022***	0.003**
	(0.001)	(0.001)	(0.001)	(0.000)
Size	0.006***	−0.002***	0.006***	−0.000
	(0.002)	(0.001)	(0.002)	(0.000)
GDP_growth	−0.013	0.005	−0.013	0.005
	(0.019)	(0.009)	(0.019)	(0.008)
Observations	3,970		3,948	
Year FE	Yes		Yes	
Country FE	Yes		Yes	
Industry FE	Yes		Yes	
Kleibergen-Paap LM statistic †	0.000		0.000	
Kleibergen-Paap Wald-statistic	55.13		55.30	
Stock and Yogo 10 % maximal IV	16.38		16.38	
Anderson-Rubin test †	0.000		0.000	

Note(s): Results of 2SLS regression. Models 1a-1b reports the results of the 2SLS regression with *Tobin's Q* as dependent variable, while Models 2a and 2b reports the results of the 2SLS regression for the dependent variable *MB*. In all Models, the 1-year lag of the independent variables *CBF* is implemented. All variables are defined in Table A1 (Appendix). Robust standard errors in parentheses.
† indicates p-values, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

pollution, and water pollution), we find that greenhouse gas emissions are the primary environmental channel through which CBF affects the firm value. In parallel, when distinguishing by type of impact (or Scope), we find that biodiversity loss is mainly transmitted through the value chain. To a lesser extent, the direct impact significantly reduces firm value.

In addition, our results reveal two fundamental channels through which biodiversity-related exposures erode firm value. First, CBF reduces firms' operating profitability (ROA): a DuPont decomposition shows that it significantly lowers profit margins. Second, CBF reduces the level and increases the volatility of operating cash flows, which are crucial determinants of firm value in discounted cash flow models.

Our results remain robust when substituting the dependent variable with Enterprise Value (EV) and using an alternative biodiversity metric based on 10-K filings proposed by Giglio et al. (2023).

The effect of CBF on firm value varies across industry, country, and firm levels. The negative association between CBF and firm value holds across sectors but is particularly strong for firms producing tangible goods. Moreover, it is particularly strong for large firms, firms headquartered in megadiverse countries and firms sited in countries that have not undergone substantial biodiversity degradation (high BHI); differently, a negative association between CBF and ROA emerges more clearly for firms placed in countries that have already experienced severe biodiversity loss (low BHI).

Table 15
Addressing endogeneity: two-step GMM regressions and LSDVC regressions.

	(1)	(2)	(3)	(4)	(5)	(6)
	Two-step GMM	LSDVC AB	LSDVC BB	Two-step GMM	LSDVC AB	LSDVC BB
Dep. variable		Tobin Q			MB	
Lag (Dep. Var)	0.365**	0.456***	0.689***	0.498***	0.611***	0.683***
	(0.142)	(0.033)	(0.020)	(0.139)	(0.031)	(0.018)
CBF	−0.027***	−0.029**	−0.035***	−0.023**	−0.046***	−0.038***
	(0.011)	(0.012)	(0.007)	(0.011)	(0.010)	(0.010)
PPE	−0.027***	0.050	0.043	−0.212**	0.132**	0.127**
	(0.087)	(0.083)	(0.049)	(0.083)	(0.062)	(0.057)
CAPEX	−0.162	−0.302**	−0.275***	−0.270	−0.251***	−0.219**
	(0.266)	(0.128)	(0.083)	(0.226)	(0.094)	(0.098)
Rev_Growth	1.834***	0.035*	0.030**	1.365***	0.002	0.015
	(0.337)	(0.021)	(0.014)	(0.366)	(0.016)	(0.017)
Leverage	−0.568***	0.006	0.018	0.040	−0.183***	−0.112***
	(0.131)	(0.055)	(0.033)	(0.049)	(0.039)	(0.038)
Cash	0.186	0.360*	0.304***	0.122	0.147	0.179
	(0.300)	(0.198)	(0.117)	(0.282)	(0.162)	(0.156)
R&D_int	3.684***	−2.370**	−1.438***	3.001***	−2.996***	−2.376***
	(1.193)	(0.946)	(0.546)	(0.988)	(0.684)	(0.649)
E_score	0.000	−0.006***	−0.006***	0.000	−0.008***	−0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Size	−0.003***	−0.000	−0.002***	−0.001***	−0.003***	−0.002***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
GDP_growth	−0.027	0.006***	0.003*	−0.019	0.001	−0.000
	(0.019)	(0.002)	(0.001)	(0.021)	(0.001)	(0.002)
Observations	4,767	4,767	4,767	4,741	4,741	4,741
N. of groups		1,279	1,340		1,273	1,335
AR1 †	0.043			0.040		
AR2 †	0.843			0.782		
Hansen J-test †	0.838			0.397		

Note(s): Results of empirical models of GMM and LSDVC estimations. Models 1 and 4 report the results of the GMM estimations for the dependent variables *Tobin's Q* and *MB*, respectively. Finally, Models 2, 3, 5 and 6 reports the LSDVC regression estimates for the dependent variables *Tobin's Q* and *MB*. In all Models, the 1-year lag of the independent variables *CBF* is implemented. All variables are defined in Table A1 (Appendix). In Models 1 and 4 robust standard errors are in parentheses. In Models 2 and 3 bootsrapped standard errors are in parentheses.
† indicates p-values.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Overall, our findings suggest that biodiversity-related exposures reduce market valuations and undermine the profitability and cash-flow foundations on which firm value depends. These results have relevant implications for investors, lenders, corporate managers, and policymakers aiming to realign capital allocation and corporate strategies with global biodiversity goals. Investors, rating agencies, and banks should consider carefully the CBF and, in general, measures of biodiversity impact of a firm, to improve screening and monitoring processes and assess and price credit and market risks more accurately, urging corporate strategies aimed at mitigating or offsetting their biodiversity impact. Corporate managers and boards should focus on and assess firms' biodiversity dependencies and impacts across the entire value chain and align their governance, risk management, and capital budgeting with nature-positive transition pathways. Policymakers may find support and validation for regulatory initiatives to promote mandatory biodiversity disclosure to enhance market transparency.

Our findings also suggest that rising investor awareness of biodiversity risks may reshape the perception of natural capital, making its long-term benefits more visible despite higher short-term transition costs. This shift could foster a firm's biodiversity-conscious culture and promote governance structures attuned to nature, biodiversity, and ecosystem services.

Naturally, our study faces limitations, particularly the reliance on a single data source (Iceberg Data Lab's CBF) to quantify firm-level biodiversity impacts. While Iceberg Data Lab's CBF is currently the most recognised metric, and the only one incorporating Scope 3 downstream impacts (Finance for Biodiversity, 2022), future research would benefit from triangulating multiple data sources to strengthen empirical robustness.

CRediT authorship contribution statement

Simona Cosma: Writing – review & editing, Writing – original draft, Validation, Supervision, Investigation, Conceptualization. **Stefano Cosma:** Writing – review & editing, Writing – original draft, Validation, Supervision, Investigation, Conceptualization. **Daniela Pennetta:** Writing – review & editing, Writing – original draft, Software, Methodology, Investigation, Data curation.

Table 16
Addressing endogeneity: firm fixed effects and entropy balancing regressions.

	(1)	(2)	(3)	(4)
	Firm FE	Entropy balancing	Firm FE	Entropy balancing
Dep. variable	Tobin Q		MB	
CBF	−0.018***	−0.087***	−0.023***	−0.085***
	(0.006)	(0.021)	(0.007)	(0.023)
PPE	−0.054	−0.324***	0.024	−0.533***
	(0.099)	(0.118)	(0.064)	(0.115)
CAPEX	−0.390***	0.940***	−0.355**	1.003***
	(0.124)	(0.296)	(0.144)	(0.295)
Rev_Growth	0.048*	0.109*	0.031	0.106
	(0.026)	(0.064)	(0.020)	(0.066)
Leverage	−0.087**	−0.661***	0.171***	0.352**
	(0.037)	(0.095)	(0.059)	(0.137)
Cash	0.464***	1.651***	0.155	1.653***
	(0.162)	(0.330)	(0.216)	(0.332)
R&D_int	−1.601**	1.875	−2.929***	3.007***
	(0.732)	(1.183)	(1.072)	(1.115)
E_score	−0.002***	−0.002	−0.002**	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Size	−0.003***	−0.004***	−0.002***	−0.002***
	(0.001)	(0.000)	(0.001)	(0.000)
GDP_growth	0.011***	0.006	0.011***	0.008
	(0.002)	(0.007)	(0.003)	(0.007)
Firm FE	Yes	No	Yes	No
Year FE	Yes	Yes	Yes	Yes
Country FE	No	Yes	No	Yes
Industry FE	No	Yes	No	Yes
Observations	4,714	4,730	4,688	4,730
R^2	0.961	0.632	0.938	0.513
Adjusted R^2	0.945	0.625	0.912	0.503

Note(s): Results of empirical models with firm FE and entropy balancing regressions. Models 1 and 3 report the results of empirical models with firm FE for the dependent variables *Tobin's Q* and *MB*, respectively. Finally, Models 2 and 4 reports the entropy balancing regression estimates for the dependent variables *Tobin's Q* and *MB*, respectively. In all Models, the 1-year lag of the independent variables *CBF* is implemented. All variables are defined in Table A1 (Appendix). In Models 1 and 3, standard errors are clustered at the firm level. In Models 2 and 4 robust standard errors are in parentheses.
*$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Giuseppe Rimo: Writing – review & editing, Writing – original draft, Software, Methodology, Investigation, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

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Table A1
Definition and source of variables.

Variable	Definition	Source
Dependent variables		
Tobin's Q	The market capitalization ratio to the replacement cost of its total assets. Implemented in its natural logarithm form.	LSEG Data & Analytics (**)
Market-to-Book (MB)	Market capitalization on total equity. Implemented in its natural logarithm form.	LSEG Data & Analytics
ROA (*)	Pretax income on total assets.	LSEG Data & Analytics
Profit_margin (*)	Pretax income on sales. Implemented in its natural logarithm form.	LSEG Data & Analytics
Asset_turnover (*)	Sales on total assets. Implemented in its natural logarithm form.	LSEG Data & Analytics
EV (*)	Enterprise value on total assets. Enterprise value is computed as the market value of equity, debt, and other non-equity claims, minus cash and cash equivalents.	LSEG Data & Analytics
Independent variables		
CBF	The biodiversity loss is caused by the company's annual economic activity. The CBF score is multiplied by −1 and implemented in its natural logarithm form.	Iceberg Data Lab

(*continued on next page*)

Table A1 (*continued*)

Variable	Definition	Source
CBF_land (*)	The biodiversity loss caused by company's occupation or transformation of land. The CBF_land score is multiplied by −1 and implemented in its natural logarithm form.	Iceberg Data Lab
CBF_ghg (*)	The biodiversity loss caused by company's GHG emissions. The CBF_ghg score is multiplied by −1 and implemented in its natural logarithm form.	Iceberg Data Lab
CBF_air (*)	The biodiversity loss caused by company's air pollution. The CBF_air score is multiplied by −1 and implemented in its natural logarithm form.	Iceberg Data Lab
CBF_water (*)	The biodiversity loss caused by company's water pollution. The CBF_water score is multiplied by −1 and implemented in its natural logarithm form.	Iceberg Data Lab
CBF_s1 (*)	The biodiversity loss caused by company's direct activities (Scope 1). The CBF_s1 score is multiplied by −1 and implemented in its natural logarithm form.	Iceberg Data Lab
CBF_s2 (*)	The biodiversity loss is caused by the company's electricity, heat, and cooling (Scope 2). The CBF_s2 score is multiplied by −1 and implemented in its natural logarithm form.	Iceberg Data Lab
CBF_s3 (*)	The biodiversity loss caused by company's indirect pressures (Scope 3). The CBF_s3 score is multiplied by −1 and implemented in its natural logarithm form.	Iceberg Data Lab
CBF/Sales (*)	CBF score divided by sales.	Iceberg Data Lab
10 K-based Count Score (*)	Binary variable equal to 1 if a 10-K statement contains at least two sentences related to biodiversity, 0 otherwise.	Giglio et al. (2023)
10 K-based Negative Score (*)	The number of negative biodiversity sentences minus the number of positive sentences in a 10-K statement.	Giglio et al. (2023)
10 K-based Regulation Score (*)	Binary variable equal to 1 if the 10-K statement of a company contains at least two biodiversity risk sentences and at least one of them is a biodiversity regulation risk sentence, 0 otherwise.	Giglio et al. (2023)
AvgCBF	Average CBF score of other firms by country, industry and year.	Iceberg Data Lab
Control variables		
PPE	Property, plant and equipment on total revenue. Implemented in its natural logarithm form.	LSEG Data & Analytics
CAPEX	Capital expenditures on total revenue. Implemented in its natural logarithm form.	LSEG Data & Analytics
Rev_Growth	Annual growth rate of total revenue.	LSEG Data & Analytics
Leverage	Total debt on total equity. Implemented in its natural logarithm form.	LSEG Data & Analytics
Cash	Cash and other short-term assets on total assets. Implemented in its natural logarithm form.	LSEG Data & Analytics
R&D_int	R&D expenses on total assets. Implemented in its natural logarithm form.	LSEG Data & Analytics
E_score	A score ranging between 0 and 100 that measures companies' environmental performance.	LSEG Data & Analytics
Size	Total assets (bn$)	LSEG Data & Analytics
GDP_growth	Annual growth rate of GDP per capita.	World Bank
Tang_product (*)	Binary variable equal to 1 when the company belongs to industries specialized in the provision of "tangible products", 0 otherwise.	Hoogendoorn et al. (2015)
Tang_service (*)	Binary variable equal to 1 when the company belongs to industries specialized in providing "tangible services", 0 otherwise.	Hoogendoorn et al. (2015)
Intang_service (*)	Binary variable equal to 1 when the company belongs to industries specialized in the provision of "intangible services", 0 otherwise.	Hoogendoorn et al. (2015)
Megadiverse (*)	Binary variable equal to 1 when the company is located in megadiverse countries, 0 otherwise.	United Nations World Conservation Monitoring Centre (WCMC)
BHI (*)	Binary variable equal to 1 when the company is located in a country whose Biodiversity Habitat Index is above the median, 0 otherwise. The BHI measures the extent to which a country has experienced habitat loss or degradation. A score of 100 indicates no habitat loss or degradation, and a score of 0 indicates complete habitat loss.	Yale Center for Environmental Law and Policy
opCF_TA (*)	Cash Flow from operating activities on total assets.	LSEG Data & Analytics
CF_volatility (*)	Standard deviation of company's Cash Flow computed on a 3-year rolling window. Implemented in its natural logarithm form.	LSEG Data & Analytics

Note(s):
(*) Variables only implemented in additional, robustness, heterogeneity and mechanism analyses.
(**) Formerly known as Refinitiv Eikon.

Table A2
Correlation matrix.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Tobin's Q (1)	1											
MB (2)	0.848***	1										
CBF (3)	−0.217***	−0.205***	1									
PPE (4)	−0.051***	−0.117***	0.031***	1								
CAPEX (5)	0.031**	−0.021	−0.086***	0.617***	1							
Rev_Growth (6)	0.021	0.015	−0.006	0.028**	0.050***	1						
Leverage (7)	−0.400***	−0.032**	0.131***	0.094***	0.015	−0.010	1					
Cash (8)	0.405***	0.308***	−0.212***	−0.192***	−0.051***	0.021*	−0.307***	1				
R&D_int (9)	0.356***	0.318***	−0.113***	−0.081***	0.036***	0.062***	−0.172***	0.365***	1			
E_score (10)	−0.235***	−0.186***	0.323***	0.005	−0.036***	−0.054***	0.139***	−0.241***	−0.096***	1		
Size (11)	−0.391***	−0.228***	0.189***	−0.080***	−0.045***	−0.008	0.172***	−0.141***	−0.096***	0.156***	1	
GDP_growth (12)	0.075***	0.069***	0.012	−0.006	0.024**	0.018	−0.018	0.028**	0.058***	−0.090***	−0.027**	1

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A3
Univariate analysis.

Panel A	Mean difference test Division of sample into CBF terciles by year and industry				Median difference test			
	Low CBF T1	High CBF T3	Diff.	t-value	Low CBF T1	High CBF T3	Diff.	z-value
Tobin's Q	0.355	−0.579	0.935	25.009***	0.469	−0.475	0.944	25.017***
MB	1.290	0.708	0.583	20.742***	1.293	0.686	0.607	21.442***
Panel B	Division of sample into CBF terciles by year and country							
	Low CBF T1	High CBF T3	Diff.	t-value	Low CBF T1	High CBF T3	Diff.	z-value
Tobin's Q	0.328	−0.616	0.944	25.228***	0.469	−0.474	0.943	24.199***
MB	1.194	0.574	0.620	20.896***	1.199	0.539	0.660	20.874***

Note(s): Mean and median tests of difference between low (T1) and high (T3) CBF terciles, identified by year and industry (Panel A) and by year and country (Panel B). *** denotes statistical significance at 1 % level.

Table A4
Granger-causality test (1-year lag length).

Null hypothesis	Wald test Chi-sq.	Prob.	Decision
CBF does not Granger-cause Tobin's Q	16.816***	0.000	Reject
Tobin's Q does not Granger-cause CBF	0.999	0.318	Accept
CBF does not Granger-cause MB	63.082***	0.000	Reject
MB does not Granger-cause CBF	3.851	0.146	Accept

Note(s): Results of the Granger-causality test between CBF and Tobin's Q and between CBF and MB. Estimates consider 1-lag structure. ** and *** denote the rejection of the null hypothesis at 5 % and 1 % level of significance, respectively.

Table A5
Sensitivity test: CBF/sales as alternative independent variable.

	(1)	(2)	(3)	(4)
	Dependent variable: Tobin's Q 1-year lag		Dependent variable: MB 2-year lag	
CBF/sales	−0.028**	−0.025*	−0.040***	−0.036**
	(0.014)	(0.014)	(0.014)	(0.014)
PPE	−0.161**	−0.141*	−0.265***	−0.232***
	(0.075)	(0.076)	(0.069)	(0.071)
CAPEX	0.555***	0.608***	0.447**	0.443**
	(0.189)	(0.210)	(0.175)	(0.192)
Rev_Growth	0.067	0.061	0.076	0.066
	(0.068)	(0.068)	(0.064)	(0.060)
Leverage	−0.601***	−0.567***	0.277***	0.317***
	(0.059)	(0.060)	(0.061)	(0.063)
Cash	2.266***	2.452***	2.209***	2.376***
	(0.230)	(0.234)	(0.222)	(0.227)
R&D_int	2.519***	2.430***	2.504***	2.472***
	(0.852)	(0.881)	(0.884)	(0.929)
E_score	−0.003***	−0.003***	−0.003***	−0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
Size	−0.004***	−0.004***	−0.002***	−0.002***
	(0.001)	(0.001)	(0.001)	(0.001)
GDP_growth	0.003	0.003	0.001	0.002
	(0.003)	(0.003)	(0.003)	(0.004)
Year FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	4,772	3,725	4,746	3,702
R^2	0.575	0.575	0.461	0.464
Adjusted R^2	0.567	0.564	0.450	0.450

Note(s): Fixed-effects regression results for the dependent variables *Tobin's Q* and *MB*. Models 1–3 implement the 1-year lag of the alternative independent variable *CBF/sales*, while Models 4–6 consider the 2-year lag. All variables are defined in Table A1 (Appendix). Standard errors in parentheses are clustered at the firm level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Data availability

The authors do not have permission to share data.

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