Biodiversity risk and stock price synchronicity

Xu Xiaoyang[a]
[a]School of Finance and Economics, Jiangsu University, No.301, Xuefu Road, Zhenjiang, 212013, Jiangsu P. R. China
xiaoyangxu@ujs.edu.cn

Destan Kirimhan[b]
[b]School of Business Administration, American University of Sharjah, University City, 26666, Sharjah, United Arab Emirates
dkirimhan@aus.edu

Brian M. Lucey[c,d,]
[b]Shanghai Lixin University of Accounting and Finance, Shanghai, China
[c]Trinity Business School, Dublin, Ireland
blucey@tcd.ie

Muhammad Ayaz[e,f*]
[e]School of Finance and Economics, Jiangsu University, No.301, Xuefu Road, Zhenjiang, 212013, Jiangsu P. R. China
[f]Department of Management Sciences, Qurtuba University of Science and IT, Peshawar Khyber Pakhtunkhwa, Pakistan
mayaziiui@gmail.com

Abstract

In this paper, we use a sample of Chinese A-share listed firms from 2007 to 2023 to investigate the relation between firm-level biodiversity risk and stock price synchronicity. Our findings show that biodiversity risk increases stock price synchronicity, suggesting greater incorporation of market- and industry-wide information into stock prices. This effect is more pronounced in financially constrained firms, non-state-owned enterprises, and those with lower management integrity. We also find that information disclosure quality and stock price crash risk act as key channels through which biodiversity risk affects stock price synchronicity. Furthermore, the impact of biodiversity risk is both systematic and idiosyncratic. While the stronger systematic component indicates that biodiversity risk can act as a systemic economic shock, potentially in sectors reliant on natural capital, the significant idiosyncratic effect highlights investor attention to firm-specific biodiversity strategies. Our results are robust to various model specifications, alternative measures of biodiversity risk and stock price synchronicity, and endogeneity concerns. Overall, we identify biodiversity risk as a systemic factor influencing stock pricing, demonstrating its relevance for corporate disclosure, risk management, and investment decision making by firms, regulators, and investors.

Keywords: Biodiversity risk; stock price synchronicity; stock price crash risk; information

transparency; China

Biodiversity risk and stock price synchronicity

Abstract

In this paper, we use a sample of Chinese A-share listed firms from 2007 to 2023 to investigate the relation between firm-level biodiversity risk and stock price synchronicity. Our findings show that biodiversity risk increases stock price synchronicity, suggesting greater incorporation of market- and industry-wide information into stock prices. This effect is more pronounced in financially constrained firms, non-state-owned enterprises, and those with lower management integrity. We also find that information disclosure quality and stock price crash risk act as key channels through which biodiversity risk affects stock price synchronicity. Furthermore, the impact of biodiversity risk is both systematic and idiosyncratic. While the stronger systematic component indicates that biodiversity risk can act as a systemic economic shock, potentially in sectors reliant on natural capital, the significant idiosyncratic effect highlights investor attention to firm-specific biodiversity strategies. Our results are robust to various model specifications, alternative measures of biodiversity risk and stock price synchronicity, and endogeneity concerns. Overall, we identify biodiversity risk as a systemic factor influencing stock pricing, demonstrating its relevance for corporate disclosure, risk management, and investment decision making by firms, regulators, and investors.

Keywords: Biodiversity risk; stock price synchronicity; stock price crash risk; information transparency; China

1. Introduction

Biodiversity risk exposure generates financial consequences for firms due to biodiversity loss, which erodes the ecosystem services that firms and economies depend on. These risks are typically classified as *physical risks*, stemming from direct disruptions to the sources of production and service delivery, such as resource scarcity or disease outbreaks, and *transition risks*, compelling market participants to respond to emerging conditions arising from changes in regulatory framework, technology, or consumer preferences aimed at protecting biodiversity (OECD, 2023). Both types of risks can affect firm revenues, asset values, and portfolio performance, highlighting the growing importance of biodiversity as a systemic financial factor.

Previous studies have examined stock returns and market risk premiums (Garel et al., 2024; Kalhoro and Kyaw, 2024; Ma et al., 2024; Apergis, 2025), with evidence that biodiversity risk can hurt firm valuation (Ma et al., 2025; Sun et al., 2025), firm performance (Bach et al., 2025; Khan and Lucey, 2025), corporate dividend payments (Zhou et al., 2025b), and lead to future stock price crash risks (Bassen et al., 2024; Liang et al., 2024). These arguments underscore the need to examine how biodiversity risk can affect stock price synchronicity, revealing how environmental factors shape both firm-specific and market-wide information incorporation into stock pricing.

By influencing both firm-specific fundamentals and market-wide dynamics, biodiversity risk can increase stock price synchronicity, reflecting a greater reliance on market- and industry-level information when firm-level signals are less reliable (Ma et al., 2022). At the same time, biodiversity risk may contain both systematic and idiosyncratic components, indicating that while some effects are common across industries, investors also respond to firm-level strategies and exposures that deviate from industry norms (Giglio et al., 2023; Balogh et al., 2025).

Biodiversity risk may influence stock price synchronicity through multiple channels that affect the flow and reliability of firm-specific information. First, exposure to biodiversity risk can reduce *information disclosure quality* as managers face trade-offs between disclosing negative environmental information and avoiding adverse market or regulatory reactions. Firms may selectively disclose or obscure environmental information to safeguard market perceptions or mitigate reputational, legal, and financing costs (Verrecchia, 1983; Yu et al., 2020). Such opaque reporting practices increase information asymmetry problem and limit investors' ability to assess firm-specific fundamentals, forcing greater reliance on market- and industry-level signals and hence, increasing stock price synchronicity. Second, biodiversity risk can heighten *stock price crash risk* as managers may hoard negative firm-specific information related to environmental exposures to avoid regulatory scrutiny and adverse market reactions (Jin & Myers, 2006; Gan et al., 2024; Zhao et al., 2024). The sudden release of accumulated negative information, for instance via policy intervention or shareholder activism, can activate sharp price corrections (Jin & Myers, 2006). Together, these channels suggest that biodiversity risk not only increases reliance on common market factors but also affects the incorporation of firm-specific information into stock prices, with systematic exposures amplifying market-wide co-movements while idiosyncratic exposures remain valid for individual firm strategies.

We test our predictions using a sample of Chinese A-share listed firms from 2007 to 2023 since their high exposure to biodiversity risks constitutes a well-suited empirical setting (He et al., 2024). Our analysis shows that biodiversity risk increases stock price synchronicity, with stronger effects for financially constrained firms, non-state-owned enterprises, and those with lower management integrity. Information disclosure quality and stock price crash risk emerge as key channels through which biodiversity risk affects synchronicity. Decomposing biodiversity risk into systematic and idiosyncratic components, we find that the systematic component drives broader market co-movements while investors also respond to firm-specific strategies that deviate from industry norms. These results are robust to alternative measures of biodiversity risk and stock price synchronicity as well as to endogeneity concerns.

Our study contributes to the literature by demonstrating that firm-level biodiversity risk increases stock price synchronicity through the channels of information disclosure quality and stock price crash risk. Furthermore, we report that both market-wide and firm-specific factors are crucial for investors. Finally, our focus on Chinese firms extends the empirical evidence beyond the U.S. and European markets and shows that our results are heterogenous across firms.

The remainder of the paper is organized as follows. Section 2 presents our research design. Section 3 provides the empirical results. While Section 4 concludes the paper, online appendix demonstrates various robustness tests.

2. Research design

2.1 Data

The study's sample comprises of all Chinese A-share listed firms on the Shanghai and Shenzhen stock exchanges from 2007 to 2023. We select 2007 as the starting year because China adopted new accounting standards in this year. The sample period ends in 2023, representing the last year for which firm-level biodiversity risk data are available for Chinese firms.

Data on biodiversity risk and climate policy uncertainty at the provincial level are gathered from the ISETS Energy Finance Network (IEFN) climate attention database[1]. Firm-level financial data and weekly stock returns are obtained from CSMAR and Wind databases, respectively.

To construct the final sample, we merge all datasets and then apply several screening filters following prior literature on stock price synchronicity. First, we require firms to have at least 30 trading weeks during the sample period to ensure sufficient data availability. Second, we eliminate financial firms and utilities due to their unique regulatory environments. Third, we drop special treatment (ST, PST) firms and those with missing information on key variables form our sample. Finally, we winsorized all continuous variables at 2% and 98% to mitigate the influence of outliers. The resulting final sample is used for the analyses.

[Please insert Tables 1A and 1B about here]

Tables 1A and 1B report the summary statistics and correlation coefficients among variables. Our analysis does not suffer from a significant multicollinearity issue marked by the correlation coefficients and the variance inflation factor (VIF) statistics.

2.2 Variable definitions

2.2.1 Stock price synchronicity

Stock price synchronicity (SYNC) is constructed in two-steps following prior studies (Gul et al., 2010). The first step involves calculating the R^2 for each firm-year observation using the conventional market model presented below:

$$R_{i,w,t} = \beta_0 + \beta_1 Market_{w,t} + \beta_2 Market_{t-1} + \beta_3 Indr_{k,t} + \beta_4 Indr_{k,t-1} + \varepsilon_{i,t} \quad [1]$$

[1]Please see https://www.cnefn.com/data/download/climate-attention-database/.

where $R_{i,w,t}$ is the weekly return of firm *i* at week *t*. $Market_{w,t}$ is the value-weighted market return at week *t*. $Indr_{k,t}$ is the average return of industry *K* excluding the subject firm i's return at week *t*. To control for the probability of non-contemporaneous correlation, the lagged market and industry return are included in Eq.[1]. In step 2, stock price synchronicity (SYN1) for each firm at time *t* is computed as the log transformation of the R-squared as in Eq. [2].

$$SYN1_{i,t} = log\left[\frac{R_{i,t}^2}{1-R_{i,t}^2}\right] \qquad [2]$$

2.2.2 Biodiversity risk

The main explanatory variable in this study is firm-level biodiversity risk which is captured through Biodiversity Risk index (*Biodiv_risk*) introduced by He et al. (2024). Using text-as-data methods, this measure examines biodiversity-related concerns highlighted in the annual reports of Chinese listed firms, in accordance with the framework developed by Giglio et al. (2023). This variable is constructed as a dummy variable that takes the value of 1 if a biodiversity related character appears more than twice in a firm's annual report, and zero otherwise. He et al. (2024) developed comprehensive firm-level biodiversity risk indices for over 40,000 Chinese firms across different sectors, covering a 23-year period. By leveraging textual information from corporate annual reports, these widely-employed indices in empirical research offer a timely and forward-looking assessment of biodiversity risk that conventional financial indicators might not adequately capture (Zhou et al., 2025a).

2.2.3 Control variables

Following previous studies on stock price synchronization (Gul et al., 2010; Ayaz et al., 2025), we control for several variables that can potentially impact SYNC. These variables are firm size, leverage, market-to-book ratio, cash flow, growth, board size, CEO duality, board independence, ownership concentration, management shareholding, and audit opinion. Appendix A displays the definitions of all variables used in our analyses.

2.3 Methodology

Grounded on previous literature on SYNC, we formulate the following panel regression model to empirically investigate the relationship between firm's exposure to biodiversity risk and stock price synchronization:

$$SYN1_{i,t} = \beta_0 + \beta_1 Biodiv_{risk_{i,t}} + \sum \beta_n \chi_{i,t} + firm_i + year_t + \varepsilon \qquad [3]$$

where i and t represent firm i at time t. The dependent variable is stock price synchronicity ($SYN1_{i,t}$) that is constructed through equation (2). The main variable of interest is $Biodiv_{risk_{i,t}}$ that captures firm's exposure to biodiversity risk. $\chi_{i,t}$ represents a set of firm- and corporate governance-level control variables. We also control for firm fixed effects and year fixed effects and t-statistics are clustered at the firm level. A positive and significant value of β_1 supports our prediction that firm's exposure to biodiversity risk increases stock price synchronicity.

3. Empirical results

3.1 Baseline results

Table 2 reports the baseline regression results investigating the relationship between *Biodiv_risk* and SYNC. Column [1] presents the regression results without control variables and firm-level fixed effects while firm-level fixed effects are added in column [2]. Results with firm-level control variables along with firm and time fixed effects are displayed in column [3]. Moreover, column [4] displays the results with full set of control variables with firm and year fixed effects. The coefficient on *Biodiv_risk* is positive and significant across columns. Our full model specification implies that one standard deviation increase in biodiversity risk leads to a 2.6 percentage point increase in stock price synchronicity, holding all other factors equal. The results indicate that higher biodiversity exposure constrains investors' and creditors' access to reliable firm-specific information stemming from limited disclosures and the elevated costs of processing ecological data which exacerbates information asymmetry and compels greater reliance on market- or industry-wide factors. The results align with prior research, showing that climate-related uncertainties create financial burdens for firms, which in turn constrain the transmission of ecological information to investors and hinder the delivery of value-relevant signals, thereby increasing stock price synchronicity (Ma et al., 2022).

Control variables exhibit the expected signs. For instance, firm size, ROA, market-to-book ratio, management shareholding, and audit opinion are positively and significantly correlated with stock price synchronization, yielding that larger, more profitable firms with higher market to book ratio, greater managerial ownership, and favorable audit opinion greatly capitalize market and industry-wide information. In contrast, firms with higher leverage, greater growth rates, and higher ownership concentration have lower stock price synchronicity. Overall, the results in Table 2 highlight that firms' biodiversity risk increases stock price synchronicity, indicating greater incorporation of market-wide information into stock prices.

[Please insert Table 2 about here]

3.2 Decomposing biodiversity risk: Idiosyncratic vs. Systematic components

We extend our analysis to investigate whether biodiversity risk contains both firm-specific and common elements, in support of our theoretical framework. This decomposition is critical for confirming that our synchronicity results capture systematic, industry-wide biodiversity risk rather than firm-specific environmental exposures that could be diversified away through sustainability initiatives or tailored firm-level strategies. By isolating these risk components, we gain deeper insights into how environmental factors shape stock performance and market behavior. Specifically, we measure the idiosyncratic component of biodiversity as the firm specific deviations from the industry-year average, whereas systematic component is measured as the mean of industry-year biodiversity exposure.

We augment Eq. [3] utilizing both components as primary independent variables. Table 3 indicates that the impact of systematic component is stronger than the idiosyncratic component. This implies that biodiversity risk often manifests as systemic economic shock, specifically in natural capital-dependent sectors. At the same time, the idiosyncratic component highlights that investors also pay attention to firm-level strategies that deviate from industry norms. These results align with Balogh et al. (2025) who similarly find that investment decisions are influenced by both firm-specific and sector-level biodiversity risk. Similarly, Giglio et al. (2023) find that portfolios sorted by firm-level exposures covary with innovations in aggregate biodiversity risk.

[Please insert Table 3 about here]

3.3 Endogeneity tests

We do not rule out the possibility of endogeneity, which may compromise the reliability of our findings. Endogeneity may arise from reverse causality, omitted variable bias, or sample selection bias, each of which can yield inconsistent estimates and misleading inferences. To address this concern, we employ a broad set of robustness tests, which are presented below.

We begin with difference-in-difference (DID) model by considering China's biodiversity conservation policy 2011-2030 as an exogenous shock to establish causality, following Zhou et al. (2025a). In 2011, the National Environmental Protection Agency of China designated 35 biodiversity priority areas covering 27 provinces or regions in the country[2]. We posit that firms located in these priority zones may experience stricter regulatory scrutiny or increased environmental penalties, which can incentivize managerial manipulative behavior to withhold negative firm-specific information, contributing to higher SYNC due to investors' inability to differentiate between companies based on their biodiversity risk exposure.

To test our prediction, we create a dummy variable, namely, *Biodiv_priority_areas*, as an indicator that equals 1 for firms that are in the designated priority regions, and 0 otherwise. The post-period (*Time*) dummy takes a value of 1 for the years after 2011, and 0 otherwise. These results are reported in Table 4. Column 1 exhibits the results without fixed effects while Column 2 presents the results considering fixed effects. The coefficient on *Biodiv_priority_areas* × *Time* is consistently positive and significant in both specifications, lending support to our prediction that biodiversity risk increases SYNC.

[Please insert Table 4 about here]

Additionally, we carry out five additional tests in online Appendix B, including propensity score matching (PSM) (*Table B1*), balance entropy (BE) (*Table B2)*, lagged independent variable (*L.Biodiv_Risk*) (*Panel A of Table B3)*, IV-2SLS (*Panel B of Table B3*), and Oster (2019) coefficient stability test (*Panel C of Table B3)*. For space constraints, we interpret these results in online Appendix B1. Collectively, we discover a positive relationship between biodiversity risk and SYNC across all tests, signifying the robustness of our main finding.

3.4 Additional analysis

In this section, we extend our analysis by performing several other robustness tests, channel analysis, and finally subsample analysis. First, we assess the robustness of our main findings using six other robustness tests. Next, we investigate the potential mechanisms to provide further insights into biodiversity risk–SYNC relation. Finally, we perform heterogeneity analysis across different subsamples. For the sake of brevity, we discuss and interpret these tests in greater detail in online appendix B1.

---

[2] Please see: https://www.cbd.int/doc/world/cn/cn-nbsap-v2-en.pdf

4. Conclusion

This study investigates how firm-level biodiversity risk affects stock price synchronicity, addressing a nascent topic in the literature on environmental risks and market behavior. Employing Chinese A-share firms from 2007 to 2023, we report that biodiversity risk increases synchronicity, with pronounced effects for financially constrained firms, non-state-owned enterprises, and those with lower management integrity. Furthermore, we find that both systematic and idiosyncratic components of biodiversity risk are incorporated into investment decisions of stock market participants. The relation between biodiversity risk and synchronicity operates through information disclosure quality and stock price crash risk channels.

Our results have important implications. First, firms need to improve their environmental disclosure practices since increased transparency can mitigate information asymmetry, facilitate timely and accurate incorporation of firm-specific and market-wide information into stock prices, and enable investors and regulators to better understand and manage the financial implications of biodiversity risks. Second, as biodiversity risk is becoming an important factor in stock price formation, taking it into consideration when assessing firm value and overall financial stability can mitigate vulnerabilities, help manage broader market risks, and reinforce the resilience of capital markets.

Our study has some limitations. First, we focus specifically on Chinese firms, which may limit the generalizability of the results to other countries or markets. Second, while we identify information disclosure quality and stock price crash risk as the primary channels through which biodiversity risk affects stock price synchronicity, additional mechanisms, such as firm-level innovation and supply chain disruptions, may also mediate this relationship. Future research can extend this work by empirically testing cross-country predictions and investigating additional channels through which biodiversity risk affects stock markets.

References

Adams, C. A. (2004). The ethical, social and environmental reporting-performance portrayal gap. *Accounting, Auditing & Accountability Journal, 17*(5), 731-757.

Apergis, N. (2025). Fresh evidence on climate and biodiversity risks in asset pricing. *Applied Economics Letters*, 1–5.

Ayaz, M., Anwer, Z., Hassan, M. K., & Xiaoyang, X. (2025). Inhabiting influence of digital finance on stock price synchronicity. *Global Finance Journal, 64*, 101057.

Bach, T. N., Hoang, K., & Le, T. (2025). Biodiversity risk and firm performance: Evidence from US firms. *Business Strategy and the Environment*, *34*(1), 1113-1132.

Balogh, A., Bekessy, S., Burgman, M., Geary, W., Karakaş, O., Layman, H., ... & Wintle, B. (2025). Flora, Fauna, and Finance: Assessing Biodiversity Risk in Investment Portfolios. Available at SSRN 5260811.

Bassen, A., Buchholz, D., Lopatta, K., & Rudolf, A. R. (2025). Assessing biodiversity-related disclosure: Drivers, outcomes, and financial impacts. *Journal of Industrial Ecology, 29*(1), 311-329.

Bassen, A., Buchholz, D., Lopatta, K., & Rudolf, A. R. (2024). Biodiversity management and stock price crash risk. *Business Strategy and the Environment*, *33*(5), 4788-4805.

Boiral, O. (2016). Accounting for the unaccountable: Biodiversity reporting and impression management. *Journal of Business Ethics*, *135*(4), 751-768.

Chen, J., Hong, H., & Stein, J. C. (2001). Forecasting crashes: Trading volume, past returns, and conditional skewness in stock prices. *Journal of Financial Economics*, *61*(3), 345-381.

Delmas, M. A., & Burbano, V. C. (2011). The drivers of greenwashing. *California Management Review*, *54*(1), 64-87.

Fan, J. P., Wong, T. J., & Zhang, T. (2007). Politically connected CEOs, corporate governance, and Post-IPO performance of China's newly partially privatized firms. *Journal of Financial Economics*, *84*(2), 330-357.

Gan, K., Li, R., & Zhou, Q. (2024). Climate transition risk, environmental news coverage, and stock price crash risk. *International Review of Financial Analysis*, *96*, 103657.

Gao, W., Zhang, Z., He, P., & Wang, X. (2025). From accountability to transparency: The role of collective litigation in enhancing corporate information disclosure. *Pacific-Basin Finance Journal, 93,* 102864.

Garel, A., Romec, A., Sautner, Z., & Wagner, A. F. (2024). Do investors care about biodiversity? *Review of Finance*, *28*(4), 1151-1186.

Giglio, S., Kuchler, T., Stroebel, J., & Zeng, X. (2023). Biodiversity risk (No. w31137). National bureau of economic research.

Gul, F. A., Kim, J.-B., & Qiu, A. A. (2010). Ownership concentration, foreign shareholding, audit quality, and stock price synchronicity: Evidence from China. *Journal of Financial Economics, 95*(3), 425–442.

Hawn, O., & Ioannou, I. (2016). Mind the gap: The interplay between external and internal actions in the case of corporate social responsibility. *Strategic Management Journal, 37*(13), 2569-2588.

He, F., Chen, L., & Lucey, B. M. (2024). Chinese corporate biodiversity exposure. *Finance Research Letters, 70*, 106275.

Jin, L., & Myers, S. C. (2006). R2 around the world: New theory and new tests. *Journal of Financial Economics, 79*(2), 257-292.

Kalhoro, M. R., & Kyaw, K. (2024). Manage biodiversity risk exposure? *Finance Research Letters*, *61*, 104989.

Khan, N., & Lucey, B. M. (2025). *Biodiversity risk, corporate governance, and firm performance: Empirical evidence from China*. SSRN. https://doi.org/10.2139/ssrn.5374258

Kim, O., & Verrecchia, R. E. (2001). The relation among disclosure, returns, and trading volume information. *The Accounting Review*, *76*(4), 633-654.

Krueger, P., Sautner, Z., & Starks, L. T. (2020). The importance of climate risks for institutional investors. *The Review of Financial Studies, 33*(3), 1067-1111.

Liang, C., Yang, J., Shen, L., & Dong, D. (2024). The role of biodiversity risk in stock price crashes. *Finance Research Letters*, *67*, 105856.

Liu, Q., & Lu, Z. J. (2007). Corporate governance and earnings management in the Chinese listed companies: A tunneling perspective. *Journal of Corporate Finance, 13*(5), 881-906.

Lu, Y., & Abeysekera, I. (2014). Stakeholders' power, corporate characteristics, and social and environmental disclosure: Evidence from China. *Journal of Cleaner Production, 64*(1), 426–436.

Lyon, T., Lu, Y., Shi, X., & Yin, Q. (2013). How do investors respond to Green Company Awards in China? *Ecological Economics*, 94, 1–8.

Lyon, T. P., & Maxwell, J. W. (2011). Greenwash: Corporate environmental disclosure under threat of audit. *Journal of Economics & Management Strategy*, *20*(1), 3-41.

Ma, C., Gao, L., Jiang, Y., & Ren, Y. S. (2025). How Biodiversity Information Disclosures Spill the Beans on Firm Value? *Finance Research Letters, 85*, 108240.

Ma, F., Wu, H., & Zeng, Q. (2024). Biodiversity and stock returns. *International Review of Financial Analysis*, *95*, 103386.

Ma, R., Marshall, B. R., Nguyen, H. T., Nguyen, N. H., & Visaltanachoti, N. (2022). Climate events and return comovement. *Journal of Financial Markets, 61*, 100731

Ma, Y., Liu, Z., Ma, D., Zhai, P., Guo, K., Zhang, D. et al. (2023). A News-Based Climate Policy Uncertainty Index for China. Scientific Data, 10, Article No. 881. https://doi.org/10.1038/s41597-023-02817-5

Mahoney, L. S., Thorne, L., Cecil, L., & LaGore, W. (2013). A research note on standalone corporate social responsibility reports: Signalling or greenwashing*? Critical Perspectives on Accounting, 24*(4-5), 350-359.

Marquis, C., Toffel, M. W., & Zhou, Y. (2016). Scrutiny, norms, and selective disclosure: A global study of greenwashing. *Organization Science, 27*(2), 483-504.

OECD. (2023, April 27). *Assessing biodiversity-related financial risks: Navigating the landscape of existing approaches*. OECD Environment Policy Papers, No. 36. https://doi.org/10.1787/d52137a5-en

Oster, E. (2019). Unobservable selection and coefficient stability: Theory and evidence. *Journal of Business & Economic Statistics, 37*(2), 187-204.

Safiullah, M., Kabir, M.N. & Miah, M.D. (2021) Carbon emissions and credit ratings. *Energy Economics*, *100*, 105330.

Shleifer, A., & Vishny, R. W. (1997). A survey of corporate governance. *The Journal of Finance*, *52*(2), 737-783.

Sun, W., Mei, J., Chen, K., & Li, Z. (2025). Biodiversity Risk and Value Creation in Emerging Markets. *Finance Research Letters*, 108069.

Verrecchia, R. E. (1983). Discretionary disclosure*. Journal of Accounting and Economics, 5*, 179-194.

Yu, E. P. Y., Van Luu, B., & Chen, C. H. (2020). Greenwashing in environmental, social and governance disclosures. *Research in International Business and Finance, 52*, 101192.

Zhang, D. (2022). Are firms motivated to greenwash by financial constraints? Evidence from global firms' data. *Journal of International Financial Management & Accounting*, *33*(3), 459-479.

Zhao, R., Zhang, D., & Guo, M. (2024). Do natural disasters affect stock price crash risk? Evidence from emerging markets. *Journal of International Financial Markets, Institutions and Money*, *93*, 102001.

Zhou, C., Chen, Y., Ji, Q., & Zhang, D. (2025a). Does public attention to biodiversity matter to stock markets? *International Review of Financial Analysis*, *98*, 103925.

Zhou, Y., Lucey, B. M., & He, F. (2025b). Dividend payouts and biodiversity risk—Chinese evidence. *Research in International Business and Finance*, *76*, 102792.

Table 1A: Summary statistics

This table shows the summary statistics of the variables used in this study: the number of observations, the mean, standard deviation (SD), 25th percentile (p25), the median, and the 75th percentile (p75) values, respectively.

	Observations	Mean	SD	p25	Median	p75
Main variables						
SYN1	41,043	-.413	0.819	-.988	-.375	.207
SYN2	41,043	-.599	0.901	-1.204	-.527	.086
Biodiversity risk (*Biodiv_risk*)	41,043	.478	0.500	0	0	1
Biodiversity_concern_frequency	41,043	0.000	0.000	0	0	0
Biodiversity_concern_cnwords	41,043	0.000	0.000	0	0	0
Biodiversity_concern_char	41,043	0.000	0.000	0	0	0
Channel variables						
Information disclosure quality	41,043	.131	0.080	.0067	.11	.195
Stock price crash risk	41,043	-.31	0.231	-.51	-.309	-.11
Control variables						
Size	41,043	22.204	1.172	21.307	22.037	22.961
Leverage	41,043	.431	0.194	.271	.427	.584
ROA	41,043	.040	0.049	.013	.037	.07
Market-to-book ratio	41,043	6.567	0.779	5.996	6.527	7.1
Cash flow	41,043	.049	0.060	.01	.048	.089
Growth	41,043	.132	0.256	-.034	.1	.259
Board size	41,043	2.283	0.220	2.197	2.197	2.398
CEO duality	41,043	.270	0.444	0	0	1
Board independence	41,043	.379	0.064	.333	.364	.429
Ownership concentration	41,043	.525	0.145	.413	.525	.639
Management shareholding	41,043	.131	0.190	0	.008	.228
Audit opinion	41,043	.973	0.161	1	1	1
Additional control variables						
Firm age	41,043	2.931	0.312	2.708	2.944	3.178
Z-score	41,043	.941	0.664	.543	.945	1.388
Asset turnover ratio	41,043	.626	0.357	.361	.551	.806
Subsample variables						
SA index	41,043	-3.831	2.875	-4.026	-3.831	-3.636
SOEs	41,043	.376	0.484	0	0	1
Management integrity	41,043	.228	0.386	0	0	.693
Other variables						
Province level climate policy uncertainty (*CPU*)	41,043	2.290	0.770	1.823	2.166	2.560

Table 1B: Correlation analysis

This table reports the correlation coefficients between the variables of interest; *a, b, and c* denote 1 %, 5 %, and 10 % level of significance, respectively.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
(1) SYN1	1.000																
(2) Biodiv_risk	-0.086a	1.000															
(3) Size	0.151a	0.252a	1.000														
(4) Leverage	0.066a	0.042a	0.459a	1.000													
(5) ROA	0.037a	-0.038a	0.009c	-0.374a	1.000												
(6) Market-to-book ratio	0.168a	0.123a	0.633a	0.578a	-0.338a	1.000											
(7) Cash flow	0.024a	0.007	0.070a	-0.155a	0.434a	-0.123a	1.000										
(8) Growth	-0.011b	-0.028a	0.040a	0.032a	0.337a	-0.118a	0.059a	1.000									
(9) Board size	0.038a	0.045a	0.235a	0.144a	-0.063a	0.173a	0.014a	-0.023a	1.000								
(10) CEO duality	-0.087a	0.020a	-0.165a	-0.145a	0.038a	-0.175a	-0.012b	0.023a	-0.166a	1.000							
(11) Board independence	-0.050a	0.019a	-0.057a	-0.070a	0.026a	-0.088a	0.000	0.004	-0.183a	0.118a	1.000						
(12) Ownership concentration	-0.018a	0.010b	0.142a	-0.057a	0.227a	0.006	0.134a	0.071a	0.002	-0.004	0.023a	1.000					
(13) Management shareholding	-0.123a	-0.008c	-0.307a	-0.304a	0.160a	-0.285a	0.004	0.076a	-0.205a	0.254a	0.161a	0.146a	1.000				
(14) Audit opinion	0.049a	0.005	0.052a	-0.098a	0.207a	-0.004	0.077a	0.095a	-0.027a	0.003	0.015a	0.088a	0.046a	1.000			
(15) SA index	-0.003	-0.007	-0.003	-0.002	0.001	-0.002	0.001	-0.002	0.005	0.005	0.001	-0.008	0.003	-0.006	1.000		
(16) SOE	0.183a	-0.021a	0.319a	0.281a	-0.101a	0.331a	0.002	-0.047a	0.258a	-0.314a	-0.171a	0.064a	-0.471a	0.036a	-0.002	1.000	
(17) Management integrity	-0.112a	0.096a	-0.019a	-0.067a	0.027a	-0.043a	0.026a	-0.013a	-0.035a	0.075a	0.046a	0.010b	0.090a	0.010b	-0.008c	-0.122a	1.000
VIF			2.26	1.82	1.89	2.31	1.26	1.20	1.12	1.10	1.06	1.11	1.29	1.06			

Table 2: Baseline results

This table reports the baseline regression results. The dependent variable is stock price synchronicity (*SYN1*), computed as the logged transformation of R^2 in equation 2. Biodiversity risk is the main variable of interest denoted with *Biodiv_risk*. All other variables are used as control variables. T-statistics clustered at the firm level are shown in parentheses. *, **, and *** signify 10%, 5%, and 1% significance levels, respectively.

	SYN1			
	(1)	(2)	(3)	(4)
Biodiv_risk	**0.107*** **	**0.043*** **	**0.023** **	**0.026*** **
	(10.406)	**(4.263)**	**(2.325)**	**(2.581)**
Size			0.084***	0.093***
			(7.035)	(7.856)
Leverage			-0.495***	-0.517***
			(-12.425)	(-13.058)
ROA			0.915***	0.970***
			(7.712)	(8.066)
Market-to-book ratio			0.237***	0.236***
			(18.758)	(18.593)
Cash flow			0.059	0.033
			(0.843)	(0.477)
Growth			-0.072***	-0.066***
			(-4.875)	(-4.470)
Board size				-0.034
				(-1.624)
CEO duality				-0.007
				(-0.534)
Board independence				0.102
				(1.559)
Ownership concentration				-0.503***
				(-8.368)
Management shareholding				0.171***
				(3.187)
Audit opinion				0.056**
				(2.293)
Constant	-0.464***	-0.433***	-3.659***	-3.610***
	(-65.896)	(-89.069)	(-15.958)	(-15.588)
Year FE	Yes	Yes	Yes	Yes
Firm FE	No	Yes	Yes	Yes
Observations	41,043	41,022	41,022	41,022
Adj. R^2	0.280	0.414	0.430	0.432

Table 3: Decomposing biodiversity risk: Idiosyncratic vs. systematic components

This table reports the regression results by decomposing the firm-level biodiversity risk exposure into its idiosyncratic component (deviation from industry-year average) and systematic component (industry-year average). Regression model employs both idiosyncratic and systemic components of biodiversity risk as the primary independent variables while controlling for firm fixed effects and year fixed effects. The same set of control variables as in the baseline regression is used. T-statistics clustered at the firm level are shown in parentheses. *, **, and *** signify 10%, 5%, and 1% significance levels, respectively.

Variables	SYN1 (1)
Biodiv_idiosyncratic_risk	**0.020****
	(1.970)
Biodiv_systematic_risk	**0.279*****
	(4.600)
Size	0.090***
	(7.555)
Leverage	-0.513***
	(-12.973)
ROA	0.966***
	(8.050)
Market-to-book ratio	0.236***
	(18.614)
Cash flow	0.038
	(0.541)
Growth	-0.066***
	(-4.417)
Board size	-0.034
	(-1.602)
CEO duality	-0.006
	(-0.511)
Board independence	0.103
	(1.566)
Ownership concentration	-0.506***
	(-8.408)
Management shareholding	0.173***
	(3.224)
Audit opinion	0.056**
	(2.304)
Constant	-3.669***
	(-15.895)
Year FE	Yes
Firm FE	Yes
Observations	41,022
Adj. R^2	0.432

Table 4: Difference-in-differences model results

This table reports the results for the difference-in-differences model. China's National Environmental Protection Agency designated 35 biodiversity priority areas in its 2011-2030 Action Plan. We define the treatment variable (*Biodiv_priority_areas*) as an indicator that equals 1 for firms that are located in the designated priority provinces or cities, and 0 otherwise. The post-period dummy (*Time*) takes a value of 1 for the years after 2011, and 0 otherwise. Column 1 includes neither year FE nor firm FE while column 2 mainly reports the estimates for the treatment variable. The same set of control variables as in the baseline regression is used. T-statistics clustered at the firm level are shown in parentheses. *, **, and *** signify 10%, 5%, and 1% significance levels, respectively.

	SYN1	
	(1)	(2)
Biodiv_priority_areas × Time	**1.323*** **	**1.067*** **
	(252.106)	**(183.253)**
Biodiv_priority_areas	**-0.013** **	
	(-1.979)	
Time	**-1.046*** **	
	(-94.283)	
Size	0.032***	0.071***
	(8.284)	(8.477)
Leverage	-0.298***	-0.355***
	(-14.234)	(-11.811)
ROA	0.652***	0.506***
	(8.014)	(5.675)
Market-to-book ratio	0.117***	0.131***
	(19.863)	(13.840)
Cash flow	-0.098*	0.009
	(-1.861)	(0.167)
Growth	-0.044***	-0.044***
	(-3.791)	(-3.831)
Board size	0.011	-0.004
	(0.780)	(-0.224)
CEO duality	0.002	0.003
	(0.246)	(0.337)
Board independence	-0.022	0.052
	(-0.485)	(1.028)
Ownership concentration	-0.123***	-0.265***
	(-5.594)	(-6.079)
Management shareholding	-0.006	0.132***
	(-0.343)	(3.309)
Audit opinion	0.050**	0.027
	(2.559)	(1.407)
Constant	-1.210***	-2.906***
	(-15.958)	(-17.397)
Year FE	No	Yes
Firm FE	No	Yes
Observations	41,043	41,022
Adj. R^2	0.578	0.659

Appendix A. Variable definitions

Variables	Definitions
Dependent variables	
SYN1	Stock price synchronicity (*SYN1*) is calculated in two steps: First, the R-squared for each firm-year observation using the following market model is calculated. $$R_{iwt} = \beta_0 + \beta_1 MKTR_{wt} + \beta_2 MKTR_{t-1} + \beta_3 INDR_{kt} + \quad (1)$$ where R_{iwt} is the weekly return of firm *i* at week *t*. *MKTR* is the value-weighted market return at week *t*. *INDR* is the average return of industry *K* excluding the subject firm *i'*s return at week *t*. Then, stock price synchronicity (*SYN1*) is computed as the log transformation of the R-squared of Eq. (1) as log ($R^2/1-R^2$). (2)
SYN2	Stock price synchronicity (*SYN2*) is calculated by using the daily returns, following the same procedures above that are employed for SYN1.
Independent variables	
Biodiversity risk (Biodiv_risk)	The biodiversity risk is a dummy variable that takes the value of 1 if a biodiversity related word appears more than twice in a firm's annual report, and 0 otherwise (He et al., 2024).
Biodiversity_concern_frequency	Biodiversity concern frequency is calculated as the number of occurrences of the word *biodiversity* divided by the total number of words in the annual reports based on Jieba's precise model, excluding stopwords, english words, and single-character terms.
Biodiversity_concern_cnwords	Biodiversity concern in Chinese words measures how many biodiversity related Chinese characters appear as a fraction of annual report's overall Chinese character count, excluding digits and punctuation.
Biodiversity_concern_char	Biodiversity concern character is defined as the number of biodiversity related characters divided by the total number of characters in the annual report, including punctuation and numeric digits.
Channel variables	
Information disclosure quality	Information disclosure quality is proxied by KV index, which is computed via the regression below after following Kim and Verrecchia (2001): $$ln \vee \Delta P_d / P_{d-1} \vee \alpha + \beta(Vol_d - Vol_0) + \varepsilon_d$$ (3) where P_d is the closing price of a firm at day *d*, Vol_d is the number of stocks traded on day *d*, and Vol_0 is the firm's average trading volume over the year. The KV index is the regression coefficient β multiplied by 100,000,000. Since a higher KV index represents poorer disclosure quality, we use it as an inverse measure for information disclosure quality.
Stock price crash risk	Stock price crash risk is the down-to-up volatility (*DUVOL*), following Chen et al. (2001). It is constructed as the log transformation of the ratio of standard deviation of down weeks to the standard deviation of the up weeks. A firm week is defined as a down (up) week if the firm-specific weekly return is below (above) its average value in a given period. A higher *DUVOL* denotes a greater crash risk. Formally, the equation is as follows: $$DUVOL = log\{[n_u - 1)\Sigma W^2 \quad / [(n_d - 1)\Sigma W^2\}$$ (4) where n_u and n_d are the number of up and down weeks in year t, respectively.
Control variables	
Size	The natural logarithm of total assets of a firm at the end of the year.
Leverage	Ratio of total debt to total assets of a firm at the end of the year.
ROA	Return on assets, calculated as the net profit divided by the average book value of assets of a firm at the beginning and end of the year.

Market-to-book ratio	Ratio of market value to book value of a firm at the end of the year.
Cash flow	Ratio of cash flow from operating activities to total assets of a firm at the end of the year.
Growth	Operating income growth, calculated as the ratio of the difference between the current and previous year's operating income to the previous year's operating income of a firm.
Board size	The natural logarithm of total number of directors on the board of the firm.
CEO duality	A dummy variable that equals 1 if the CEO of the firm is also the chairperson of the board and 0 otherwise.
Board independence	The ratio of the total number of independent directors over the total number of directors on the board of the firm.
Ownership concentration	The percentage of equity shares held by the top five largest shareholders of the firm.
Managerial shareholdings	The percentage of equity shares held by the management of the firm.
Audit opinion	A dummy variable equals 1 if the firm receives a modified audit opinion in the current year, and 0 otherwise.
Additional control variables	
Firm age	The natural logarithm of the number of years since the foundation of the firm.
Z-score	Z-score represents an inverse measure for firm default risk. It is calculated as 1.2x(Working capital/Total assets) + 1.4x(Retained earnings/Total assets) + 3.3x(Operating income/Total assets) + 0.6x(Market capitalization/Total liabilities) + (Net sales/Total assets).
Asset turnover ratio	The ratio of net sales to average total assets of a firm.
Subsample variables	
State-owned enterprises (*SOEs*)	A dummy variable that equals 1 if a firm is a state-owned enterprise and 0 otherwise.
SA index	SA index measures the degree of financial constraints of a firm. After following Hadlock and Pierce (2010), we measure it as follows: $SA = -0.737*Size+0.043*Size^2-0.04*Age \quad (5)$ Higher values of the SA index represent lower financial constraints for a firm.
Management integrity	Management integrity index is computed as the percentage of occurrence of the term *integrity* in relation to the total number of words in the MD&A section of firm annual report multiplied by 100. A higher management integrity value indicates a greater level of managerial honesty and sincerity.
Other variables	
Climate policy uncertainty *(CPU)*	A news-based province-level climate policy uncertainty index developed by Ma et al. (2023).

Online Appendix B. Additional robustness tests

Additional endogeneity tests

We next adopt propensity score matching (PSM) to address potential sample selection bias such that firms with higher biodiversity risk may be substantially different from those with lower biodiversity risk, and thus baseline regression model may produce spurious estimates. Therefore, we classify the firms into treatment and control group based on their exposure to biodiversity risk. The treatment group consists of all exposed enterprises, whereas the control group consists of firms that are unexposed to biodiversity related risk. Using a one-to-four matching with 0.01 caliper based on control variables, we obtain 20,122 firm-year observations. To assess the suitability of the firms in treatment and control groups based on the mean of each characteristics, two different t-tests are utilized. As shown in Panel A of Table B1, the differences in firm characteristics between treated and control firms are not statistically significant, suggesting that the matching procedure achieved balance between the two groups. Using this newly matched sample, we re-estimate our baseline model with results presented in Panel B of the same table. The coefficient on biodiversity risk shows a positive and significant impact on SYNC, supporting our prediction that biodiversity risk increases SYNC.

[Please insert Table B1 about here]

One disadvantage of PSM is that it drops the unmatched observations, which reduces the overall sample size. Consequently, we further adopt balance entropy (BE) and summarize the results in Table B2. Panel A of this table contains covariate balance before (without weighting) and after (with weighting). Panel B of the same table presents the regression results with entropy-balanced sample. The estimated coefficient on *Biodiv_risk* is positive and significant at 5% level, suggesting that our main conclusion is robust to sample selection bias.

[Please insert Table B2 about here]

Although we employ DID, PSM, and BE models to mitigate endogeneity concerns, the issue may persist. Firms with higher biodiversity risk could differ systematically from those with lower risk, causing baseline regressions to yield biased estimates. Moreover, firms that are less transparent or poorly governed may simultaneously exhibit higher stock price synchronicity and greater exposure to biodiversity risk, raising the possibility of reverse causality. To address endogeneity arising from reverse causality in the biodiversity risk—SYNC relation, we first employ one-year lagged value of biodiversity risk. Results in Panel A of Table B3 indicate that lagged biodiversity risk is positively and significantly associated with SYNC, which is consistent with our primary conclusion.

Furthermore, while incorporating lagged biodiversity risk helps alleviate concerns of reverse causality, endogeneity issues may still persist due to the inherent persistence of stock price synchronicity. Therefore, as a second step, we employ an IV-2SLS approach. We employ geographic location as an exogenous instrument, following Safiullah et al. (2021) and Zhou et al. (2025a), who argue that it satisfies both the relevance condition, meaning that geographic location is directly associated with biodiversity risk, and the exogeneity condition, meaning that geographic location has no direct effect on a firm's stock price synchronicity. Specifically, we measure geographic location (*Zip*) as average biodiversity risk exposure for firms located in the same three-digit zip code areas in China. Panel B of Table B3 summarizes the findings of instrumental variable approach. Column 2 presents the first stage results, showing that *Zip* is positively associated with biodiversity risk, confirming that our instrumental variable significantly affects the biodiversity risk exposure. Column 3 presents the second stage results of the instrumental variable approach. We observe that biodiversity risk significantly increases SYNC, yielding empirical support for our primary finding.

Furthermore, there may be unobserved factors that are omitted in our regression model which simultaneously influence both biodiversity risk and stock price synchronicity, introducing omitted variable bias. Failing to account for omitted variable bias can lead to misleading conclusions. Therefore, we apply Oster's (2019) test for unobservable selection as a robustness check against omitted variable bias by assessing the influence of unobserved factors on coefficient stability. This approach quantifies how strong omitted variables would have to be to eliminate the observed relationship. The test evaluates changes in the estimated coefficient and the R-squared between regressions with and without control variables. Applying Oster's (2019) test to our baseline regression, we find that the effect of unobservables would need to be more than 13.0196 times that of observables to overturn our main results (Panel C Table B3). According to Oster, a ratio greater than 1 or less than -1 indicates robust results, demonstrating that omitted variables would need to be substantially stronger than the observed factors to invalidate our primary conclusion.

[Please insert Table B3 about here]

Other robustness tests

In this section, we perform six different robustness tests. First, we employ an alternative measure of stock price synchronization (*SYN2*) that is measured through daily stock returns. The results show that biodiversity risk increases SYNC, which supports our primary finding (Panel A Table B4). Second, we use alternative measures of biodiversity risk, namely biodiversity concern index, following He et al (2024)[3]. We then replicate our baseline regression and find that biodiversity risk is positively and significantly related to SYNC (Panel B Table B4).

[Please insert Table B4 about here]

One potential concern is that our results might be driven by other climate change policies. To address this concern, we control for climate policy uncertainty at province level during analysis. We observe that the coefficient on climate policy uncertainty is statistically insignificant (Table B5), confirming that our results are not spuriously driven by such uncertainties.

[Please insert Table B5 about here]

Next, we adopt alternative fixed effects (i.e., firm FE, city FE, and year FE) to sustain that city level unobserved time-invariant heterogeneity does not affect our results. The results displayed in Panel A Table B6 reveal that the coefficient on biodiversity risk remains positive and statistically significant at 1 % level, which further supports our main finding. We perform two additional tests: controlling for province-specific temporal shocks (Panel B Table B6) and two-way clustered standard errors (Panel C Table B6). We then replicate Eq. [3] for each test separately. Results show that the coefficient on biodiversity risk is positive and statistically significant, which is consistent with our primary hypothesis that firm exposure to biodiversity risk can significantly increase stock price synchronicity.

[Please insert Table B6 about here]

[3]He et al. (2024) define biodiversity concern in three different ways: *Biodiversity_concern_frequency, Biodiversity_concern_cnwords*, and *Biodiversity_concern_char*. Please see Appendix A for variable definitions.

Next, we incorporate additional firm-level control variables, including firm age, Z-score, and asset turnover ratio, to mitigate the concern of omitted variable bias. The results in Table B7 show similar results with those reported in Table 2, supporting our baseline conclusion.

[Please insert Table B7 about here]

Finally, we present our results by excluding the global financial crisis (2007-2008), China's stock market crash (2015), and the COVID-19 pandemic (2020-2023) to provide further robustness of our main findings. The results in Table B8 demonstrate that biodiversity risk has positive and significant impact on SYNC, yielding support for our primary finding.

[Please insert Table B8 about here]

Overall, we observe that the results across all different specifications remain qualitatively similar to those reported in Table 2, corroborating the robustness of our findings.

Channel Analysis

Our baseline results show that biodiversity risk increases stock price synchronization. In this part, we investigate the potential mechanisms through which *Biodiv_risk* influences SYNC. Previous research finds that biodiversity risk can intensify information asymmetry and affect stock price crash risk (Bassen et al., 2024; Liang et al., 2024). Thus, we study these two mechanisms in order to provide deeper insights into how biodiversity risk influences stock price synchronicity.

Quality of information disclosure

The voluntary disclosure theory posits that managers have incentives to engage in selective disclosure when negative information detrimentally affects firm value, aiming to avoid adverse selection problems (Verrecchia, 1983). This theoretical lens offers valuable insights into how environmental uncertainty surrounding firm biodiversity risk may increase SYNC through information disclosure mechanism.

Firms exposed to biodiversity risk face a disclosure trade-off: transparent environmental reporting can fulfil regulatory requirements and stakeholder demands, benefiting the firm in the long run, but simultaneously may trigger negative market reactions, environmental penalties, higher borrowing costs, and increased litigation risks. Yu et al. (2020) report that investors tend to favor positive news about firms with higher ESG scores while overlooking negative news about those with lower scores. Given this trade-off, managers of firms that are exposed to higher biodiversity risk may engage in selective disclosure or greenwashing practices to obscure negative environmental information (Mahoney et al., 2013; Marquis et al., 2016). Lyon and Maxwell (2011) and Marquis et al. (2016) report that firms selectively disclose environmental information to sustain market legitimacy while Krueger et al. (2020) indicate that firms strategically release environmental information in response to environmental pressure. Research also indicates that firms often provide vague or "superficial information" by masking damaging facts to obscure potential material risk (Boiral, 2016; Bassen et al., 2025).

Consequently, firms susceptible to biodiversity risk are likely to adopt selective disclosure strategies that undermine their disclosure quality, widening information gaps in the market. This opaque reporting impairs investors' ability to accurately evaluate the financial implications of environmental risks, leading to capital market inefficiencies and lower stock price informativeness. By limiting firm-specific information available to investors, opaque reporting may force market participants to rely more heavily on industry- and market-wide signals. As a result, stock returns may comove more with common factors, thereby increasing stock price synchronicity.

To examine whether biodiversity risk increases SYNC by reducing information disclosure quality, we follow previous studies and measure information disclosure through the KV index (Kim and Verrecchia, 2001; Gao et al., 2025). Since a higher KV index represents poorer disclosure quality, we use it as an inverse measure for information disclosure quality. Panel A of Table B9 presents the results, showing a positive relationship between biodiversity risk and the KV index (column 1), which suggests that biodiversity risk reduces information disclosure quality. The positive relationship between the KV index and SYNC (column 2) indicates that lower disclosure quality constitutes a potential mechanism through which biodiversity risk incorporates broader market or industry-wide information into stock returns, contributing to higher synchronicity.

Stock price crash risk

Biodiversity exposed firms often face increased regulatory and operational uncertainties that create managerial incentives to withhold bad firm-specific news from capital market. Jin and

Myers (2006) suggest that when all negative firm-specific information reaches a certain threshold, stock prices result in an unexpected crash upon simultaneous release of accumulated negative information. Building on their findings, we argue that biodiversity exposure may incentivize managerial manipulative behavior to hoard bad firm-specific information to prevent adverse regulatory scrutiny and market reactions. This information opacity facilitates the accumulation of unreported negative news linked with biodiversity impacts, including overexploitation of natural capital, water pollution from corporate operations, or regulatory violations. Therefore, enterprises facing higher biodiversity risks exhibit heightened vulnerability to stock price crashes following the sudden revelation of hidden information through shareholder activism or policy intervention.

A burgeoning strand of empirical literature substantiates this relation, indicating a significant positive relation between climate change risk and future stock crashes, with information opacity acting as a critical mechanism that intensifies this relation (Gan et al., 2024; Zhao et al., 2024). Recently, Liang et al. (2024) report that biodiversity risk exposure significantly increases the future stock price crash risk of firms in the United States. In the light of these arguments, we expect that firms exposure to biodiversity risk leads to greater stock price crash risk.

Following Chen et al. (2001), we employ firm down-to-up volatility (DUVOL) as measure of stock price crash risk. Results presented in Panel B of Table B9 display significantly positive coefficient on stock price crash risk in column 2, suggesting that crash risk serves as a potential mechanism through which biodiversity risk increases stock price synchronicity.

[Please insert Table B9 about here]

Subsample analysis

The impact of biodiversity risk on SYNC may vary in firms with different management integrity, ownership structure, and financial constraints. Specifically, we anticipate more pronounced impact among firms with lower management integrity, non-state-owned enterprises (non-SOEs), and higher exposure to financial constraints, as these enterprises will have more inclination for adopting opportunistic disclosure behavior or information hoarding about biodiversity risk exposure. Hence, we perform subsample analysis to investigate these heterogenous associations between biodiversity risk and SYNC.

We first consider management integrity. We predict stronger positive impact of *Biodiv_risk* on SYNC in firms with lower management integrity than those with higher management integrity. Firms with lower management integrity may have larger propensity for opportunistic disclosure practices to greenwash their environmental impacts, resulting in opaque financial reporting. Prior research provides supporting evidence that weak governance and low ethical standards such as corruption or insider trading, incentivize withholding or misrepresenting sustainability-related disclosure (Hawn and Ioannou, 2016; Kim and Zhang, 2011). Such selective reporting can aggravate information asymmetry between managers and investors as it generates an environment where investors may not be fully capable of accessing firm-specific information. Consequently, investors rely heavily on market-wide or industry-wide information when assessing these firms, thereby contributing to higher stock price synchronization.

To test our conjecture, we divide the sample into firms with lower management integrity vs. higher management integrity[4]. Results in Panel A of Table B10 reveal that the coefficient of *Biodiv_risk* is positive and significant for firms that exhibit lower integrity, suggesting that biodiversity risk strongly affects SYNC when management integrity is weak.

Next, we investigate whether the effect of biodiversity risk on SYNC is altered by ownership structure. Evidence shows that relative to SOEs, non-SOEs often encounter greater regulatory scrutiny and lower access to government subsidies as well as preferential bank credit, forcing them to rely heavily on market-based funding for their capital requirement (Fan et al., 2007). Such market reliance can motivate non-SOEs to engage in greenwashing practices[5] to attract investors and sustain capital market access (Marquis et al., 2016). Previous literature claim that market pressure increases greenwashing mechanisms in non-SOEs, especially when their actual environmental performance falls below market expectations (Delmas and Burbano, 2011; Yu et al., 2020). Such greenwashing behavior aggravates information asymmetry, leading to lower financial performance.

---

[4] Firms are classified into higher (lower) integrity based on bottom (top) one-third quantile of their management integrity.

[5] According to Mahoney et al. (2013), greenwashing is the selective disclosure of positive social and environmental actions, resulting in misleading and biased reporting. Adams (2004) find that companies often disclose a small portion of their negative environmental performance compared to their actual environmental performance, aiming to portray themselves as good corporate citizens.

Furthermore, ownership concentration is a prevailing attribute of Chinese non-SOEs which further aggravates agency conflicts between controlling shareholders and outside investors. Ownership concentration empowers controlled shareholders to withhold unfavourable firm environmental performance and extract private benefits at the expense of external investors (Shleifer and Vishny, 1997). Liu and Lu (2007) demonstrate that group ownership in China is more inclined to adopt related-party transactions for earnings manipulation and value tunneling. This self-serving behavior widens the information gap between better-informed insiders and outside investors, who have incomplete information about firm fundamentals. Thus, investors may greatly rely on market-wide information or industry trends following this information inequality during their decision-making process, thereby reducing stock price informativeness and increasing SYNC. To evaluate this concern, we group firms into state-owned-enterprises (SOEs) and non-state-owned enterprises (non-SOEs). Results in Panel B of Table B10 display that the coefficient on *Biodiv_risk* is positive and significant for non-SOEs. The findings are aligned with the view that the positive impact of biodiversity risk on SYNC is more pronounced in non-SOEs.

Finally, we turn to inspect biodiversity risk—SYNC relation in firms with different financial positions. Specifically, we divide our full sample into financially constrained and unconstrained firms using the SA index. Firms in the bottom (top) one-third quantile of the SA index ranking are classified financially unconstrained (constrained) firms. We expect more pronounced association between *Biodiv_risk* and SYNC in financially constrained firms than unconstrained counterparts.

Intuitively, relative to their unconstrained counterparts, financially constrained enterprises experience higher information asymmetry and agency problems that intensify the effect of biodiversity risk on SYNC. Such firms often lack adequate resources to establish comprehensive environmental disclosure frameworks because capital constraints restrict their capacity to invest in environmental sustainability (i.e., investments in clean technologies) and reporting systems. Consequently, they adopt selective reporting or greenwashing strategies to improve their perceived environmental performance (Lu & Abeysekera, 2014). Empirical evidence backed this argument, indicating that firms with negative ESG performance strategically adopt selective disclosure to deceive external investors to avoid negative externalities (Mahoney et al., 2013;

Marquis et al., 2016). This creates significant valuation challenges for investors, as firms may engage in greenwashing to obfuscate their true environmental impact (Lyon et al., 2013; Marquis et al., 2016; Zhang, 2022).

To test this intuition, we perform separate regressions for both financially constrained and unconstrained firms. The findings presented in Panel C of Table B10 demonstrate that *Biodiv_risk* significantly increases SYNC of financially constrained firms.

Overall, results for these subsamples are consistent with our arguments, suggesting that biodiversity risk–SYNC relation is contingent on management integrity, ownership structure, and financial constraints. Specifically, enterprises with lower managerial integrity, weak government relationships, and a shortfall of financial resources exhibit greater stock return co-movement with the broader market when they are exposed to biodiversity risk.

[Please insert Table B10 about here]

Table B1: Propensity score matching

This table displays the results for the propensity score matching (PSM). First, treated and control groups are created based on firm's exposure to biodiversity risk. Then, we use a one-to-four matching with 0.01 caliper based on control variables. Panel A documents the mean of both treated and control groups for the matched sample. Using the newly matched sample, the baseline regression is re-estimated, and the regression results are presented in Panel B. The same set of control variables as in the baseline regression is used. T-statistics clustered at the firm level are shown in parentheses. *, **, and *** signify 10%, 5%, and 1% significance levels, respectively.

Panel A. PSM matched sample

Variable	Unmatched(U) Matched (M)	Mean Treated	Mean Control	t-test
	U	22.512	21.921	52.69
Size	M	22.512	22.517	-0.43
	U	0.439	0.423	8.56
Leverage	M	0.439	0.441	-1.04
	U	0.038	0.042	-7.69
ROA	M	0.038	0.038	0.4
	U	6.666	6.475	25.01
Market-to-book ratio	M	6.666	6.661	0.67
	U	0.050	0.049	1.41
Cash flow	M	0.050	0.050	-0.44
	U	0.124	0.139	-5.76
Growth	M	0.124	0.128	-1.32
	U	2.294	2.274	9.05
Board size	M	2.294	2.295	-0.79
	U	0.279	0.262	4.02
CEO duality	M	0.279	0.274	1.14
	U	0.381	0.378	3.76
Board independence	M	0.381	0.381	-0.24
Ownership	U	0.527	0.524	2.04
concentration	M	0.527	0.532	-3.33
Management shareholding	U	0.130	0.133	-1.64
	M	0.130	0.131	-0.66
	U	0.974	0.973	0.99
Audit opinion	M	0.974	0.976	-1

Panel B. PSM matched regression results

Variables	SYN1
Biodiv_risk	**0.026*** **
	(1.816)
Size	0.095***
	(5.831)
Leverage	-0.548***
	(-9.691)
ROA	1.232***
	(6.907)
Market-to-book ratio	0.241***
	(13.966)
Cash flow	0.073
	(0.711)
Growth	-0.112***
	(-5.016)
Board size	-0.013
	(-0.438)
CEO duality	-0.016
	(-0.913)
Board independence	-0.043
	(-0.453)
Ownership concentration	-0.490***
	(-5.850)
Management shareholdings	0.215***
	(2.808)
Audit opinion	0.026
	(0.681)
Constraints	-3.670***
	(-11.326)
Time FE	Yes
Firm FE	Yes
Observations	20,122
Adj. R^2	0.442

Table B2: Entropy balancing estimates

This table displays the results for endogeneity test via entropy balancing approach. Panel A reports the results for covariate balance before—without weighting and after—with weighting. Panel B portrays the regression results by using the entropy-balanced sample. The same set of control variables as in the baseline regression is used. T-statistics clustered at the firm level are shown in parentheses. *, **, and *** signify 10%, 5%, and 1% significance levels, respectively.

Panel A. Covariate balance (*Biodiv_risk*)

	Before: Without weighting						After: With weighting					
	Treated			Control			Treated			Control		
Variables	Mean	Variance	Skewness	Mean	Variance	Skewness	Mean	Variance	Skewness	Mean	Variance	Skewness
Size	22.510	1.434	0.279	21.920	1.153	0.660	22.510	1.434	0.279	22.510	1.435	0.279
Leverage	0.439	0.036	0.051	0.423	0.040	0.111	0.439	0.036	0.051	0.439	0.036	0.051
ROA	0.038	0.002	-0.149	0.042	0.002	-0.132	0.038	0.002	-0.149	0.038	0.002	-0.149
Market-to-book ratio	6.666	0.625	0.092	6.475	0.573	0.241	6.666	0.625	0.092	6.666	0.625	0.092
Cash flow	0.050	0.003	0.072	0.049	0.004	0.053	0.050	0.003	0.072	0.050	0.003	0.072
Growth	0.124	0.065	0.694	0.139	0.066	0.613	0.124	0.065	0.694	0.124	0.065	0.694
Board size	2.294	0.051	0.137	2.274	0.046	0.247	2.294	0.051	0.137	2.294	0.051	0.137
CEO duality	0.279	0.201	0.983	0.262	0.193	1.084	0.279	0.201	0.983	0.279	0.201	0.983
Board independence	0.381	0.004	0.365	0.378	0.004	0.504	0.381	0.004	0.365	0.381	0.004	0.365
Ownership concentration	0.527	0.021	0.006	0.524	0.020	-0.035	0.527	0.021	0.006	0.527	0.021	0.006
Management shareholding	0.130	0.033	1.342	0.133	0.039	1.349	0.130	0.033	1.342	0.130	0.033	1.342
Audit Opinion	0.974	0.025	-5.993	0.973	0.027	-5.804	0.974	0.025	-5.993	0.974	0.025	-5.991

Panel B. Regression results with entropy-balanced sample

Variables	SYN1
Biodiv_risk	**0.026****
	(2.440)
Size	0.093***
	(7.426)
Leverage	-0.517***
	(-12.344)
ROA	0.970***
	(7.625)
Market-to-book ratio	0.236***
	(17.576)
Cash flow	0.033
	(0.451)
Growth	-0.066***
	(-4.225)
Board size	-0.034
	(-1.535)
CEO duality	-0.007
	(-0.505)
Board independence	0.102
	(1.474)
Ownership concentration	-0.503***
	(-7.910)
Management shareholding	0.171***
	(3.013)
Audit opinion	0.056**
	(2.167)
Constant	-2.312***
	(-8.870)
Year FE	Yes
Firm FE	Yes
Observations	41,043
Adj. R^2	0.432

Table B3: Endogeneity tests—Lagged value of biodiversity risk and IV-2SLS

This table reports the results for various endogeneity tests. Panel A displays the results for one-year lagged value of biodiversity risk (*L.Biodiv_risk*). Panel B reports the regression results for IV-2SLS. We employ the zip code (*Zip*) as our instrument following previous studies (Safiullah et al., 2021; Zhou et al., 2025a). Column 2 shows the first stage regression results while column 3 displays the second stage results. Panel C at the bottom of this table demonstrates the results of the Oster (2019) test for omitted variable bias. The same set of control variables as in the baseline regression is used. T-statistics clustered at the firm level are shown in parentheses. *, **, and *** signify 10%, 5%, and 1% significance levels, respectively.

	Panel A. Lagged value of biodiversity risk	**Panel B. IV-2SLS regression results**	
		First stage	Second stage
	SYN1	Biodiv_risk	SYN1
	(1)	(2)	(3)
L.Biodiv_risk	**0.045***** **(4.121)**		
Zip		**0.044**** **(2.455)**	
Biodiv_risk			**1.026*** **(1.725)**
Size	0.092*** (6.997)	0.100*** (12.280)	-0.008 (-0.132)
Leverage	-0.498*** (-11.218)	-0.042 (-1.348)	-0.475*** (-10.053)
ROA	0.887*** (6.802)	0.166** (2.166)	0.805*** (5.258)
Market-to-book ratio	0.222*** (15.893)	-0.013 (-1.549)	0.249*** (16.786)
Cash flow	0.027 (0.349)	-0.082* (-1.951)	0.114 (1.343)
Growth	-0.049*** (-3.032)	-0.011 (-1.236)	-0.055*** (-3.400)
Board size	-0.016 (-0.709)	0.030** (2.354)	-0.065** (-2.402)
CEO duality	-0.015 (-1.124)	0.016* (1.852)	-0.023 (-1.477)
Board independence	0.110 (1.549)	-0.039 (-0.987)	0.141** (2.057)
Ownership concentration	-0.536*** (-7.878)	0.114*** (2.679)	-0.616*** (-6.796)
Management shareholding	0.146** (2.395)	0.001 (0.023)	0.169*** (3.148)
Audit opinion	0.045* (1.711)	0.013 (0.756)	0.042 (1.636)
Constant	-3.552*** (-13.746)	-1.800*** (-10.871)	-1.822* (-1.666)
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Observations	35,004	41,022	41,022
Adj. R^2	0.435	0.518	0.432

Panel C. Oster (2019) test for omitted variable bias

Dependent variable: *SYN1*
Independent variable: *Biodiv_risk*

Model	Beta	R-squared	Delta
Uncontrolled	.0434	0.4139	
Controlled	.0256	0.4321	13.0196

Table B4: Robustness Tests –alternative measures of main variables

This table reports the results of robustness tests for alternative measures of main variables. Panel A displays the results for alternative measure of stock price synchronization, denoted by *SYN2*. Panel B (columns 2-4) reports the results for alternative measures of biodiversity risk. The same set of control variables as in the baseline regression is used. T-statistics clustered at the firm level are shown in parentheses. *, **, and *** signify 10%, 5%, and 1% significance levels, respectively.

	Panel A. Alternative measure of the dependent variable	**Panel B. Alternative measures of the biodiversity risk**		
	SYN2	SYN1		
	(1)	(2)	(3)	(4)
Biodiv_risk	**0.026****			
	(2.354)			
Biodiversity_concern_frequency		**83.348*****		
		(2.820)		
Biodiversity_concern_cnwords			**121.769*****	
			(2.928)	
Biodiversity_concern_char				**190.193****
				(2.401)
Size	0.107***	0.093***	0.093***	0.093***
	(8.082)	(7.862)	(7.840)	(7.886)
Leverage	-0.591***	-0.518***	-0.518***	-0.518***
	(-13.212)	(-13.065)	(-13.069)	(-13.063)
ROA	1.146***	0.967***	0.967***	0.969***
	(8.598)	(8.041)	(8.041)	(8.053)
Market-to-book ratio	0.282***	0.236***	0.236***	0.236***
	(20.145)	(18.571)	(18.577)	(18.589)
Cash flow	0.071	0.033	0.033	0.033
	(0.920)	(0.476)	(0.477)	(0.473)
Growth	-0.077***	-0.066***	-0.066***	-0.066***
	(-4.650)	(-4.468)	(-4.467)	(-4.471)
Board size	-0.040*	-0.034	-0.035	-0.034
	(-1.716)	(-1.628)	(-1.631)	(-1.621)
CEO duality	-0.008	-0.007	-0.007	-0.007
	(-0.594)	(-0.535)	(-0.542)	(-0.533)
Board independence	0.056	0.102	0.101	0.101
	(0.785)	(1.551)	(1.549)	(1.548)
Ownership concentration	-0.527***	-0.506***	-0.506***	-0.505***
	(-7.960)	(-8.401)	(-8.400)	(-8.382)
Management shareholding	0.178***	0.168***	0.168***	0.168***
	(2.992)	(3.125)	(3.124)	(3.139)
Audit opinion	0.061**	0.056**	0.056**	0.056**
	(2.236)	(2.275)	(2.271)	(2.282)
Constant	-4.347***	-3.610***	-3.606***	-3.616***
	(-16.739)	(-15.557)	(-15.530)	(-15.581)
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Observations	41,022	41,022	41,022	41,022
Adj. R^2	0.426	0.432	0.432	0.432

Table B5: Robustness test— controlling for climate policy uncertainty

This table reports the regression results after controlling for the climate policy uncertainty at the province level (*CPU*). The same set of control variables as in the baseline regression is used. T-statistics clustered at the firm level are shown in parentheses. *, **, and *** signify 10%, 5%, and 1% significance levels, respectively.

Variables	**Panel A. Controlling for climate policy uncertainty** SYN1 (1)
Biodiv_risk	**0.026*****
	(2.580)
CPU	0.007
	(0.132)
Size	0.093***
	(7.856)
Leverage	-0.517***
	(-13.058)
ROA	0.970***
	(8.065)
Market-to-book ratio	0.236***
	(18.593)
Cash flow	0.033
	(0.478)
Growth	-0.066***
	(-4.470)
Board size	-0.034
	(-1.623)
CEO duality	-0.007
	(-0.534)
Board independence	0.102
	(1.560)
Ownership concentration	-0.503***
	(-8.367)
Management shareholding	0.171***
	(3.186)
Audit opinion	0.056**
	(2.292)
Constant	-3.626***
	(-13.812)
Year FE	Yes
Firm FE	Yes
Observations	41,022
Adj. R^2	0.432

Table B6: Robustness tests—alternative fixed effects, controlling for province-specific time shocks, and two-way clustering

This table displays the results for various robustness tests. Panel A summarizes the estimates using alternative fixed effects (firm, city, and year fixed effects). Panel B introduces province × year fixed effects to control for province-specific time trends. Panel C employs two-way clustering of standard errors at the firm and industry×year levels to account for cross-sectional and temporal dependence. The same set of control variables as in the baseline regression is used. T-statistics clustered at the firm level (for Panels A and B) and at the firm and industry×year level (for Panel C) are shown in parentheses. *, **, and *** signify 10%, 5%, and 1% significance levels, respectively.

	Panel A. Alternative fixed effects (Firm FE, city FE, and year FE)	**Panel B. Controlling for province-specific time shocks**	**Panel C. Two-way clustering (Firm and industry×year level)**
	(1)	(2)	(3)
Biodiv_risk	**0.026***	**0.027***	**0.026**
	(2.587)	**(2.655)**	**(2.482)**
Size	0.089***	0.084***	0.093***
	(7.428)	(6.977)	(7.840)
Leverage	-0.530***	-0.541***	-0.517***
	(-13.279)	(-13.410)	(-12.750)
ROA	0.973***	0.976***	0.970***
	(8.074)	(8.027)	(7.780)
Market-to-book ratio	0.242***	0.250***	0.236***
	(18.857)	(19.196)	(18.109)
Cash flow	0.029	0.042	0.033
	(0.413)	(0.606)	(0.455)
Growth	-0.067***	-0.063***	-0.066***
	(-4.481)	(-4.207)	(-4.275)
Board size	-0.037*	-0.036*	-0.034
	(-1.723)	(-1.667)	(-1.558)
CEO duality	-0.008	-0.009	-0.007
	(-0.638)	(-0.685)	(-0.516)
Board independence	0.113*	0.116*	0.102
	(1.725)	(1.770)	(1.492)
Ownership concentration	-0.495***	-0.476***	-0.503***
	(-8.180)	(-7.764)	(-8.315)
Management shareholding	0.179***	0.186***	0.171***
	(3.305)	(3.410)	(3.165)
Audit opinion	0.058**	0.054**	0.056**
	(2.330)	(2.159)	(2.194)
Constant	-3.562***	-3.512***	-3.610***
	(-15.171)	(-14.916)	(-15.557)
Year FE	Yes	No	Yes
Province x Year FE	No	Yes	No
City FE	Yes	Yes	No
Firm FE	Yes	Yes	Yes
Observations	41,020	41,020	41,022
Adj. R^2	0.429	0.433	0.432

Table B7: Robustness test—additional firm-level control variables

This table reports the results of robustness tests with additional control variables, including *Firm age, Z-score, and Asset turnover ratio*. The same set of control variables as in the baseline regression is used. T-statistics clustered at the firm level are shown in parentheses. *, **, and *** signify 10%, 5%, and 1% significance levels, respectively.

Variables	SYN1 (1)
Biodiv_risk	**0.025**** **(2.520)**
Size	0.093*** (7.814)
Leverage	-0.441*** (-8.645)
ROA	0.012 (0.039)
Market-to-book ratio	0.233*** (18.205)
Cash flow	0.007 (0.100)
Growth	-0.076*** (-4.987)
Board size	-0.034 (-1.595)
CEO duality	-0.006 (-0.518)
Board independence	0.099 (1.502)
Ownership concentration	-0.527*** (-8.670)
Management shareholding	0.157*** (2.931)
Audit opinion	0.055** (2.259)
Firm age	-0.144** (-1.985)
Z-score	0.084*** (3.039)
Asset turnover ratio	0.087*** (3.581)
Constant	-3.293*** (-10.442)
Year FE	Yes
Firm FE	Yes
Observations	41,022
Adj. R^2	0.433

Table B8: Exclusion of crisis periods

This table reports the main regression results by excluding three major financial crises: the global financial crisis (2007-2008), China's stock market crash (2015), and the COVID-19 pandemic (2020-2023). The same set of control variables as in the baseline regression is used. Standard errors are shown in parentheses. *, **, and *** signify 10%, 5%, and 1% significance levels, respectively.

	SYN1
	(1)
Biodiv_risk	**0.023****
	(1.685)
Size	0.013
	(0.946)
Leverage	-0.581***
	(-10.735)
ROA	1.364***
	(8.211)
Market-to-book ratio	0.331***
	(20.611)
Cash flow	-0.032
	(-0.335)
Growth	-0.105***
	(-5.159)
Board size	0.018
	(0.627)
CEO duality	0.004
	(0.268)
Board independence	-0.030
	(-0.333)
Ownership concentration	-0.585***
	(-8.169)
Management shareholding	0.166**
	(2.462)
Audit opinion	0.044
	(1.378)
Constant	-2.399***
	(-8.542)
Year FE	Yes
Firm FE	Yes
Observations	21,539
Adj. R^2	0.323

Table B9: Channel analysis

This table reports the regression results for two underlying channels behind our main finding: information disclosure quality and stock price crash risk. Information disclosure quality is proxied by the KV index, as computed through equation (3) in Appendix A. Since a higher KV index represents poorer disclosure quality, we use it as an inverse measure for information disclosure quality. As our second channel, stock price crash risk is proxied by down-to-up volatility (DUVOL), calculated via equation (4) in Appendix A. The same set of control variables as in the baseline regression is used. T-statistics clustered at the firm level are shown in parentheses. *, **, and *** signify 10%, 5%, and 1% significance levels, respectively.

	Panel A. Information disclosure quality		**Panel B. Stock price crash risk**	
	Information disclosure quality	SYN1	Stock price crash risk	SYN1
	(1)	(2)	(3)	(4)
Biodiv_risk	**0.004*** **	**0.025** **	**0.020*** **	**0.022** **
	(3.925)	**(2.518)**	**(5.756)**	**(2.208)**
Information disclosure quality		**0.155*** **		
		(2.603)		
Stock price crash risk				**0.185*** **
				(12.630)
Size	0.036***	0.087***	-0.008**	0.094***
	(25.794)	(7.205)	(-2.341)	(7.996)
Leverage	-0.000	-0.517***	-0.045***	-0.509***
	(-0.095)	(-13.060)	(-3.270)	(-12.872)
ROA	0.206***	0.938***	0.021	0.966***
	(16.665)	(7.791)	(0.527)	(8.051)
Market-to-book ratio	-0.027***	0.240***	0.037***	0.229***
	(-18.687)	(18.618)	(9.379)	(18.068)
Cash flow	-0.025***	0.037	-0.031	0.039
	(-3.697)	(0.533)	(-1.224)	(0.560)
Growth	0.005***	-0.067***	-0.013**	-0.064***
	(3.752)	(-4.521)	(-2.460)	(-4.318)
Board size	-0.001	-0.034	-0.001	-0.034
	(-0.459)	(-1.617)	(-0.075)	(-1.621)
CEO duality	0.002	-0.007	-0.002	-0.006
	(1.618)	(-0.562)	(-0.587)	(-0.499)
Board independence	-0.000	0.102	-0.005	0.103
	(-0.022)	(1.561)	(-0.235)	(1.579)
Ownership concentration	0.024***	-0.507***	0.012	-0.505***
	(3.529)	(-8.430)	(0.643)	(-8.420)
Management shareholding	0.040***	0.165***	-0.019	0.174***
	(6.300)	(3.072)	(-1.083)	(3.250)
Audit opinion	0.003	0.055**	-0.028***	0.061**
	(1.581)	(2.273)	(-3.304)	(2.498)
Constant	-0.521***	-3.529***	-0.333***	-3.548***
	(-19.474)	(-15.058)	(-4.738)	(-15.352)
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Observations	41,022	41,022	41,022	41,022
Adj. R^2	0.481	0.659	0.046	0.435

Table B10: Subsample analysis

This table displays the regression results for various subsample analyses. Panel A presents the estimates of subsamples based on management integrity level. Firms are classified into higher (lower) integrity based on bottom (top) one-third quantile of their management integrity. Panel B reports the regression results for subsamples based on ownership structure of firms. The main sample is divided into state-owned-enterprises (SOEs) and non-state-owned enterprises (Non-SOEs). Panel C summarizes the estimates of subsamples based on firm financial constraints. The full sample is divided into financially constrained firms and unconstrained firms based on the SA index. Firms in the bottom (top) one-third quantile of the SA index ranking are classified financially unconstrained (constrained) firms. The same set of control variables as in the baseline regression is used. T-statistics clustered at the firm level are shown in parentheses. *, **, and *** signify 10%, 5%, and 1% significance levels, respectively.

	Panel A. Higher management integrity vs. lower management integrity		**Panel B. State-owned enterprises vs. non-state-owned enterprises**		**Panel C. Financially constrained firms vs. unconstrained firms**	
	Higher management integrity	Lower management integrity	SOEs	Non-SOEs	Constrained	Unconstrained
	SYN1		SYN1		SYN1	
	(1)	(2)	(3)	(4)	(5)	(6)
Biodiv_risk	**0.030**	**0.026****	**-0.008**	**0.033*****	**0.052*****	**0.016**
	(1.067)	**(2.241)**	**(-0.469)**	**(2.626)**	**(2.648)**	**(1.319)**
Size	0.148***	0.091***	0.099***	0.086***	0.094***	0.101***
	(4.113)	(7.045)	(4.900)	(5.589)	(4.489)	(7.764)
Leverage	-0.740***	-0.530***	-0.702***	-0.395***	-0.494***	-0.535***
	(-5.811)	(-11.627)	(-10.181)	(-7.728)	(-6.654)	(-11.318)
ROA	0.072	1.072***	0.924***	0.986***	1.227***	0.859***
	(0.200)	(7.618)	(4.246)	(6.736)	(5.187)	(6.034)
Market-to-book ratio	0.265***	0.230***	0.208***	0.258***	0.208***	0.246***
	(7.267)	(15.919)	(9.836)	(15.690)	(8.901)	(16.843)
Cash flow	0.351*	0.020	-0.088	0.076	0.025	0.024
	(1.696)	(0.238)	(-0.787)	(0.850)	(0.172)	(0.284)
Growth	-0.043	-0.069***	-0.080***	-0.062***	-0.088***	-0.058***
	(-0.942)	(-4.002)	(-3.470)	(-3.231)	(-2.820)	(-3.171)
Board size	-0.044	-0.021	-0.007	-0.042	-0.038	-0.045*
	(-0.707)	(-0.817)	(-0.189)	(-1.515)	(-0.897)	(-1.781)
CEO duality	-0.003	0.003	-0.031	0.007	0.020	-0.023
	(-0.088)	(0.182)	(-1.191)	(0.485)	(0.831)	(-1.592)
Board independence	0.069	0.067	0.232**	0.004	0.162	0.071
	(0.359)	(0.868)	(2.135)	(0.046)	(1.265)	(0.899)
Ownership concentration	-0.556***	-0.577***	-0.500***	-0.468***	-0.381***	-0.574***
	(-3.083)	(-8.629)	(-4.614)	(-5.848)	(-3.613)	(-8.493)
Management shareholding	0.199	0.186***	-0.226	0.212***	0.102	0.233***
	(1.384)	(2.909)	(-1.194)	(3.583)	(1.048)	(3.724)
Audit opinion	-0.043	0.073**	0.030	0.058**	0.057	0.066**
	(-0.621)	(2.523)	(0.664)	(1.995)	(1.142)	(2.322)
Constant	-4.829***	-3.475***	-3.388***	-3.728***	-3.550***	-3.778***
	(-6.482)	(-13.859)	(-8.645)	(-12.232)	(-8.746)	(-14.545)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6026	29590	15,373	25,585	11466	28411
Adj. R^2	0.425	0.438	0.434	0.407	0.427	0.439