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Sowing Sustainability: How does fintech mitigate agricultural financial risk from climate change vulnerability

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ABSTRACT

This study examines the impact of climate vulnerability on agricultural finance and explores the moderating role of fintech in this nexus. Using a sample of 1017 firms from 24 countries, we find that climate vulnerability is positively associated with agricultural finance, indicating that climate change exacerbates financial constraints for firms. Interestingly, our analysis of fintech's moderating effect reveals that fintech mitigates the negative impact of climate vulnerability on agricultural finance by promoting climate-smart agricultural practices and encouraging the adoption of insurance by farmers. Furthermore, our findings highlight that the Fourth Industrial Revolution, strong institutional quality, higher levels of innovation, and a country's readiness for technological adoption play critical roles in reducing the effects of climate vulnerability. Digital technologies, by improving operational efficiency and enabling better measurement and tracking of climate impacts, help reduce carbon emissions. These insights offer important managerial and policy implications, emphasising the need for integrating fintech and digital solutions to enhance resilience in agricultural finance.

1. Introduction

Climate vulnerability is one of the major global challenges of our time, and its impacts are expected to grow more severe in the coming decades (Guo et al., 2024; Karki et al., 2020; Zhang et al., 2020). It refers to the degree to which people and ecosystems are affected by climate-related changes, such as droughts, rising global temperatures, and sea level rise. Developing countries, in particular, face increasing risks—especially in the agricultural sector, which is highly sensitive to climate shocks. According to UNEP FI (2023), continued global warming could significantly disrupt agricultural production. There is an average of 84 percent damages and losses caused by droughts in the agriculture sector in sub-Saharan Africa during 2003–2013 (World Bank, 2017). Moreover, Hasan and Kumar (2021) found evidence that average crop yields declined by 2.91 % annually between 1970 and 2017 due to climatic trends and variations, equating to a loss of 2.4 million tons per year in Bangladesh. FAO (2009) estimates suggest that agricultural productivity

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could decline by an additional 9 %–21 % in developing regions. Palmer (2016) emphasises that without increasing capital allocation toward climate-smart agricultural investments, it will be difficult to mitigate and build resilience against climate change. Agricultural finance plays a critical role in addressing climate vulnerabilities by providing pathways to improve sustainability in the sector (Njangang et al., 2024). It supports farmers and agribusinesses by offering access to essential financial tools—such as loans, credit, and insurance—helping them invest in climate-resilient practices and manage climate-related risks. Evidence shows that access to credit for farmers could encourage their participation in small-scale irrigation, adoption of climate-smart agricultural technologies, and likely investment in resilient practices such as drip irrigation and agroforestry (Bojago & Abrham, 2023; Khatri-Chhetri et al., 2017; World Bank, 2016).

However, agricultural finance faces several challenges at the project, national, and global levels. These challenges include high transaction costs, commodity price risks, interest rate fluctuations, extended payback periods, agronomy-related hazards, weak institutional frameworks, and geopolitical uncertainties (Apampa et al., 2021; World Bank, 2016; Zhao et al., 2023). Due to the inherently risky and low-profit nature of agricultural investments, access to finance in the sector is often constrained (Palmer, 2016). The complex relationship between climate change and agricultural finance necessitates further investigation to ensure the agricultural sector's vitality and continued development (Guo et al., 2021).

In this context, this study explores the potential of financial technology (Fintech) to act as a buffer for climate vulnerabilities in agricultural finance.[1] Fintech refers to the use of technology in financial management to make services cheaper, faster, and more accessible. The adoption of fintech services and products can potentially foster sustainability and resilience in agriculture by connecting farmers with finance and providing innovative financial solutions (Chang, 2022; Cheng et al., 2023). If integrated effectively into the agricultural sector, fintech could contribute up to $500 billion in value to global GDP by 2030, with productivity gains of 7 %–9 % (Goedde et al., 2020). Fintech platforms can make financial services more accessible, empowering farmers to mitigate climate risks through climate-smart agriculture, insurance products, and advisory services (Chai et al., 2025; You et al., 2023). For instance, Chang (2022) demonstrated how fintech reduced agricultural carbon emissions in China by facilitating farmers' entrepreneurship, urbanization, and agricultural innovation.

Although fintech holds significant potential to alleviate financial constraints, smallholder firms in developing countries often face challenges in accessing these innovations. To address this issue, international organizations such as The Food and Agriculture Organization of the United Nations (FAO), in collaboration with local governments and financial institutions, are working to improve access through digital platforms, mobile money, and other digital financial services. For instance, the FAO launched the digital platform 'microbanking system' (MBWin) in Bangladesh to provide innovative agribusiness services to rural farmers. In China, fintech innovations like Alibaba's and Milbank's 'Tomtit' platform—leveraging satellite imaging and AI to assess farmland and crop types—enable financial institutions to offer tailored loans for planting and harvesting. Similarly, India's Digital Green Loop connects farmers with entrepreneurs and transporters, enhancing trading efficiency and reducing transaction costs (Hinson et al., 2019). These examples demonstrate fintech's potential to reduce the adverse effects of climate vulnerability on agricultural finance. Nenavath (2022) further suggests that fintech growth contributes to lower sulfur dioxide (SO_2) emissions, promoting environmental safety and encouraging sustainable investments. While a growing body of literature has explored the environmental impacts of financial development—particularly its influence on carbon emissions (Charfeddine and Kahia, 2019; Nelson et al., 2010; Zhang et al., 2020; Zhao et al., 2022)—the specific role of fintech in addressing climate vulnerability within agricultural finance remains underexplored. This study aims to bridge that gap by examining how fintech can help mitigate the financial constraints imposed by climate change on the agricultural sector.

Using a dataset of 1017 firms from 24 countries spanning 2011 to 2021, this study employs CGM (Cameron, Gelbach, and Miller) two-way clustering and OLS estimation techniques to assess the relationship between climate vulnerability and agricultural finance. The findings reveal that climate vulnerability significantly exacerbates financial constraints in the agricultural sector. However, fintech plays a moderating role, reducing the negative impact of climate vulnerability on agricultural finance by promoting climate-smart practices and facilitating access to insurance. In economic terms, one additional Fintech decreases the effect of climate vulnerability on agricultural finance from 2.73 % to 3.70 %. These results remain robust after addressing endogeneity concerns using the generalized method of moments (GMM) and controlling for self-selection bias with Propensity Score Matching (PSM). Additional channel analyses confirm the significance of the Fourth Industrial Revolution and institutional quality in mitigating climate-related risks, with digital technologies improving operational efficiency and reducing carbon emissions. The study's findings remain consistent even when excluding non-European countries from the sample.

This study makes four key contributions. First, we contribute to the growing literature on climate change (Alam et al., 2024; Gul et al., 2022; Huang et al., 2018) by providing new insights into how climate change impacts agricultural finance. While prior studies have focused on macroeconomic conditions (Dirir and Aden, 2024; Zeng et al., 2024) and gender differentials (Alao et al., 2020), this study examines the impact of climate change on agricultural finance. Our study provides strong empirical evidence that climate vulnerability significantly affects the financing of agricultural firms. Second, this study offers a new perspective by detailing how fintech can mitigate the adverse impact of climate change risks on agricultural financing. This is motivated by the study by Tao et al. (2022), who argued that fintech could help reduce carbon emissions. Consistent with their findings, we demonstrate that fintech platforms offer a promising means to alleviate the effects of climate vulnerability in agricultural finance. Fintech supports climate-smart agriculture and promotes the adoption of insurance, helping farmers manage climate-related risks. Moreover, the Fourth

[1] In this study, agricultural finance refers to agricultural financial risk or agricultural financial leverage. These terms—agricultural finance, agricultural financial risk, and agricultural financial leverage—are used interchangeably throughout the study.

Industrial Revolution plays a crucial role in addressing climate vulnerability, as digital technologies enhance operational efficiency, improve climate impact measurement, and reduce carbon emissions. Third, we apply the natural resource-based view (NRBV) framework to analyse the relationship between climate vulnerability and agricultural finance, as well as the moderating role of fintech. This extends NRBV theory by incorporating the dimension of climate change, enriching its application in the context of agricultural finance. It also responds to the call by Gibson et al. (2021) to extend the resource-based view to ensure sustainability. Finally, we employ a panel data technique that controls for unobserved heterogeneity across firms, ensuring that our results are robust across various analyses. This methodological rigor strengthens the reliability and generalizability of our findings.

The remainder of this paper is organized as follows: Section 2 discusses the theory and develops our hypotheses; Section 3 discusses the research methods while Section 4 discusses and presents the results; Section 5 presents robustness tests and Section 6 provides additional/channel analysis; Section 7 discusses the study's implications and concludes the paper.

2. Theory and hypothesis development

Researchers have used several approaches to investigate the nexus of carbon emissions, agricultural production, and efficiency. In this study, we explore the impact of climate change on agricultural financial risk in the presence of Fintech. Therefore, to understand this nexus, we used the natural resource-based view theory (Hart, 1995), an extension of the resource-based view theory. According to Ghadge et al. (2020), the resource-based view (RBV) is suitable for predicting supply chain sustainability performance. Further, the theory contends that gaining a competitive advantage can be more effectively achieved by concentrating on internal resources, including physical, financial, and human resources (Barney, 1991).

According to Torres and Augusto (2017), understanding these competencies might help farmers be more strategically positioned to meet the needs of different market segments. However, the RBV theory has come under fire for failing to consider the biophysical and natural environment or the critical natural resource limitations that create a crucial context for strong innovative capability. Therefore, the natural resource-based view (NRBV) theory was developed (Hart, 1995) using a strong connection to nature. According to NRBV theory, farmers should focus on climate relations and ensure sustainable growth while attempting to increase their global financial gains through technological innovations through inclusive finance and climate prevention (Hart, 1995). This shows that the above initiatives can address environmental problems, including emissions and climate change, by sustaining and enhancing agricultural finance accessibility through green innovations and equal financial services (Bansal and Priya Nangia, 2022; Guo et al., 2021). Hence, these studies apply the Natural resource-based view (NRBV) as a basis for investigating the role of Fintech in the effect of climate change on agricultural financial risk. Similar calls have been made to extend RBV to ensure sustainability (Gibson et al., 2021). To the best of the researcher's knowledge, no study has used this theory on the impact of climate change on agricultural financial risk through Fintech. Understanding and getting full accessibility to financial technologies could position farmers to be strategic in innovating green products and productions which address climate change conditions, leading to achieving SDGs through environmental sustainability. Hence, this study applied NRBV theory as a basis for investigating and analysing cross-country data on the impact of climate change on agricultural financial risk with the mediating role of Fintech. Fig. 1 illustrates the conceptual framework of the study.

During the past two decades, improvements have been made to the complex infrastructure of agriculture, agri-food supply chains, and fibre production. Finance is involved in essential infrastructure developments and managerial tasks in agriculture. Agricultural financial markets and institutions play an integral role in financing significant stages of the agri-food supply chain. Agriculture has

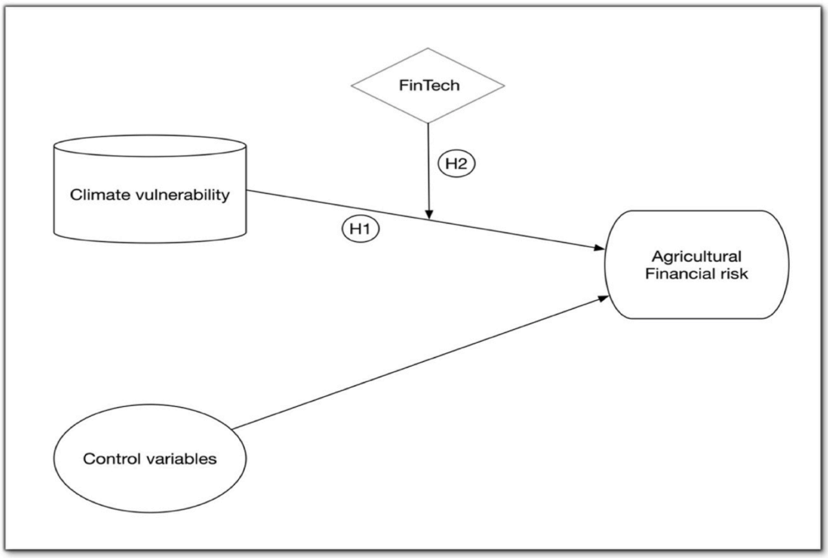

Fig. 1. Conceptual framework.

been the primary economic activity for humans, and problems with agriculture directly influence human lives (Guo et al., 2021; Zilberman et al., 2018). Agriculture is also a crucial component of a country's economy and serves as a foundation for the growth of secondary and tertiary industries. Before economic development, the stability and prosperity of the agricultural sector should be guaranteed (Rehman et al., 2021; Zhang et al., 2020). Due to the agricultural system's vulnerability and its dependence on climate conditions, researchers believe climate change has intensely affected the sustainability of agricultural production (Mu et al., 2017). Investigating the impact of climate change on agricultural financial risk is critical for farmers, scholars, and policymakers (Hellin and Fisher, 2019; Mu et al., 2017). Climate change affects different agricultural areas owing to its unique effects on climate resources. Climate change significantly impacts farmers from a small-scale perspective (Karki et al., 2020). A system that influences the efficient use of climatic resources needs to be adjusted, and an appropriate financial strategy should be adopted to reduce the impact of climate change on agricultural production (Guo et al., 2015).

The effects of climate change on agricultural production have been the subject of several studies (Chen et al., 2016; Gul et al., 2022). Adamišin et al. (2015) found that climate change affected agricultural productivity and efficiency. Gu et al. (2022) discovered that climate factors have emerged as a damaging Pakistan agricultural production crisis. Similarly, climate change may increase the hazards associated with agricultural output in the Philippines (Laureta et al., 2021). This suggests that agricultural productivity is affected by climate change in several nations worldwide. Most existing studies use agricultural productivity to assess how agricultural production responds to climate change and comprehend climate's effects on agricultural financing. For example, Liang et al. (2017) found that climate change negatively impacted agricultural productivity in the United States. Chen and Gong (2021) showed that high temperatures undermine Chinese agricultural productivity. This evidence indicates that climate change significantly and negatively impacts the agricultural industry. In a related study, Buhr et al. (2018) argued that climate change increases the cost of borrowing, and creditors are reluctant to lend to a country already struggling with payments and climate vulnerability, making it difficult for firms to borrow. Liu et al. (2025) added that the effects of climate change on agriculture decrease production efficiency and increase property damage, which in turn affects farmers' ability to repay debts and their willingness to borrow. A recent global survey by the EDF and Deloitte (2022) reported that 83 % of agricultural finance institutions expect climate change to increase the likelihood of default and default in the future. Based on the above discussion, it can be argued that greater vulnerability to climate change raises the cost of capital and exacerbates financial risk. Therefore, we propose the following hypothesis.

H1. Climate change heightens the agricultural financial risks for farmers.

Mitigation and adaptation are two crucial strategies for reducing the impacts of the changing climate (Chen et al., 2016; Duffy et al., 2021). Technology is one of the primary mitigating factors (Nilson et al., 2016). Recent innovations in Fintech, such as those that use technology to provide and facilitate financial services (Arner et al., 2015), have demonstrated immense potential in this field. Mobile phones, internet-connected devices, or cards linked to secure digital payment systems are some of the ways in which financial intermediation services are delivered (Manyika et al., 2016; Hasan et al., 2024). This is a critical step toward expanding inclusive business practice (Wang et al., 2014). Using the current technology's financial and communication applications, agriculture and farmers can experience rapid growth and sustainability. It is estimated that the EU could reduce its agriculture-related GHG emissions by 6 % if farmers adopted climate-smart practices by 2030 (UNEP FI, 2023). The NRBV theory contends that farmers' full utilisation and access to inclusive finance is related to sustainable development, considering economic, environmental, and social issues on a global scale (Hart, 1995), which promotes positive and significant impact operations.

In this context, inclusive financial systems benefit the environment by promoting mobility and accessibility and adopting sustainable environmental practices to reduce the effects of climate change (Ullah et al., 2022). A study by Muganyi et al. (2021) argued that Fintech platforms promote cleaner production through intelligent manufacturing and other green management practices. Yu et al., 2020 pointed out that Fintech promotes green agricultural practices by confirming credit availability, addressing information asymmetry, and increasing trust among farmers. Fintech is essential for combating climate change (Liu et al., 2021) because many small businesses and farm owners lack the financial resources to invest in renewable energy. The increasing adoption of technologies, including smartphones, has enabled various Fintech services to reach even the most isolated regions of economies (Alwi, 2021). Fintech offers finance to farmers more conveniently and at an affordable rate through crowdfunding and digital platform systems (SAFIN, 2022). In a recent study, Abbasi et al. (2025) further added that using big data technology, Fintech increases the availability of funds when firms face heightened climate risk, thereby enhancing firm value. As a result, these services have enabled farmers to access financing and other forms of commerce, increasing the versatility of various products. We suggest that using Fintech applications might give farmers access to financial innovations and services that would promote sustainability by reducing climate change risk. Hence, we propose the following hypotheses.

H2. Fintech moderates the relationship between climate vulnerability and agricultural financial risk.

3. Data and methods

3.1. Data

Our data come from several sources: i) the S&P capital database for firm-specific data; ii) the Notre Dame Global Adaptation Initiative (NDG) for climate change vulnerability-delta index (VAL) data; iii) Crunchbase provides Fintech-related data (we consider the number of peer-to-peer lending Fintech in the country in a particular year), and iv) the World Development Indicators (WDI) and World Governance Indicators (WGI) databases for macroeconomic factors. Initially, we searched for firm-specific (financial) data on agricultural firms (producing agricultural products such as fruits, vegetables, nuts, grains, and field beans) in the S&P capital database and found 5751 firms. However, unfortunately, the data of most of the firms are missing, and after filtering, the final sample of this study is 1017 agricultural firms from 24 countries over the period–2011-2021. We consider this period because Fintech data are available from 2011 onwards. However, the number of firms varies yearly owing to data unavailability. Thus, our study considered unbalanced panel data. A breakdown of the sample is presented in Table 1. We winsorise each variable at the 1st and 99th percentiles to reduce the effect of outliers.

3.2. Variables

3.2.1. Agricultural financial risk

Following Kling et al. (2021), we take the firm's total debt-to-total assets ratio (financial leverage/risk) as a dependent variable. Firms with high leverage are highly indebted and thus riskier.

$$\text{Agricultural financial risk}, TDTA = \frac{Total\ debt}{Total\ assets} \tag{1}$$

3.2.2. Climate vulnerability

The ((NDG) measures overall vulnerability by considering six life-supporting sectors: food, water, health, ecosystem services, human habitat, and infrastructure. This index considers a country's exposure, sensitivity, and capacity to adapt to the harmful effects of climate change. In our study, we consider the vulnerability delta index (VAL), the independent variable as a proxy for climate change, following Alam et al. (2024) and Kling et al. (2021). Based on the literature and NRBV, we predict that agricultural firms will suffer more if the country's climate is more vulnerable and, thus, more financially riskier.

3.2.3. Fintech

To assess the moderating impact on the link between agricultural financial risk and climate change, we employ the number of peer-to-peer lending Fintech as a proxy for Fintech, following the methodology of Abbasi et al. (2021). This metric, which measures the number of peer-to-peer lending Fintech in a specific country within a given year, serves as a proxy for Fintech. The rationale behind using this proxy is that peer-to-peer (P2P) lending represents one of the most prominent and quantifiable innovations within the fintech sector, particularly in the domains of financial inclusion and alternative financing. It bypasses traditional financial intermediaries, offering direct, technology-enabled access to credit—an essential component of fintech. The number of P2P lending firms in a country reflects the maturity, scale, and adoption of fintech-driven credit markets. Moreover, P2P lending has been particularly impactful in agriculture and rural sectors, where conventional finance is often inaccessible, making it a relevant and effective proxy for capturing fintech activity in the context of agricultural finance.

Table 1
Sample breakdown.

Country	Firm	Observations	Percent
Austria	2	17	0.24
Belgium	13	113	1.62
Bulgaria	7	29	0.42
Croatia	12	36	0.52
Denmark	7	44	0.63
Finland	2	22	0.32
France	124	1011	14.48
Germany	52	461	6.6
Ireland	6	36	0.52
Italy	200	1638	23.46
Japan	19	111	1.59
Netherlands	24	212	3.04
Norway	5	49	0.7
Poland	14	48	0.69
Portugal	19	156	2.23
Romania	30	113	1.62
Russia	89	348	4.98
Serbia	17	50	0.72
Slovakia	11	44	0.63
Slovenia	3	10	0.14
Spain	123	985	14.11
Sweden	14	128	1.83
USA	144	564	8.08
United Kingdom	80	758	10.85
Total	1017	6983	100

3.2.4. Firm-specific and macroeconomic variables

This study controlled for several firms- and country-specific factors. This study uses the logarithm of total assets (firm size, SIZE) to capture the 'size' hypothesis. The ratio of fixed assets to total assets (TANG) accounts for Tangibility following Kling et al. (2021). We also consider the current ratio (CR), other operating expenses (OOEXP), and return on assets (ROA) to control profitability.

To address country-specific variation, we consider annual GDP per capita growth (GDPCG). To control for institutional quality (IQ), we used the standardised approach of the governance indicators stated in Kaufmann et al. (2010) and Banna (2025). The WGI consists of six components: Control of Corruption, Government Effectiveness, Political Stability and Absence of Violence/Terrorism, Regulatory Quality, Rule of Law, and Voice and Accountability.

3.3. Estimation techniques

The regression below investigates the impact of climate change on agricultural financial risk and the moderating role of Fintech on this nexus.

$$Y_{ijt} = \alpha + \beta 1 VAL_{jt} + \beta 2 (VALxFINTECH)_{jt} + \gamma B_{ijt} + \varphi M_{jt} + \varepsilon_{ijt} \tag{2}$$

Y_{ijt} (i.e., TDTA as a dependent variable is the proxy for the agricultural financial leverage/risk of the firm 'i' of country 'j' in year' t.' VAL_{jt} = Vulnerability delta index of country 'j' in year' t.' $(VALxFINTECH)_{jt}$ = Interaction effect between VAL and FINTECH of country 'j' in year 't.' *and* B_{ijt} = firm-specific factors of bank 'i' of country 'j' in year 't'. M_{jt} = Macroeconomic factors of country 'j' in year 't.' β, γ, φ = coefficients of the variables and ε_{ijt} = error term.

In this study, we use Cameron, Gelbach, and Miller's (2011) two-way clustering (CGM) estimation technique with heteroscedasticity-corrected clustered robust standard error and robust interference to reduce the general issues of sequential correlation and cross-sectional dependence along with OLS. We used dynamic two-stage system-GMM tests (2GMM-CGM) as a robustness test to address endogeneity and dynamism and propensity score matching (PSM) technique to minimise self-selection bias.

4. Results and analysis

Table 2 presents the descriptive statistics for the key variables used in the sample, and the definitions and sources of the variables are presented in Appendix 1. We find that agricultural financial risk is, on average, 0.26, and the range (0.925) suggests variations in the data. The mean value of climate vulnerability was −0.045 with a standard deviation of 0.031. Except for Fintech and Net income, the values of the variables do not vary across firms over time. Fintech has a mean of 104.303 but a high standard deviation of 201.552, indicating that this value varies across firms over time, which facilitates our empirical tests. This is because all agricultural firms may not have access to Fintech finance. The net income margin standard deviation is 16.699, which is relatively high, indicating variation in income across the firm over time. Table 3 presents the correlation matrices for the variables. All correlations are below 0.60, lower than the benchmark 0.80 (Berry et al., 1985) of severe multicollinearity, indicating no multicollinearity issues.

Table 4 reports the CGM and OLS regression results. The results show that climate vulnerability is positively related to agricultural financial risk, with a one-unit increase in climate vulnerability leading to a 0.762-unit increase in financial risk. This suggests that environmental shocks, which often damage agricultural assets, leave firms with limited borrowing capacity for recovery. In some cases, they may be forced to borrow at higher interest rates, further increasing their financial burden. This vulnerability is largely due to the lack of environmental management capabilities among many agricultural firms, which heightens their financial exposure. These findings align with the NRBV, which argues that firms must invest in resource-based strategies such as sustainable practices and

Table 2
Descriptive statistics.

Variable	Obs	Mean	Std.Dev.	Min	Max
TDTA	4163	0.26	0.212	0	0.925
VAL	6983	−0.045	0.031	−0.095	0.038
FINTECH	6982	104.303	201.552	1	1080
SIZE	6981	16.339	1.774	0.226	25.067
TANG	6599	0.343	0.238	0	0.913
CR	6721	2.322	3.457	0.117	26.867
LOOEXP	5165	14.107	2.144	4.633	18.458
ROA	5470	3.114	5.909	−16.328	28.076
GDPCG	6983	0.63	3.393	−11.253	7.336
IQ	6983	−0.261	0.801	−2.572	1.133

Note: This table provides the descriptive statistics (number of observations, mean, standard deviation, minimum and maximum value) of the variables used in this study. TDTA, VAL, FINTECH, SIZE, TANG, CR, LOOEXP, ROA, GDPCG, and IQ refer to total debt over total assets, vulnerability delta index, number of peer-to-peer lending, firm size (ln (total assets)), fixed assets over total assets (tangibility), current ratio, ln (other operating expense), return on assets, GDP per capita growth, and institutional quality respectively. IQ index is standardized using six (6) components of good governance namely, control of corruption, government effectiveness, political stability and absence of violence/terrorism, regulatory quality, rule of law, and voice and accountability. Source: S&P Capital, Notre Dame Global Adaptation Initiative (NDG), Crunchbase, World Development Indicators (WDI), and World Governance Indicators (WGI).

Table 3
Pairwise correlations.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) TDTA	1.000								
(2) VAL	0.038*	1.000							
(3) SIZE	0.046*	−0.075*	1.000						
(4) TANG	−0.416*	0.054*	0.088*	1.000					
(5) CR	−0.158*	0.081*	−0.034*	0.448*	1.000				
(6) LOOEXP	−0.001	0.274*	0.514*	0.134*	0.057*	1.000			
(7) ROA	−0.183*	−0.025	0.063*	0.280*	0.162*	0.120*	1.000		
(8) GDPCG	−0.042*	0.114*	−0.015	0.049*	0.050*	0.031*	0.070*	1.000	
(9) IQ	−0.071*	0.261*	−0.170*	−0.040*	−0.067*	−0.154*	−0.109*	−0.003	1.000

Note: This table shows the pairwise correlation results. TDTA, VAL, SIZE, TANG, CR, LOOEXP, ROA, GDPCG, and IQ refer to total debt over total assets, vulnerability delta index, firm size (ln (total assets)), fixed assets over total assets (tangibility), current ratio, ln (other operating expense), return on assets, GDP per capita growth, and institutional quality respectively. * shows significance at the 0.05 level.

Table 4
Climate change and Agricultural financial risk.

	(1)	(2)	(3)	(4)
	Dep: TDTA			
	CGM		OLS	
VAL	0.606**	0.762**	0.606**	0.762**
	(0.296)	(0.384)	(0.296)	(0.384)
SIZE	0.017***	0.017***	0.017***	0.017***
	(0.003)	(0.007)	(0.003)	(0.007)
TANG	−0.456***	−0.457***	−0.456***	−0.457***
	(0.019)	(0.037)	(0.019)	(0.037)
CR	0.006***	0.006*	0.006***	0.006*
	(0.002)	(0.003)	(0.002)	(0.003)
LOOEXP	−0.004	−0.004	−0.004	−0.004
	(0.002)	(0.004)	(0.002)	(0.004)
ROA	−0.002**	−0.002	−0.002**	−0.002
	(0.001)	(0.001)	(0.001)	(0.001)
GDPCG		−0.002***		−0.002***
		(0.001)		(0.001)
IQ		−0.084		−0.084
		(0.069)		(0.069)
Constant	0.223***	0.200*	0.306***	0.372***
	(0.048)	(0.105)	(0.045)	(0.106)
Obs.	3286	3286	3286	3286
R-squared	0.280	0.281	0.280	0.281
F	129.878***	26.087***	180.030***	182.24***
Country fixed effect	yes	yes	yes	yes
Firm cluster	yes	yes	yes	yes
SE cluster	yes	yes	yes	yes

Note: This table shows the estimation results of the Agricultural Finance (TDTA) – Climate Change (VAL) nexus controlling the bank-specific and macroeconomic variables deploying CGM (2011) two-way clustering techniques and the ordinary least square (OLS) estimation technique using full sample. TDTA, VAL, SIZE, TANG, CR, LOOEXP, ROA, GDPCG, and IQ refer to total debt over total assets, vulnerability delta index, firm size (ln (total assets)), fixed assets over total assets (tangibility), current ratio, ln (other operating expense), return on assets, GDP per capita growth, and institutional quality respectively. *, **, and *** denote statistical significance at the 10 %, 5 %, and 1 % levels, respectively and clustered robust standard errors are in parenthesis. Sources: S&P Capital, NDG, Crunchbase, WDI, WGI.

climate resilience to better manage environmental uncertainty and reduce financial risk. Therefore, it supports hypothesis 1.

Table 5 presents the moderating effect of Fintech using CGM and OLS. Both methodologies yielded consistent results. The results show that Fintech moderates the relationship between climate vulnerability and agricultural financial risk, indicating that climate vulnerability weakens the positive effects of climate vulnerability on agricultural financial risk. In economic terms, one other Fintech decreases the effect of climate vulnerability on agricultural financial risk from 2.73 % (i.e., 0.024/0.880) to 3.70 % (i.e., 0.024/0.648). Fintech helps farmers build climate resilience through climate-smart agriculture and encourages the adoption of insurance against environmental shocks. In addition, it is argued that Fintech facilitates credit to SMEs by accurately measuring creditworthiness using big data and charging lower interest rates because they have low operational costs (Abbasi et al., 2021; Jagtiani and Lemieux, 2019; Lee and Shin, 2018). Therefore, Hypothesis 2 was supported. These results support the NRBV by demonstrating that technological innovations, when integrated into a firm's natural resource-based strategy, serve as vital tools for enhancing resilience, promoting sustainability, and gaining a competitive advantage in the face of climate-related risks. The results of the control variables are

Table 5
Climate change, Agricultural financial risk, and fintech.

	(5)	(6)	(7)	(8)
	Dep: TDTA			
	CGM		OLS	
VAL	0.648*	0.880*	0.648*	0.880*
	(0.364)	(0.459)	(0.364)	(0.459)
FINTECH	−0.001***	−0.001***	−0.001***	−0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
VAL*FINTECH	−0.024***	−0.024***	−0.024***	−0.024***
	(0.006)	(0.007)	(0.006)	(0.007)
SIZE	0.017***	0.018***	0.017***	0.018***
	(0.003)	(0.007)	(0.003)	(0.007)
TANG	−0.457***	−0.458***	−0.457***	−0.458***
	(0.019)	(0.037)	(0.019)	(0.037)
CR	0.006**	0.006*	0.006**	0.006*
	(0.002)	(0.003)	(0.002)	(0.003)
LOOEXP	−0.004*	−0.005	−0.004*	−0.005
	(0.002)	(0.004)	(0.002)	(0.004)
ROA	−0.002**	−0.002	−0.002**	−0.002
	(0.001)	(0.001)	(0.001)	(0.001)
GDPCG		−0.002**		−0.002**
		(0.001)		(0.001)
IQ		−0.065		−0.065
		(0.073)		(0.073)
Constant	0.213***	0.205*	0.314***	0.370***
	(0.050)	(0.105)	(0.046)	(0.108)
Obs.	3286	3286	3286	3286
R-squared	0.283	0.284	0.283	0.284
F	98.371***	21.594***	217.912***	191.30***
Country fixed effect	yes	yes	yes	yes
Firm cluster	yes	yes	yes	yes
SE Cluster	yes	yes	yes	yes

Note: This table shows the estimation results of the Agricultural Finance (TDTA) – Climate Change (VAL) nexus and the moderating role of Fintech controlling the bank-specific and macroeconomic variables deploying CGM (2011) two-way clustering techniques and the ordinary least square (OLS) estimation technique using full sample. TDTA, VAL, FINTECH, SIZE, TANG, CR, LOOEXP, ROA, GDPCG, and IQ refer to total debt over total assets, vulnerability delta index, number of peer-to-peer lending, firm size (ln (total assets)), fixed assets over total assets (tangibility), current ratio, ln (other operating expense), return on assets, GDP per capita growth, and institutional quality respectively. *, **, and *** denote statistical significance at the 10 %, 5 %, and 1 % levels, respectively and clustered robust standard errors are in parenthesis. Sources: S&P Capital, NDG, Crunchbase, WDI, WGI.

consistent with those in the existing literature.

5. Robustness test

5.1. *Alternative agricultural financial risk and fintech variables*

To validate our results as part of a robustness test, we considered alternative proxies for agricultural financial risk and fintech. In line with Katchova and Enlow (2013), we used 'the ratio of total liabilities to total assets (TLTA)' as an alternative proxy for agricultural financial risk. Additionally, following Čihák et al. (2012), we employed 'the percentage of individuals aged 15 and above who use mobile phones to pay bills' as an alternative proxy for fintech. The results presented in Table 6 confirm our baseline findings that climate vulnerability positively affects agricultural financial risk, and fintech serves as a moderating factor in reducing this risk.

5.2. *European and High-income sample*

Thus far, we have discussed the results based on a sample of 24 countries. Given that the United States and Japan are the only non-European countries in the sample, we are interested in examining whether the results remain consistent after excluding these two nations, as presented in Table 7. Additionally, as Serbia is the sole Middle-income country in the sample, we are also interested in investigating whether the results exhibit similar patterns after excluding this country, as outlined in Table 7. Our results remain consistent with the above findings. This shows that despite splitting the sample, the results are homogenous, suggesting that vulnerability in the climate increases the agricultural financial risk (positive relation with TDTA) and Fintech moderates the risk positively.

Table 6
Alternative fintech and alternative agricultural financial risk.

	(9)	(10)
	Alternative Agri. Finance	Alternative Fintech
	Dep: TLTA	Dep: TDTA
VAL	0.392*	1.376**
	(0.211)	(0.638)
FINTECH	−0.002**	
	(0.001)	
VAL x FINTECH	−0.009**	
	(0.004)	
FINTECH_A		−0.007**
		(0.003)
VAL x FINTECH_A		−0.175***
		(0.051)
Obs.	4805	3286
R-squared	0.988	0.284
F	22391.924***	22.107***
Control	yes	yes
Country fixed effect	yes	yes
Firm cluster	yes	yes
SE cluster	yes	yes

Note: This table shows the estimation results of the Alternative Agricultural Finance (total liabilities over total assets - TLTA) – Climate Change (VAL) nexus and the moderating role of Fintech as well as TDTA-VAL nexus and the moderating role of alternative fintech (FINTECH_A) ('Mobile phone used to pay bills (% age 15+)' controlling the bank-specific and macroeconomic variables deploying 2 step-system dynamic CGM-GMM (2011) two-way clustering techniques using full sample. We also control all other variables. *, **, and *** denote statistical significance at the 10 %, 5 %, and 1 % levels, respectively and clustered robust standard errors are in parenthesis. Sources: S&P Capital, NDG, Crunchbase, Global Findex, WDI, WGI.

Table 7
European and High-Income sub-sample.

	(11)	(12)	(13)	(14)
	Dep: TDTA			
	Europe		High Income	
	Agri-finance & climate	Fintech	Agri-finance & climate	Fintech
VAL	0.704**	0.823**	0.762**	0.880**
	(0.300)	(0.386)	(0.300)	(0.385)
FINTECH		−0.001***		−0.001***
		(0.000)		(0.000)
VAL x FINTECH		−0.025***		−0.024***
		(0.006)		(0.006)
Obs.	3175	3175	3236	3236
R-squared	0.255	0.258	0.281	0.284
F	87.527***	70.788***	101.054***	81.417***
Control	yes	yes	yes	yes
Country fixed effect	yes	yes	yes	yes
Firm cluster	yes	yes	yes	yes
SE cluster	yes	yes	yes	yes

Note: This table shows the estimation results of the Agricultural Finance (TDTA) – Climate Change (VAL) nexus and the moderating role of Fintech controlling the bank-specific and macroeconomic variables deploying CGM (2011) two-way clustering techniques using European and High-Income sample. *, **, and *** denote statistical significance at the 10 %, 5 %, and 1 % levels, respectively and clustered robust standard errors are in parenthesis. Sources: S&P Capital, NDG, Crunchbase, WDI, WGI.

5.3. Two-step system dynamic CGM-GMM regression

Table 8 presents the robustness tests using a two-system dynamic CGM-GMM regression. The System CGM-GMM approach is used to mitigate endogeneity concerns. Sargan tests confirm that our instruments are valid in the model. The regression results of these robustness tests confirm the baseline conclusion that climate vulnerability is positively related to agricultural financial risk, and Fintech innovation moderates this relationship between climate vulnerability and agricultural financial risk.

Table 8
Two-step-system dynamic CGM-GMM regression.

	(15)	(16)
	Dep: TDTA	
	Agri-finance & climate	Fintech
L.TDTA	0.791***	0.844***
	(0.071)	(0.063)
VAL	1.407***	1.221***
	(0.551)	(0.249)
FINTECH		−0.001***
		(0.000)
VAL*FINTECH		−0.016***
		(0.005)
Obs.	2693	2693
AR (1) – P-value	0.000	0.000
AR (2) – P-value	0.353	0.297
Sargan Test – P-value	0.166	0.110
Number of Groups	480	480
Number of Instruments	98	134
F statistics	15.08***	408.62***
Control	yes	yes
Country fixed effect	no	no
Firm cluster	yes	yes
SE cluster	yes	yes

Note: This table shows the estimation results of the Agricultural Finance (TDTA) – Climate Change (VAL) nexus and the moderating role of Fintech controlling the bank-specific and macroeconomic variables deploying 2 step-system dynamic CGM-GMM (2011) two-way clustering techniques using full sample. We also control all other variables. *, **, and *** denote statistical significance at the 10 %, 5 %, and 1 % levels, respectively and clustered robust standard errors are in parenthesis. Sources: S&P Capital, NDG, Crunchbase, WDI, WGI.

5.4. *Propensity Score Matching (PSM)*

One concern is that the relationship between climate vulnerability and agricultural financial risk may be affected by self-selection bias if certain types of agricultural firms or regions self-select into accessing agricultural finance based on their climate vulnerability status. For example, if agricultural firms in more vulnerable regions proactively seek out and access agricultural finance due to their higher vulnerability to climate risks, while those in less vulnerable regions do not, it could result in a biased sample. To minimise the impact of self-selection bias, we apply propensity score matching (PSM) technique. Table 9 presents the PSM test. Using PSM, we match sample firms with control firms with similar characteristics based on covariates in order to control self-selection (Rosenbaum

Table 9
Propensity Score Matching (PSM).

	(17)	(18)
	Dep: TDTA	
	Climate change	Fintech
VAL_dummy	0.037***	0.021**
	(0.012)	(0.011)
VAL_dummy*FINTECH		−0.001***
		(0.000)
Obs.	2814	2734
R-squared	0.248	0.209
F	11.260***	10.061***
Control	yes	yes
Country fixed effect	yes	yes
Firm cluster	yes	yes
SE cluster	yes	yes

Note: This table presents the results of the PSM tests. First, the sample is divided into two groups: Treatment and Control groups, based on the climate vulnerability (VAL_dummy). Treatment is defined as 1 if firms have a value higher than the median of VAL, while Control is defined as 0 if firms have a value lower than the median of VAL. Next, firms are matched one-to-one without replacement, based on all sets of control variables such as SIZE, TANG, CR, LOOEXP, ROA, GDPCG, UMP, and IQ. Subsequently, we re-run the baseline regression to examine the relationship using the matched sample.

and Rubin, 1983). First, the sample is divided into two groups: Treatment and Control groups, based on climate vulnerability (VAL_dummy). Treatment is defined as 1 if firms have a value higher than the median of VAL, while Control is defined as 0 if firms have a value lower than the median of VAL. Next, firms are matched one-to-one without replacement, based on all sets of control variables such as SIZE, TANG, CR, LOOEXP, ROA, GDPCG, and IQ. Subsequently, we re-run the baseline regression to examine the relationship using the matched sample. Our baseline results continue to hold, reaffirming that fintech could mitigate climate vulnerability and better manage agricultural financial risk.

Additionally, we employ Two-step Heckman selection model to control the survival bias issue (in Appendix 2) following Amin and Cumming (2023). We find the similar results that climate vulnerability is positively related to agricultural finance, and Fintech innovation moderates this relationship between climate vulnerability and agricultural financial risk.

6. Additional/channel analysis

6.1. The role of Industrial Revolution 4.0

As Fintech strongly connects with Industrial Revolution 4.0 (IR 4.0) (Banna et al., 2021), we examine whether agricultural financial risk, climate change, and the Fintech nexus have different relationships in the pre-and post-IR 4.0 period. Following Banna et al. (2021), we divide our sample into two periods: pre-IR 4.0 (2011–2015) and post-IR 4.0 (2016–2021). We can also consider post-IR 4.0 as IR 4.0 era. The results in Table 10 show that before 2016 (pre-IR 4.0 era), the agricultural financial risk-vulnerability nexus was positive but insignificant, and the moderating effect of Fintech was also insignificant, although the coefficient sign remained the same. It is due to the fact that, in the initial implementation stage, technology-based services involve a considerable amount of capital, operational, and communication costs (Banna et al., 2021). On the other hand, during IR 4.0, the results remain consistent with the above findings, suggesting that vulnerability in the climate increases the agricultural financial risk (positive relationship with TDTA), and Fintech moderates the risk positively in the IR 4.0 era. This argues that, over time, Fintech is becoming a robust moderating tool to minimise agricultural financial risk despite being vulnerable to climate change.

6.2. The role of institutional quality

Strong institutional quality facilitates better access to P2P lending fintech as suggested by Abbasi et al. (2021). Following Abbasi et al. (2021), we have separated low institutional-quality countries and high institutional-quality countries. The institutional quality scores that are more than mean is considered as high institutional quality and vice versa. Table 11 shows that fintech can better mitigate climate vulnerability under good institutional quality. A good infrastructure in place promotes farmers to get easy and accessible loans for plantation and provides options for insurance against climate vulnerability, which may reduce the impact of climate vulnerability on agricultural finance. In addition, good institutional quality can enable effective regulation of industries that contribute the fewer carbon emissions and promote the development of renewable energy sources.

Table 10
The role of industrial revolution 4.0

	(19)	(20)
	Dep: TDTA	
	Pre-IR 4.0	Post-IR 4.0
VAL	0.726	2.574***
	(1.069)	(0.761)
FINTECH	−0.002	−0.003***
	(0.003)	(0.001)
VAL*FINTECH	−0.033	−0.062***
	(0.038)	(0.015)
Obs.	1466	1820
R-squared	0.202	0.282
F	25162.351***	190.949***
Control	yes	yes
Country fixed effect	yes	yes
Firm cluster	yes	yes
SE cluster	yes	yes

Note: This table shows the estimation results of the Agricultural Finance (TDTA) – Climate Change (VAL) nexus and the moderating role of Fintech controlling the bank-specific and macroeconomic variables deploying CGM (2011) two-way clustering techniques using pre-IR 4.0 (2011–2015) and post-IR 4.0 (2016–2021) period. TDTA, VAL and FINTECH refer to total debt over total assets, vulnerability delta index, and number of peer-to-peer lending respectively. We also control all other variables. *, **, and *** denote statistical significance at the 10 %, 5 %, and 1 % levels, respectively and clustered robust standard errors are in parenthesis. Sources: S&P Capital, NDG, Crunchbase, WDI, WGI.

Table 11
The role of institutional quality.

	(21)	(22)
	Dep: TDTA	
	IQ_H	IQ_L
VAL	1.965**	−1.843
	(0.705)	(1.217)
FINTECH	−0.002**	0.004
	(0.001)	(0.001)
VAL*FINTECH	−0.044**	0.039
	(0.017)	(0.023)
Obs.	751	2535
R-squared	0.348	0.227
F	827.794***	69.19***
Control	yes	yes
Country fixed effect	yes	yes
Firm fixed effect	yes	yes
SE Cluster	yes	yes

Note: This table shows the estimation results of the Agricultural Finance (TDTA) – Climate Change (VAL) nexus and the moderating role of Fintech controlling the bank-specific and macroeconomic variables deploying CGM (2011) two-way clustering techniques by considering interaction with High institutional quality (IQ_H) vs Low institutional quality (IQ_L). Following Banna et al. (2021), we consider IQ_H = 1 if the value of IQ is above average and zero otherwise. IQ_L is calculated 1 minus IQ_H. TDTA, VAL and FINTECH refer to total debt over total assets, vulnerability delta index, and number of peer-to-peer lending respectively. We also control all other variables. *, **, and *** denote statistical significance at the 10 %, 5 %, and 1 % levels, respectively and clustered robust standard errors are in parenthesis. Sources: S&P Capital, NDG, Crunchbase, WDI, WGI.

6.3. *The role of global innovation index*

The global innovation index (GII) ranks countries based on innovation performance. We split the countries into highly innovative vs low innovative based on GII rank. The top 20 countries in the GII are considered highly innovative countries and the rest are considered low innovative countries. Table 12 shows that the direct effect of climate vulnerability on agricultural finance is significantly positive, but the effect is lessening when interacting with fintech in greater innovative countries. This is due to the fact that innovative countries are more likely to invest in research and development and provide support and funding for the adoption of new technologies and ideas such as the fintech startup which can help to drive growth in the agricultural industry. In addition, innovative countries can leverage fintech to create new solutions to address climate change and reduce its impact on the agricultural industry.

6.4. *The role of various readiness index*

We separated the samples' countries based on high and low readiness index. More than average index is considered a high-readiness country whereas lower than average is considered a low readiness country. In addition, we split the readiness into three categories namely economic, governance and social readiness. Table 13 shows that in all categories fintech can better manage agricultural finance and mitigate climate change vulnerability in a greater readiness environment. A high-readiness environment is likely to have better technology infrastructure which can help fintech companies to reach and serve farmers in remote and rural areas. In addition, higher readiness helps to create a supportive ecosystem that enables fintech companies to address climate vulnerability.

7. Conclusion and implications

Climate change is a global issue affecting all sectors, but the agricultural industry is particularly vulnerable due to its heavy dependence on climate conditions. Climate change poses significant challenges to maintaining agricultural yield growth and ensuring food security for a growing global population. As a result, agricultural firms require substantial financing to reduce carbon emissions, build resilience, and adapt to climate impacts. In this sense, climate change has become a key driver of agricultural finance. This study examines the relationship between climate vulnerability and agricultural finance. Using CGM (Cameron, Gelbach, and Miller) and OLS estimations on a sample of 1017 firms from 24 countries, we find that climate vulnerability is positively associated with financial constraints in the agricultural sector. In other words, climate change exacerbates financial risks for agricultural firms. However, our analysis also reveals that fintech plays a critical moderating role in this relationship. The results show that fintech reduces the negative effects of climate vulnerability on agricultural finance by promoting climate-smart agricultural practices and encouraging the adoption of insurance. Economically, the introduction of one additional fintech platform decreases the impact of climate vulnerability on agricultural finance by 2.73 %–3.70 %. These findings remain consistent after robustness checks using GMM (generalized method of

Table 12
The role of global innovation index.

	(23)	(24)
	Dep: TDTA	
	Countries with High GII	Countries with Low GII
VAL	2.188***	−0.291
	(0.738)	(0.804)
FINTECH	−0.002**	0.001
	(0.001)	(0.002)
VAL*FINTECH	−0.031**	−0.005
	(0.013)	(0.021)
Obs.	1144	2142
R-squared	0.262	0.293
F	7.743***	27.767***
Control	yes	yes
Country fixed effect	no	no
Firm cluster	yes	yes
SE Cluster	yes	yes

Note: This table shows the estimation results of the Agricultural Finance (TDTA) – Climate Change (VAL) nexus and the moderating role of Fintech controlling the bank-specific and macroeconomic variables deploying CGM (2011) two-way clustering techniques using Global Innovation Index (GII) in which countries with top 20 ranked considered as High GII and countries with more than 20 ranked considered as Low GII. TDTA, VAL and FINTECH refer to total debt over total assets, vulnerability delta index, and number of peer-to-peer lending respectively. We also control all other variables. *, **, and *** denote statistical significance at the 10 %, 5 %, and 1 % levels, respectively and clustered robust standard errors are in parenthesis. Sources: S&P Capital, NDG, Crunchbase, WDI, WGI.

moments) estimation and Propensity Score Matching (PSM) techniques, which help address endogeneity and selection bias. Additionally, we find that the Fourth Industrial Revolution has played an important role in mitigating climate vulnerability. Digital technologies enhance operational efficiency, improve climate impact tracking, and reduce carbon emissions. The consistency of our results across both European and non-European regions further confirms that our findings are not biased by geographic factors.

Our study has several important managerial and policy implications. The findings show that fintech can mitigate the impact of climate vulnerability and promote sustainability by improving farmers' access to finance. For agricultural managers, this suggests that increased investment in climate-smart agriculture, supported by fintech solutions, can help address climate-related risks and provide a competitive advantage. Implementing adaptation strategies and leveraging digital technologies, such as fintech, can also enhance the effectiveness of climate financing. From a policy perspective, these findings are particularly relevant in the context of the challenges posed by the Covid-19 pandemic, which severely impacted the agricultural sector by disrupting food demand, supply chains, labor availability, and production. Fintech has the potential to unlock financial resources, increase efficiency, and promote diversity, thereby supporting a sustainable and inclusive recovery from the negative effects of Covid-19. Policymakers should therefore prioritize the continued expansion of fintech platforms as part of broader recovery strategies. Additionally, the final agreement of COP27 emphasized the importance of investing in transformative technologies to mitigate climate risks and achieve net-zero emissions by 2050. Given that fintech can facilitate the transition to a low-carbon economy, governments should adopt a proactive approach by increasing investments in fintech adaptation to support climate resilience. Fintech can also play a critical role in times of conflict. For instance, during the Russian invasion of Ukraine, fintech enabled Ukrainian farmers to access affordable financing, equipment, and services for farming and harvesting (SAFIN, 2022). Policymakers and managers should encourage and support fintech startups and other innovative solutions that can help address crises like war, promote global stability, and ensure continued agricultural productivity. IMF (2019) recommends that policymakers integrate fintech topics into national financial inclusion and literacy strategies to promote greater adoption. To encourage fintech uptake among smallholder farmers and agribusinesses, policymakers can implement targeted incentives such as five-year tax holidays, R&D tax credits, and grants or matching funds. Additional measures include reducing import duties on climate-smart technologies, fostering public-private partnerships, and facilitating co-investment with financial institutions.

Ethics approval and consent to participate

Not applicable.

Consent for publication

All authors are very positive to publish this manuscript on this journal.

Availability of data and materials

Data will be made available upon reasonable request.

Table 13
The role of various readiness index.

	(25)	(26)
	Dep: TDTA	
	Above average	Below average
Panel A: Economic Readiness Index		
VAL	2.650***	0.918
	(0.691)	(0.822)
FINTECH	−0.002***	−0.001
	(0.001)	(0.002)
VAL*FINTECH	−0.038***	−0.026
	(0.013)	(0.020)
Obs.	1292	1994
R-squared	0.255	0.300
F	8.679***	25.424***
Control	yes	yes
Country fixed effect	no	no
Firm cluster	yes	yes
SE Cluster	yes	yes
Panel B: Governance Readiness Index		
VAL	2.702***	−0.101
	(0.662)	(0.735)
FINTECH	−0.002***	0.001
	(0.001)	(0.001)
VAL*FINTECH	−0.038***	−0.006
	(0.013)	(0.017)
Obs.	1304	1982
R-squared	0.265	0.291
F	9.187***	23.804***
Control	yes	yes
Country fixed effect	no	no
Firm cluster	yes	yes
SE cluster	yes	yes
Panel C: Social Readiness Index		
VAL	2.320***	0.022
	(0.746)	(0.768)
FINTECH	−0.002**	0.000
	(0.001)	(0.002)
VAL*FINTECH	−0.032**	−0.014
	(0.013)	(0.020)
Obs.	1156	2130
R-squared	0.260	0.295
F	7.735***	28.283***
Control	yes	yes
Country fixed effect	no	no
Firm cluster	yes	yes
SE cluster	yes	yes

Note: This table shows the estimation results of the Agricultural Finance (TDTA) – Climate Change (VAL) nexus and the moderating role of Fintech controlling the bank-specific and macroeconomic variables deploying CGM (2011) two-way clustering techniques using Economic Readiness Index, Governance Readiness Index and Social Readiness Index (split the sample into two: a) above average and b) below average). TDTA, VAL and FINTECH refer to total debt over total assets, vulnerability delta index, and number of peer-to-peer lending respectively. We also control all other variables. *, **, and *** denote statistical significance at the 10 %, 5 %, and 1 % levels, respectively and clustered robust standard errors are in parenthesis. Sources: S&P Capital, NDG, Crunchbase, WDI, WGI.

Competing interests

There is no competing interest among the authors.

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Appendix 1. Variables' definitions and sources

Variables	Source
Agricultural Financial risk (TDTA): Total Debt over total assets - Debt as a percent of total equity	S & P Capital
Climate Vulnerability Delta (VAL): Notre Dame Global Adaptation Initiative (NDG) measures overall vulnerability by considering six life-supporting sectors – food, water, health, ecosystem service, human habitat, and infrastructure	Notre Dame Global Adaptation Initiative
Fintech (FINTECH): The number of peer-to-peer lending fintech in a particular country each year	Crunchbase
Firm size (SIZE): Logarithm of total assets	S & P Capital
Tangibility (TANG): Total fixed asset over total assets	S & P Capital
Current Ratio (CR): Total current assets as a multiple of total current liabilities	S & P Capital
Ln (Other Operating Expense) (LOOEXP): Other operating expenses incurred in the ordinary course of business, which are recurring in nature	S & P Capital
Return on Assets (ROA): Percent of returns to total assets of the company	S & P Capital
GDP per capita growth (GDPCG): Annual percentage growth rate of GDP per capita	WDI
Institutional quality (IQ): IQ index is standardized using six (6) components of good governance namely, control of corruption, government effectiveness, political stability and absence of violence/terrorism, regulatory quality, rule of law, and voice and accountability.	WGI

Note: This table provides the definition and sources of variables.

Appendix 2. Two-step Heckman selection model

Dep: TDTA	VAL and Fintech
VAL	2.271***
	(0.411)
FINTECH	−0.003***
	(0.000)
VAL*FINTECH	−0.059***
	(0.007)
Obs.	2462
Wald Chi^2	852.29***
Control	yes
Country fixed effect	yes
Firm cluster	yes
SE cluster	yes

Note: This table presents the results of the Heckman selection model. In this model we consider lagged (2) of climate vulnerability and fintech as instrumental variables.

Data availability

Data will be made available on request.

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