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Can public expenditure on agriculture mitigate the effect of climate variability on agricultural credit in Africa?

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Abstract

This study investigates how public agricultural expenditure can mitigate the effect of climate variability on banks' agricultural credit supply in sub-Saharan Africa. Data was collected from 23 countries over the period 2006 to 2021 and analysed with the two-step generalised method of moments. The study found that banks exhibit dynamic agricultural credit supply behaviour, with temperature variability negatively effecting it and precipitation positively. In the presence of public agricultural expenditure, the influence of temperature variability on agricultural credit supply is not significantly mitigated, although the effect of precipitation is mitigated. Governments should deliberately direct adequate financial resources to develop greenhouse and climate-smart technologies, scale up agricultural credit guarantee schemes with banks and provide subsidised climate-resistant seeds and irrigation infrastructure to mitigate the effect of climate variability on agricultural credit supply. This will reduce banks' risk perception of the sector and encourage them to lend more to agriculture for growth.

Key words: climate variability, public expenditure, agricultural credit supply, banks

1. Introduction

Sustainable development goal (SDG) 13 of the United Nations requires that countries across the world take urgent action to combat climate change and its impact through integrating measures such as education, resilience and adoptive capacity, among others, into national policies (United Nations

2020). This call is now more urgent than ever, given the increasing threat of climate change to economies, particularly agriculture. As one of the major challenges facing the world today (Mungai *et al*. 2021), climate change may occur naturally or be caused by human activities such as greenhouse gas emissions (Intergovernmental Panel Climate Change 2023). This may disrupts food production, water availability and energy generation, with agriculture being vulnerable due to its over-reliance on climatic conditions (Organization for Economic Cooperation and Development 2022; Tetteh *et al*. 2022). It is estimated that climate-related hazards cost the world economy about US$520 billion per year (United Nations 2020), and between US$290 and US$440 billion to Africa, depending on the degree of warming (World Meteorological Organization 2023). This calls for urgent action from all stakeholders, such as governments and development partners, to address this global problem.

According to the African Union (2022), Africa contributes the least to greenhouse gas (GHG) emissions, at about 2%, but is the most affected by climate change, at about 21% (United Nations Ghana 2023). Given that agricultural production in sub-Saharan Africa (SSA) is mainly rain-fed (Mapanje *et al*. 2023), climate change has led to crop failures, livestock losses and reduced agricultural productivity (Atanga & Tankpa 2021), and has exerted significant pressure on agricultural systems and altered crop suitability zones (Thornton *et al*. 2014). Subsistence farmers, who are in the majority (52%) of agricultural producers in the region, face food insecurity, income instability and vulnerability to poverty (Brar *et al*. 2021). Climate change also makes it difficult for farmers to effectively and efficiently participate in the business of agriculture (Brar *et al*. 2021), which may be compounded by low financial investment.

Agricultural credit is a lifeline for farmers in sub-Saharan Africa, enabling them to invest in essential inputs, technologies and infrastructure to increase productivity (Boliko 2019; Zaidi *et al*. 2022). Although the sector contributes a significant proportion of the GDP of many economies in Africa, it does not benefit proportionately from credit. According to the FAO (2023), the share of total global credit supplied to agriculture in Africa in 2022 was 8.8%, an increase of 0.4% over that of 2013. This does not compare well, however, with the share of 52% and 26% of Asia and Europe respectively (FAO 2023, 2024). Unfortunately, climate risk has complicated the credit supply landscape of financial institutions on the continent (Guthrie 2016), as banks are taking credit decisions that do not favour agriculture. Uncertainty about weather patterns and potential crop failures have increased the perceived risk of lending to farmers, leading to tighter credit conditions, higher interest rates, or outright credit rationing by banks (Nadolnyak *et al*. 2016; Mueller & Sfrappini 2022).

In recent years, banks are considering climate change in agricultural lending decision due to its potential impact on production and loan repayment (Islam & Singh 2022), raising research interest in understanding the relationship between climate change and banks' credit supply. A few studies have examined the effect of climate change/risk on credit supply in general in developed countries and found a negative effect (Faiella & Natoli 2019; Aslan *et al*. 2022; Alvarez-Roman *et al*. 2023; Li & Wu 2023; Li *et al*. 2024). Other studies investigated climate change and affordability or cost of bank loans and cost of borrowing (Javadi & Masum 2021), as well as the credit market (Islam & Singh 2019), and found adverse effects. Nadolnyak *et al*. (2016) and Abay *et al*. (2022) also investigated the effect of climate variability on agricultural credit delinquency and uptake, but not on agricultural credit supply. There thus is a gap in our understanding of the nexus between climate variability and banks' agricultural credit supply, particularly on the African context.

In an effort to address the adverse effect of climate change on agricultural output, public agricultural expenditure has emerged as a critical success factor. However, how this mitigates the effect of climate variability on banks' agricultural credit supply has not been tested empirically. A few studies have investigated the effect of government spending on climate change and agricultural productivity

(Ogujiuba & Terfa 2012; Hao *et al*. 2024), but not on credit supply. Hence, can public expenditure on agriculture mitigate the effect of climate variability on banks' agricultural credit supply? According to the theory of public goods of Samuelson (1954), public goods are non-excludable and non-rivalry: their use and consumption do not exclude others from using and consuming them. These two characteristics of public goods make public expenditure a crucial tool in addressing not only market imperfections, but also mitigating the effect of climate change, a global public good, on agricultural credit supply. Therefore, public agricultural expenditure initiatives such as climate-resilient infrastructure investment could mitigate the effect of climate risk, thereby attracting private investments and credit from financial institutions into the agricultural sector (FAO 2017).

Temperature and precipitation are two main factors that influence climatic conditions (Javadinejad *et al*. 2021). High temperatures increase evapotranspiration and reduce soil moisture and fertility, thereby limiting access to water and nutrients for crops (Asare-Nuamah & Botchway 2019; Mumuni & Aleer 2023). Also, frequent dry spells associated with climate change limit farmers' access to water for production (Lefe *et al*. 2024), and therefore may affect banks' credit supply to the sector. Against this background, the current study investigates how public expenditure on agriculture can mitigate the effect of climate variability on banks' agricultural credit supply in sub-Saharan Africa. The paper contributes to the literature by providing valuable insights into the nexus between the two variables and the role of public agricultural spending. Secondly, the findings will inform policy makers, agricultural credit lenders and development partners on the need to provide targeted financial resources and strategies to build a strong climate-resilient agricultural system. The recommendations of the study will also go a long way to reduce the risk perceptions of financial institutions such as banks, and encourage them to lend adequately to the agricultural sector for sustainable growth and development.

The rest of the paper is structured into four sections: this section is followed immediately by the methodology used for the study. The next section presents the results and discussion, while the final section contains the conclusions and policy recommendations.

2. Data and methodology

2.1 Data and sample

Data was collected from 23 sub-Saharan African countries[1] over the period 2006 to 2021, with at least one country from each of the Western, Eastern, Central and Southern blocks of the continent. The choice of these countries was influenced by data availability, as these countries have the full dataset of the key variables used in the study, namely climate variability (temperature and precipitation), public agricultural expenditure and banks' agricultural credit supply. The selected countries are characterised by a tropical climate, with diverse degrees of rainy and dry seasons. Also, the agriculture sector contributes significantly to overall GDP, especially in Liberia, Guinea-Bissau and Niger. Moreover, banks' credit to the agricultural sector is limited and inaccessible, as most farmers rely on informal sector credit. Thus, these variables vary significantly between the selected countries. Data on public agricultural expenditure, non-performing loans, capital-to-asset ratio, bank branches, inflation rate, agricultural gross domestic product (GDP) and average precipitation were obtained from the World Development Indicators (WDI) database, whilst temperature and credit to the agricultural sector were obtained from the Food and Agricultural Organization (FAO). These are recognised and reliable database sources that are frequently used by many researchers.

[1] Angola, Burkina Faso, Burundi, Cabo Verde, Cote d'Ivoire, Democratic Republic of the Congo, Gabon, Ghana, Guinea-Bissau, Kenya, Lesotho, Liberia, Malawi, Mozambique, Namibia, Niger, Nigeria, Rwanda, Senegal, Seychelles, Tanzania, Uganda and Zambia.

2.2 Econometric model

The two-step generalised method of moments (GMM) was used to investigate how public agricultural expenditure can mitigate the effect of climate variability on banks' agricultural credit supply. This method is effective in dealing with endogeneity, autocorrelation, heteroscedasticity and measurement errors in panel data analysis. The ordinary least squares estimator (pooled OLS) is not appropriate to model the effect of climate variability on banks' agricultural credit supply due to its limitation of "zero correlation assumption" (Wooldridge 2001). However, this drawback is solved by fixed-effects models by controlling the effect of variables that change across countries and evolve over time, but not across borders. The fixed-effects model is more likely to be appropriate, but is limited by its inability to address dynamism. It is a static model and may have reverse causality (Galiani *et al*. 2017), as well as endogeneity. It is also affected by autocorrelation, which may result in inconsistent estimation. The use of multiple countries with diverse social, political, cultural and technological backgrounds creates a heterogeneity problem that can be addressed by deploying a better approach. The GMM technique of Arellano and Bond (1991) is used to deal with these challenges.

The GMM was appropriate for this study because the cross-sectional units, in this case countries (23), were larger than the time dimension (15) ($N > T$). Arellano and Bond (1991) devised the difference GMM, which requires levels of independent variables that are at least two periods apart. Although this model performs better than the pooled OLS and fixed-effects models, it may face persistence of variable(s), resulting in a weak instrument (Arellano & Bover 1995). According to Blundell and Bond (1998), the difference GMM estimator performs poorly, resulting in large sample biases and weak instruments that cannot address differenced variables in a difference estimator. To address this problem, Arellano and Bover (1995) advised the use of the system GMM estimator, which integrates first difference and level variables. The increased moment conditions with system GMM significantly increase efficiency (Blundell & Bond 1998). In computing the system estimator, differenced variables are instrumented with lags of their levels, whilst levels are instrumented with lags of their difference (Bond *et al*. 2001). Explanatory variables may be associated with a country's specific fixed effect, but their differences are uncorrelated, making the system GMM more asymptotically efficient in estimation.

To address over-identifying instruments, the use of selected specific lags is collapsed, rather than using all available lags (Roodman 2009). The system GMM can control for time-invariant country-specific effects, deal with endogeneity of lagged dependent variables, eliminate reverse causality, allow for a certain degree of endogeneity in other regressors, and optimally combine information on cross-country variations in levels with information on within-country variation, which other models cannot do (Fukase 2010). Ullah *et al*. (2021) argue that system GMM is suitable because it can change the lag effect of its dependent variable in the long run, allowing for more accurate future predictions. It also accounts for potential sample biases and asymptotic imprecision in the difference estimator (Blundell & Bond 1998). Based on the above reasons, this study used the two-step system GMM estimator.

2.2.1 Model specification

This paper adopted two estimation strategies. In the first strategy, the two proxies of climate variability, namely temperature variability (TPV) and average precipitation (AvPre), were entered into equations (1) and (2) respectively.

$$CTA_{it} = \alpha_0 + \alpha_1 CTA_{it-1} + \alpha_2 TPV_{it} + \alpha_3 NPL_{it} + \alpha_4 BKB_{it} + \alpha_5 CAR_{it} + \alpha_6 INF_{it} + \alpha_7 AgricGDP_{it} + \varepsilon_{it} \tag{1}$$

In Equation (1), temperature variability, *TPV*, was entered into the model with the expected $\alpha_2 < 0$, and in Equation (2), average precipitation, *AvPre*, was entered into the model with the expected $\beta_2 > 0$.

$$CTA_{it} = \beta_0 + \beta_1 CTA_{it-1} + \beta_2 AvPre_{it} + \beta_3 NPL_{it} + \beta_4 BKB_{it} + \beta_5 CAR_{it} + \beta_6 INF_{it} + \beta_7 AgricGDP_{it} + \varepsilon_{it} \tag{2}$$

In addition, public agricultural expenditure, *GovExp*, was entered into Equation (3) to ascertain the impact of public agricultural expenditure on banks' credit supply to the agriculture sector in the absence of climate variability proxies, with the expected $\gamma_2 > 0$.

$$CTA_{it} = \gamma_0 + \gamma_1 CTA_{it-1} + \gamma_2 GovExp_{it} + \gamma_3 NPL_{it} + \gamma_4 BKB_{it} + \gamma_5 CAR_{it} + \gamma_6 INF_{it} + \gamma_7 AgricGDP_{it} + \varepsilon_{it} \tag{3}$$

In the second strategy, the specified models explore how public agricultural expenditure can mitigate the effect of climate variability on banks' agricultural credit supply, as in equations 4 and 5 below:

$$CTA_{it} = ƛ_0 + ƛ_1 CTA_{it-1} + + ƛ_2 TPV_{it} + ƛ_3 NPL_{it} + ƛ_4 BKB_{it} + ƛ_5 CAR_{it} + ƛ_6 INF_{it} + ƛ_7 AgricGDP_{it} + ƛ_8 (TPV_{it} * GovExp_{it}) + \varepsilon_{it} \tag{4}$$

Equation (4) furthermore examines the mitigating effect of public agricultural expenditure on climate variability and its subsequent impact on credit supply in the agricultural sector by interacting temperature variability (TPV) and public agriculture expenditure (GovExp). Similarly, in Equation (5), we interacted average precipitation (AvPre) with public agricultural expenditure (GovExp) to ascertain how the latter mitigates the impact of the former on banks' credit supply to the agriculture sector.

$$CTA_{it} = \mho_0 + \mho_1 CTA_{it-1} + \mho_2 AvPre_{it} + \mho_3 NPL_{it} + \mho_4 BKB_{it} + \mho_5 CAR_{it} + \mho_6 INF_{it} + \mho_7 AgricGDP_{it} + \mho_8 (AvPre_{it} * GovExp_{it}) + \varepsilon_{it} \tag{5}$$

To investigate the total or marginal effect of climate variability on banks' agricultural credit supply in the presence of public expenditure on agriculture, the partial derivative of equations (4) and (5), as used by Baltagi *et al*. (2009), was estimated to derive equations (6) and (7) respectively. Put simply, equations (6) and (7) seek to estimate the marginal effect, which describes how credit to agriculture changes in response to changes in dimensions of climate variability (temperature and average precipitation), whilst taking into account the influence of public agricultural expenditure.

$$\frac{\text{ØCTA}_{\text{i,j,t}}}{\text{ØTPV}_{\text{i,j,t}}} = ƛ_2 + ƛ_8 * GovExp_{i,\text{j,t}} \tag{6}$$

$$\frac{\text{ŊCTA}_{\text{i,j,t}}}{\text{ŊAvPre}_{\text{i,j,t}}} = \mho_2 + \mho_8 * GovExp_{i,\text{j,t}} \tag{7}$$

In the above equations, CTA_{it} is credit to agriculture, measured as the annual percentage of total credit offered by banks to agriculture; $\mathrm{CTA}_{\mathrm{it-1}}$ is the lag of credit to agriculture, indicating the dynamic process in the GMM equation, and reduces heteroscedasticity. TPV_{it} is temperature variability, defined as the fluctuations in surface temperature from the mean over time. It is measured as the difference between annual figures and the mean and is expected to have a negative effect on credit to agriculture (CTA). *AvPre* is annual average precipitation in millimetres, which is expected to positively affect CTA; $\mathrm{GovExp}_{\mathrm{it}}$ represents public expenditure on agriculture, measured as the share of public agricultural expenditure in total expenditure. This is expected to positively affect CTA. $(TPV_{it} * GovExp_{it})$ and $(AvPre_{it} * GovExp_{it})$ are the interaction terms of public agricultural expenditure and temperature variability, and average precipitation proxies respectively.

Inflation rate (INF_{it}), measured by the consumer price index, is the annual percentage change in the average consumer price of a basket of goods and services at specified intervals and is expected to have a negative effect on CTA. Agricultural GDP ($AgricGDP_{it}$) is the share of the agricultural sector's contribution to the total GDP of a country. It is expected to have a positive impact on CTA. Non-performing loans (NPL_{it}) is the value of non-performing loans divided by the total value of the loan portfolio (including nonperforming loans before the deduction of specific loan-loss provisions). It is expected to have a negative effect on CTA. The capital-to-asset ratio (CAR_{it}) is the bank capital to assets ratio (%) and is expected to have a positive effect on CTA. The bank branches (BKB_{it}) variable is the retail locations of resident commercial banks and other resident banks that function as commercial banks and provide financial services to customers, measured as commercial bank branches per 100 000 adults. This variable is expected to have a positive influence on CTA. i is a country-specific variable, t is the period, ε is the error term, and α, β, γ, ƛ and Ʊ are estimable coefficients. Table 1 further provides the description, measurement and descriptive statistics of the variables used in this study.

3. Results and discussion

Table 1 presents the descriptive statistics of the main variables used in the study. Banke' share of agricultural credit in total credit disbursed over the period of the study was 5.248, with a standard deviation of 5.376. This implies that 5.25% of the total loans provided by banks are allocated to the agriculture sector in the region. This is very low, and not comparable to the average of 26% in other parts of the world (FAO 2023). This share does not reflect the sector's contribution of 35% to overall GDP (OECD/FAO, 2016). Financial institutions such as banks should consider the agricultural sector as a strategic one and lend more credit to enhance productivity. The climate variability proxies used in the study, namely temperature and precipitation, reflect changing weather conditions on the continent. The mean temperature variability over the period was 1.031°C, with a standard deviation of 0.375. This value is higher than the 0.5470°C obtained by Dia and Beaudelaire (2021), projected by the Intergovernmental Panel on Climate Change (GIEC 2007) to reach 1.5°C for the decade until 2020. The increasing temperature variability can be attributed to growing human activity and urbanisation on the continent. Agricultural credit-lending banks may continue to perceive the sector as risky if appropriate measures are not taken to reduce this riskiness. The mean value of average precipitation,[2] on the other hand, is 1 124 mm per year, with a standard deviation of 560.67 mm, suggesting some variability among the countries used for the study. This finding is almost similar to the 1 155.92 mm obtained by Lefe *et al*. (2024) in their study.

[2] Average precipitation is the long-term average in depth (over space and time) of annual precipitation in a country. Precipitation is defined as any kind of water that falls from clouds as a liquid or a solid (World Development Indicators).

Table 1: Description of variables and summary statistics

Variable description	Measurement	A priori expectation	Mean	Std. dev.	Min	Max
Credit to agricultural sector (CTA)	Credit to agriculture scaled by total bank credit		5.238	5.376	0.002	36.336
Temperature variability (TPV)	Temperature fluctuations from the mean over time	Negative	1.031	0.375	0.014	2.267
Average precipitation (AvPre)	Average precipitation in depth (mm per year)	Positive	1 124.043	560.673	151	2 391
Public expenditure (GovExp)	Share of public expenditure in agriculture over total expenditure	Positive	3.622	3.594	0.29	24.71
Non-performing loans ratio (NPL)	Non-performing loans scaled by total loans	Negative	8.322	5.299	0.251	37.253
Bank branches (BKB)	Commercial bank branches per 100 000 adults.	Positive	7.293	10.795	0.23	55.07
Capital adequacy ratio (CAR)	Bank capital-to-assets ratio	Positive	7.465	7.096	0.04	56.995
Inflation (INF)	Annual percentage change in the average consumer price	Negative	11.131	4.49	1.49	35.185
Share of agriculture in GDP (AgricGDP)	Agricultural sector's contribution in total GDP	Positive	0.201	0.122	0.02	0.656

Source: Authors' computation

Table 2: Pairwise correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) CTA	1.000								
(2) TPV	-0.048	1.000							
(3) AvPre	0.048	0.039	1.000						
(4) GovExp	0.439	0.007	-0.171	1.000					
(5) NPL	-0.043	0.243	0.074	0.088	1.000				
(6) BKB	-0.217	-0.197	0.175	-0.155	-0.145	1.000			
(7) CAR	0.244	-0.043	0.231	0.017	0.120	-0.071	1.000		
(8) INF	-0.013	0.171	0.022	0.051	0.330	-0.141	-0.105	1.000	
(9) AgricGDP	-0.049	0.198	0.180	0.211	0.395	-0.505	0.086	0.304	1.000

Notes: CTA = credit to agricultural sector; TPV = temperature variability; AvPre = average precipitation; GovExp = public expenditure; NPL = non-performing loans ratio; BKB = bank branches; CAR = capital adequacy ratio; INF = inflation; AgricGDP = share of agriculture in GDP
Source: Authors' computation.

The mean value of the public agricultural expenditure share is 3.62%, with a standard deviation of 3.594, indicating that the governments of selected countries spend about 3.6% of their national budget on agriculture. This proportion is 0.28 higher than the 2.32% obtained for African countries by the FAO (2023), but 6.4% cent lower than the 10% national budget allocation commitment to agriculture and rural development made by heads of state and government in Maputo in 2003 (CAADP 2003). Governments on the continent must seriously and deliberately commit themselves to the 2003 Maputo Declaration to allocate at least 10% of their national budget to agriculture to reduce food insecurity, poverty and malnourishment on the continent, as well as to promote sustainable development. This may send positive signal to the banks and encourage them to lend more to the sector.

The correlation matrix in Table 2 reveals interrelationships among the variables, with none of the variables exceeding the 0.8 limit proposed by Porter and Gujarati (2009), suggesting the absence of multicollinearity among the variables. Furthermore, the study performed three main pre-estimation tests before estimating the system GMM. These were tests of heteroscedasticity, cross-sectional dependence and first-order autocorrelation, as shown in Table 3. The Breusch-Pagan/Cook-Weisberg test for heteroskedasticity revealed a chi-square value of 51.44, statistically significant at 1%. This indicates a violation of the assumption of constant variance in the error terms and might result in inflated standard errors and biased coefficients. Also, Pesaran's CD test (Pesaran 2004) and Friedman's test (Friedman 1937) were used to guarantee cross-sectional independence, which is a fundamental factor for reliable panel data analysis. Pesaran's CD test statistic provided a value of 0.660, and Friedman's test statistic was 17.885; these were not significant at 5%. These findings imply no cross-sectional interdependence across the cross-sectional countries. By establishing no cross-sectional interdependence, the study could proceed with greater confidence with the knowledge that the behaviour of one country was unlikely to be unduly influenced by the characteristics or experiences of another country.

Table 3: Tests of heteroskedasticity, cross-sectional independence and first-order autocorrelation

Test	Test statistic	P-values
BP/Cook-Weisberg test for heteroscedasticity, chi^2 (1)	51.44	0.000
Pesaran's test of cross-sectional independence	0.660	0.5094
Friedman's test of cross-sectional independence	17.885	0.7128
Wooldridge test statistics, F(1, 22)	2.473	0.1301

Source: Authors' computation

A critical step in panel data analysis is to confirm the lack of autocorrelation in the error term, thereby to ensure the validity of the statistical models employed. To investigate this, we used the Wooldridge test proposed by Wooldridge (2002), which is used to detect first-order autocorrelation in panel data. The Wooldridge test produced an F-statistic of 2.473 and a p-value of 0.1301, suggesting no statistical significance at 5%, hence no second-order autocorrelation in the residuals of the panel data model. This increased the validity of the model and the reliability of subsequent analyses.

3.1 Results of the two-step GMM estimation

The study further conducted a fundamental preliminary test, the pooled ordinary least square (POLS) test, to properly decide on the suitability of the two-step system GMM. The results of the POLS test, shown in Table 4, aim to justify the choice of the model, whilst the two-step system GMM is presented in Table 5.

Table 4: Results of POLS test

Variable	(POLS)	(Fixed effects [FE])	(One-step)
CTA = L,	0.6863*** (0.0342)	0.2442*** (0.0502)	0.1645* (0.0900

Source: Authors' computation

The choice of the two-step system GMM as the appropriate model for this study was based on the evidence of the coefficient, 0.2442, of the lag-dependent variable, credit to agriculture, in the fixed-effects model. This is more than the lag coefficient of 0.1645 in the one-step difference GMM model. According to Kruiniger (2018), and Phillips and Han (2019), when the lag of the dependent variable in the fixed-effects (FE) model exceeds the lag in the one-step difference GMM model, the two-step system GMM becomes a better model to use. The higher lag of the fixed-effects model indicates greater persistence in the dependent variable, which is better accounted for by the two-step system GMM than by the one-step difference GMM. By selecting the two-step system GMM, the model is better equipped to capture persistence in the dependent variable in this context.

Temperature variability and precipitation are the two proxies of climate variability used in this study. Column 1 of Table 5 shows the effect of temperature variability on credit to agriculture (CTA). Temperature variability (TPV) negatively and significantly affects agricultural credit supply, implying that, all things being equal, a unit increase in temperature variability decreases credit to agriculture by 0.5404%. An increase in temperature increases evapotranspiration and drought, leading to a reduction in soil moisture and nutrients, hence increasing the risk of crop failure. This increases risk perception and the fear of loan default among banks, thereby discouraging them from lending to the sector. This finding is consistent with that of Anginer *et al*. (2021), Aslan *et al*. (2022), Hrazdil *et al*. (2023) and Li and Wu (2023).

Contrary to the negative effect of temperature variability on agricultural credit supply, precipitation has a positive effect. From column 2 in Table 5, the coefficient of AvPre, 0.0123, is positive and significant. This underscores the relevance of precipitation in ensuring crop success and consequently affecting banks' lending decisions. Therefore, with an increase in precipitation, farmers are able to harvest more yields and generate more revenue to repay their loans (Abay *et al*. 2022). This will encourage banks to lend more to the sector. Therefore, climatic variability through high temperature and low precipitation reduces crop yield and increases the risk of loan default, thereby causing banks to be more cautious in extending credit to farmers.

The results in column 3 of Table 5 furthermore show that public agricultural expenditure has a positive and significant effect on banks' agricultural credit supply. All things being equal, a unit increase in public agriculture expenditure increases banks' credit supply to the sector by 0.8469%. Public investment in appropriate infrastructure or guarantee schemes may be enough to reduce banks' risk perception of agriculture, thereby motivating them to extend more credit to the sector. This finding is consistent with Ebenezer *et al*. (2019) and Ngobeni and Muchopa (2022).

Table 5: Results of the two-step system GMM estimations

Variables	**(CTA) 1**	**(CTA) 2**	**(CTA) 3**	**(CTA) 4**	**(CTA) 5**
CTA = L	0.1174***	0.2618***	0.2772***	0.8657***	0.3203***
	(0.0279)	(0.0572)	(0.0446)	(0.0483)	(0.0560)
TPV	**-0.5404*** **			-6.3535***	
	(0.1832)			(0.8566)	
NPL	0.1431***	0.0739*	0.1557***	0.0672	0.0926
	(0.0322)	(0.0379)	(0.0208)	(0.0482)	(0.0660)
BKB	0.0472	0.3302*	0.2681**	-0.0531	0.4734
	(0.0514)	(0.1679)	(0.1151)	(0.0532)	(0.3449)
CAR	0.0934***	-0.1086**	0.0857***	0.0449*	-0.0693*
	(0.0322)	(0.0414)	(0.0278)	(0.0235)	(0.0380)
INF	-0.1367**	-0.1425**	-0.2394***	0.2373***	0.1964
	(0.0536)	(0.0639)	(0.0621)	(0.0703)	(0.1793)
AgricGDP	-13.2148***	8.8150	-15.7640**	-12.3454***	7.3247
	(4.4444)	(10.1917)	(5.6027)	(3.3273)	(9.7526)
AvPre		**0.0123** **			0.0186**
		(0.0049)			(0.0083)
GovExp			**0.8469*** **	-0.8903***	3.4354**
			(0.0889)	(0.1840)	(1.2383)
c.TPV#c.GovExp				**1.6698*** **	
				(0.1900)	
c.AvPre#c.GovExp					**-0.0028** **
					(0.0012)
Total Effect ($\lambda_2 + \lambda_8$ * GovExp) (dy/dx)				**-0.07112** (0.6288)	
Total Effect ($\mho_2 + \mho_8$ * GovExp) (dy/dx)					**0.0022*** ** (0.0005)
Constant	6.6216***	-12.9639	2.4007	3.5366**	-26.3392*
	(1.1302)	(7.9178)	(1.7518)	(1.4023)	(12.9211)
Number of ID	23	23	23	23	23
Instruments	20	21	21	22	21
Sargan P-value	0.189	0.977	0.0108	1.39e-08	1
Hansen P-value	0.210	0.799	0.242	0.178	0.776
AR(2)	0.321	0.261	0.713	0.403	0.325

Source: Authors' computation

Notes: Standard errors in parentheses, *** = p < 0.01, ** = p < 0.05, * = p < 0.1. CTA = credit to agricultural sector; TPV = temperature variability; AvPre = average precipitation; GovExp = public expenditure; NPL = non-performing loans ratio; BKB = bank branches; CAR = capital adequacy ratio; INF = inflation; AgricGDP = share of agriculture in GDP.

Columns 4 and 5 of Table 5 examine the role of public agricultural expenditure in mitigating the climate variability effect on banks' agricultural credit supply. In column 4, the coefficient (1.6698) of the interaction term between the temperature variability and public agricultural expenditure variables is positive and significant. However, following standard practice and empirical evidence (Doku *et al*. 2023; Iddrisu *et al*. 2023), the paper focuses more attention on the total effects. The coefficient (0.07112) of the total effect in column 4 is negative, but not significant. Public expenditure not targeted directly towards temperature-resistant technologies to mitigate the temperature effect may bring about some uncertainties. This may not motivate banks, thereby discouraging them from lending adequately to the sector. This finding does not align with that of Li and Wu (2023), who found that the adverse impact of climate risk on bank loan supply is mitigated by government's climate protection performance.

Finally, in column 5, the coefficient of the total effect is positive and significant. Public expenditure support in the form of modern irrigation infrastructure and rain harvesting by the sector may act as a safety net providing insurance for farmers to cultivate the whole year round. Therefore, with targeted public spending on climate risk-resilient technologies or infrastructure, banks' risk perception of agriculture may reduce, thereby encouraging them to lend to the sector. This finding is consistent with expressions by existing scholars (Li & Wu 2023; Liu *et al*. 2025). It also corroborates the work of Ngobeni and Muchopa (2022), who found that a more risk-tolerant lending climate for financial institutions increases their confidence in providing loans to the agricultural sector.

4. Conclusions and recommendations

Climate change has become an important consideration in banks' lending decisions in recent years. However, public agricultural expenditure has emerged as a critical factor that can mitigate its impact on banks' agricultural credit supply. This study investigates how public expenditure on agriculture can mitigate the effect of climate variability on banks' agricultural credit supply in 23 sub-Saharan African countries. The study found that banks exhibit dynamic agricultural credit supply behaviour by adapting to different economic and market conditions. It also found that temperature variability has a negative effect on agricultural credit supply, as does precipitation. However, in the presence of public expenditure on agriculture, the negative effect of temperature on banks' credit supply to the sector is not mitigated significantly if the expenditure is not directly targeted at temperature-resistant technologies. In the case of precipitation, public agricultural expenditure enhances banks' credit supply. These findings suggest the need to direct financial resources to the threat of climate variability to mitigate its impact, and thereby to reduce banks' risk perception of the sector for lending.

Based on these findings, it is recommended that governments in Africa should re-commit themselves to the declaration made in Maputo in 2003, namely to allocate a minimum of 10% of their national budget to agriculture and rural development. A significant proportion of this budget allocation should be channelled to developing greenhouse technologies, scaling up agricultural credit guarantee schemes with banks, and providing subsidised, climate-resistant seeds and irrigation infrastructure to support farmers. In addition, public expenditure should be allocated to develop farmers' capacity to adopt appropriate climate risk management strategies. These efforts will reduce banks' risk perceptions and encourage them to increase credit to the sector. By doing so, the agricultural sector will unleash its growth potential and drive the attainment of the United Nations Sustainable Development Goals envisioned for 2030.

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