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Remoteness and its impact on productivity growth among Malawi's smallholder household farmers: A Malmquist and tobit regression approach

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Abstract

This study examines the impact of remoteness on productivity growth among Malawian smallholder farmers. Utilising data from four rounds of the Integrated Household Survey Panel (2010–2019), a combined Malmquist data envelopment analysis and Tobit regression approach suggests remoteness as a crucial determinant of technical change and productivity growth. The findings underscore the need for targeted interventions, particularly for farmers in remote areas. Policy recommendations include investing in digital infrastructure, electronic agricultural extension services, climate-resilient practices, and farm output price transparency initiatives to address spatial disparities and promote inclusivity in Malawi's smallholder agricultural sector. Specifically, prioritising innovative, decentralised rural development initiatives leveraging electronic platforms and piloting digital villages is recommended. This study informs policy decisions in Malawi and offers valuable insights for similar contexts, such as sub-Saharan Africa and South Asia.

Key words: Malmquist DEA, productivity remoteness, technical change, tobit regression

1. Introduction

This study examines the impact of remoteness on the agricultural productivity of household smallholder farmers in Malawi.

The Malawi government has implemented various strategies and policies to drive agricultural productivity. Vision 2020 (1998–2020) aimed to move the nation to middle-income status through industrialisation and poverty reduction, laying the groundwork for subsequent development frameworks. The Malawi growth and development strategies (MGDSs) are aligned with the Sustainable Development Goals (SDGs) and prioritise agricultural development. Building on these efforts, Vision 2063 (MW2063) focuses on wealth creation, self-reliance and sustainability, with the first 10-year implementation plan (MIP-1) outlining priorities for agricultural transformation. The National Agriculture Policy (NAP) is aligned with regional and international frameworks, including the Comprehensive Africa Agriculture Development Programme (CAADP) and the SDGs. A key component of the government's strategy has been the Farm Input Subsidy Programme (FISP), recently referred to as the Affordable Input Programme (AIP), which provides subsidised fertilisers and seeds to smallholder farmers.

Despite its importance in the government's strategy, the impact of FISP on agricultural productivity has been mixed. Malawi's agricultural productivity showed some improvement in the early 2000s, particularly due to the FISP implemented in 2005/2006 (Phiri *et al*. 2012; Ricker-Gilbert *et al*. 2013). However, productivity growth was not considered sustainable due to significant budgetary strain, underfunded research and development (R&D), and weak extension delivery systems (Phiri *et al*. 2012). The programme has shown positive effects in areas with greater access to subsidised fertiliser, increasing maize yields and reducing pressure to expand into marginal lands, thereby decreasing deforestation (Abman & Carney 2020). Nevertheless, concerns about ethnic favouritism in subsidy allocation persist, potentially leading to unequal access to resources and opportunities by farmers.

Studies have highlighted persistent productivity gaps and challenges in Malawi's agricultural sector. A notable gender productivity gap exists, with female-managed plots being 14.6% to 23.1% less productive than male-managed plots (Tufa *et al*. 2022). However, Julien *et al*. (2023) suggest that, by controlling for socio-economic, geographical and agroecological characteristics, gender-related productivity gaps can fade or even reverse. In addition, limited access to education and training may exacerbate productivity challenges, as educational levels have been shown to influence the adoption of climate-smart agriculture practices (Pangapanga-Phiri & Mungatana 2021).

While these studies provide valuable insights into the challenges facing smallholder farmers and low productivity, our study focuses on the impact of remoteness on productivity growth among these farmers, an area that remains underexamined in the existing literature. Despite the government's commitment to improving agricultural productivity through various policies, the specific impact of remoteness on productivity growth among smallholder farmers warrants further investigation. This study is motivated by the recognition that existing development strategies often overlook the differences in circumstances and needs between households in rural and urban areas. As noted by Gollin (2023), existing models of transformation and growth often assume no difference between urban farmers and farmers in remote places with limited services and links.

Remoteness and productivity challenges manifest themselves in multifaceted ways. The challenges associated with residing long distances away from urban centres increase difficulties in accessing essential services, markets, extension services and other support. Rugged terrain, also associated with rural residence, hampers innovative practices and technological advancements. Furthermore, the collapse of a market system has weakened farmers' collective bargaining power, exposing them to exploitation. Lack of access to finance continues to be a key challenge to investment (Malawi Government 2017). Limited collective action undermines price negotiations, while weakened extension services deprive farmers of critical support for innovation and improvement.

This study investigates the impact of remoteness on productivity and efficiency among smallholder farmers in Malawi, seeking to answer the research question: How does remoteness influence technical efficiency and productivity growth among these farmers? Guided by this question, the study pursues three specific objectives. Firstly, it determines the total factor productivity (TFP) and the sources of its growth or decline in recent times. Secondly, it identifies the key determinants of productivity through technical change (TC). Thirdly, it analyses the relationship between geographical factors (rural/urban location, market access and distance to district centres) and technical change and productivity growth among smallholder farmers in Malawi.

The study hypothesises that remoteness negatively affects technical change and TFP growth in Malawi. To test this hypothesis, the study employs a two-step methodology, combining Malmquist data envelopment analysis (MDEA) and tobit regression with data from four rounds of Malawi Integrated Household Survey Panel (2010 to 2019). By shedding light on these aspects, we aim to provide valuable insights into the dynamics of agricultural productivity and poverty reduction in rural Malawi, which have far-reaching implications for policymakers and stakeholders alike. By doing so, this study contributes to the ongoing discussion on agricultural development and poverty reduction in Malawi, and our findings have the potential to inform policy decisions and interventions aimed at improving the livelihoods of smallholder farmers, particularly those facing challenges accessing essential services and markets, often associated with remoteness.

2. Methods

2.1 Theoretical framework

This study uses the censored tobit regression model, originally developed by Tobin (1958), to examine factors influencing productivity growth among smallholder household farmers in Malawi's agricultural sector. The analysis builds upon the estimation of total factor productivity and its components, including technical change (TC), using the Malmquist productivity index (MPI), which is detailed in Section 3.2. The tobit model is then employed to investigate the determinants of TC, providing insights into the factors driving productivity growth.

2.2 Empirical specification

Equation (1) introduces the censored tobit regression model:

$$Y^* = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n + \mathcal{E}, \quad (1)$$

$Y = Y^*$ if $Y^* > 0$, and

$Y = 0$ if $Y^* \leq 0$.

In this model, Y^* is a latent variable representing unobserved productivity growth, while Y is the observed dependent variable, censored at zero. X_1, X_2, ... X_n are independent variables, and β_0, β_1, β_2 … β_n are coefficients. $\mathcal{E}$ is defined as the value of the error term, which is assumed to have a normal distribution with a zero mean and constant variance.

The independent variables ($X_1, X_2, \ldots X_n$) in the tobit model include:

- The literacy level of the head of the family (binary variable)
- The education level of the head of the family (categorical variable)
- Urban-rural residence (binary variable)
- Region (categorical variable)
- Sex of the head of the family (binary variable)
- Soil erosion (binary variable)
- Soil quality (binary variable)
- Terrain or slope of the garden (binary variable)
- Religion of the head of family (categorical variable)
- Access to loans (binary variable)
- Distance to boma, the district administrative centre (continuous variable)
- Age (continuous variable)

The tobit model is particularly suitable for this analysis because it accounts for the censoring of productivity growth at zero, providing consistent estimates of the relationships between the independent variables and productivity growth (McDonald & Moffitt 1980). In contrast, ordinary least squares (OLS) would be inappropriate due to the censored nature of the dependent variable, as it would likely produce biased and inconsistent estimates (Greene 2011). Specifically, OLS would fail to account for the clustering of observations at zero, leading to incorrect inferences about the relationships between the independent variables and productivity growth. The tobit model offers several other advantages, including facilitating coefficient interpretation and correcting for censoring, which mitigates extreme value distortions.

2.3 Data

This study draws on secondary data from the Integrated Household Survey (IHS) conducted by the National Statistics Office (NSO) of Malawi in collaboration with the World Bank Living Standards Measurement Study (LSMS) programme. The IHS Panel (IHSP), a subset of the IHS, tracked a nationally representative sample of households across the country. The survey employed a stratified sampling design to select enumeration areas (EAs) in 2010. In addition to region (Northern, Central, Southern), urban/rural location and six other strata were included in the sampling. The survey was conducted in a way that minimised recall bias among households. A relatively low 5.6% household attrition rate and 13% individual attrition rate were observed. The data was collected at plot level across the country.

A two-step process was used in the data analysis. The first step was extracting IHSP data using STATA software and conducting analysis using data envelopment analysis program (DEAP) software to obtain total factor productivity (TFP) and efficiency measures, including technical change. Yield was the sole output variable used to measure agricultural productivity or TFP, representing the aggregated agricultural output from various crops reported by household farmers nationwide.

A decision on input variables was based on the theory of microeconomic production and the principles of agricultural economics (Cobb & Douglas 1928). The following input variables were obtained from the agriculture and household modules of the IHS survey to estimate total factor productivity and TFP growth:

- Land: Total cultivated area (acres) for all crops
- Labour: Man-hours worked on up to seven plots, covering land preparation, planting, weeding, harvesting and other activities
- Capital: Household-owned equipment, such as tractors, oxcarts and hand tools
- Fertiliser inputs: Organic and inorganic fertilisers (kg)
- Seeds: Number of seeds planted (kg)

Secondly, the study explored the determinants of technical change, extracting relevant data from the four IHSP survey rounds using Stata software. Inputs were grouped into farmer attributes (age, education, gender), policy-related variables (access to credit, extension services), plot-level factors (terrain, erosion), and agroecological characteristics (regional and soil quality variations). Using Stata software, the data was analysed using censored tobit regression.

2.4 Methodology

2.4.1 The Malmquist productivity index (MPI)

In this study, total factor productivity (TFP) is estimated using the Malmquist productivity index (MPI), as described by Fare *et al*. (1994). According to the output-oriented distance function, MPI can be described by the following equations:

$$MPI^{t} = \frac{D^{t}(x^{t+1},\ y^{t+1})}{D^{t}(x^{t},\ y^{t})} \tag{2}$$

and

$$MPI^{t+1} = \frac{D^{t}(x^{t+1},\ y^{t+1})}{D^{t+1}(x^{t},\ y^{t})}, \tag{3}$$

where x^t and x^{t+1} represent an input vector bridging consecutive periods t and $t+1$; and y^t and y^{t+1} represent output vectors. The distance between t and $t+1$, relative to the frontier D^t and D^{t+1}, is effectively measured by distance functions.

The geometric mean in Equation (3) provides a weighted average of the two MPIs, as shown below:

$$MPI^{t+1}(x^{t},\ y^{t},\ x^{t+1}, x^{t+1}) = \left[\frac{D^{t}(x^{t+1}, y^{t+1})}{D^{t+1}(x^{t+1}, y^{t+1})}, \quad \frac{D^{t+1}(x^{t}, y^{t})}{D^{t}(x^{t}, y^{t})}\right]^{1/2} * \frac{D^{t+1}(x^{t+1}, y^{t+1})}{D^{t}(x^{t}, y^{t})}. \tag{4}$$

The Malmquist productivity index comprises two primary components: technical efficiency change (TEC) and technical change (TC). TEC indicates improvements in efficiency from time t to $t + 1$, enabling frontier achievement using inputs from time t to $t + 1$. TEC encompasses two categories: pure efficiency change (PEC), enhancing production processes, and scale efficiency change (SEC), optimising production levels. TC represents the transition from an earlier frontier to a new one between time t and $t + 1$.

Equation (5) correctly represents the decomposition of the Malmquist productivity index (MPI):

$$MPI^{t,t+1} = TFP^{t,t+1} = TEC^{t,t+1} * TC^{t,t+1}$$
$$= PEC^{t,t+1} * SEC^{t,t+1} * TC^{t,t+1} \quad (5)$$

2.4.2 Censored tobit model

The censored tobit model was employed to investigate the determinants of technical change (TC) in Malawi's agricultural sector, given the notable 27.4% decline in TC observed in our analysis of the Malmquist productivity index. As detailed in Section 2.2, this model is particularly suited to analysing censored data and provides reliable estimates by accounting for the latent nature of productivity growth.

3. Results

3.1 Descriptive analysis

Table 1 presents summary statistics of the variables used in the analysis. The yield (output) of smallholder farmers decreased significantly between 2016 and 2019, with the mean yield dropping from 185 000 kg to 42 000 kg. This decline is notable, given the relatively consistent landholding sizes across the two periods. Labour input, measured in man-hours, decreased slightly, from 1 349 to 1 297. The use of capital and fertiliser also declined, with capital decreasing from 28 700 MK[1] to 19 300 MK and fertiliser usage dropping from 380 kg to 251 kg. These trends suggest potential productivity challenges facing smallholder farmers, which may be attributed to various factors, including changes in input usage and efficiency.

Table 1: Summary statistics of variables

	2016				2019			
Variable	**Mean**	**SD**	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**
Yield ('000 kg)	185	300	0.5	2 720	42	67	0.1	682
Land (acres)	2	1	0	7	2	1	0	7
Labour (man-hours)	1 349	1 669	0	12 273	1 297	1 455	18	11 736
Capital ('000 Mk)	28.7	193	0	2 347	19.3	189	0	2 331
Seeds (kg)	44	141	1	1 512	29	52	0	510
Fertiliser (kg)	380	1 925	0	21 290	251	623	0	5 365

Table 2 presents the descriptive statistics, revealing some notable trends. Literacy levels among household heads increased from 54.74% in 2016 to 72.15% in 2019. Education levels remained relatively low, with most households having no formal education. Most households (around 90%) reside in rural areas, highlighting the rural nature of the sample. The average distance to the boma remained relatively stable, at around 16 km in 2016 and 25.9 km in 2019. Soil erosion is a significant issue, affecting over 85% of households in 2016 and around 57% in 2019. Access to loans is relatively high, with around 76% of households obtaining loans in both periods.

These trends reflect the broader challenges faced by households in our sample, which is characterised by significant difficulties, including considerable distances to essential services, high illiteracy rates, persistent gender imbalances, and limited access to affordable credit, with many facing high interest rates and small loan amounts, as documented by Finmark Trust (2023).

[1] Malawian kwacha

Table 2: Descriptive statistics for tobit model variables

	2016		2019	
Variable	**Frequency**	**Percentage**	**Frequency**	**Percentage**
Literacy level of the head of family				
Yes	104	54.74	329	72.15
No	86	45.26	127	27.85
Education level of the head of family				
None	156	82.11	340	74.56
Primary school level	12	6.32	48	10.53
Junior certificate level	12	6.32	34	7.46
Malawi schools secondary certificate/GCSE level	7	3.68	24	5.26
Diploma	3	1.58	9	1.97
Degree			1	0.22
Urban/rural residence				
Urban	18	9.47	45	9.87
Rural	172	90.53	411	90.13
Region				
North	12	6.32	51	11.18
Central	54	28.42	249	54.61
Southern	124	65.26	156	34.21
Gender of the head of the family				
Male	80	42.11	344	75.44
Female	110	57.89	112	24.56
Whether the soil is eroded or not				
There is no erosion	105	55.26	194	42.54
There is erosion	85	44.74	262	57.46
Whether soil is good				
Not good soil quality	82	43.16	213	46.71
Good soil quality	108	56.84	243	53.29
Terrain or slope of the garden				
The garden is sloped	105	55.26	198	43.42
The garden is flat	85	44.74	258	56.58
Religion of the head of the family				
None	4	2.11	18	3.96
Traditional	1	0.53	6	1.32
Christianity	148	77.89	332	72.97
Islam	37	19.47	97	21.32
Other religion			2	0.44
Whether household obtained a loan				
Yes	145	76.32	347	76.1
No	45	23.68	109	23.90

	2016				2019			
Variable	**Mean**	**SD**	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**
Distance to boma, km	16.04	1	106	16.04	25.85	16.02	0	107
Age	16.3	23	90	16.3	47.9	15.1	19	94

3.2 Productivity analysis

Table 3 shows the productivity analysis for the country, as well as for the regions, which car also divided into TEC, technical change, PEC and SEC.

Table 3: Overview of MPI for 2019

	TFP	Percentage change	TEC	TC	Percentage change	PEC	SEC
Country	0.939	-0.6	1.293	0.726	-27.4	1.025	1.226
North	1.135	13.5	1.379	0.824	-17.6	1.373	1.004
Centre	0.894	-10.6	1.355	0.660	-34.0	0.965	1.404
South	1.196	19.6	1.009	1.185	18.5	0.938	1.076

Notes: TFP = total factor productivity; TEC = technical efficiency change; TC = technical change; PEC = pure efficiency change; SEC = scale efficiency change

Malawi's smallholder household farmers experienced a 6.1% decrease in total factor productivity between 2016 and 2019, primarily due to a 27.4% decrease in technical change, which we attribute to the limited adoption of productivity-enhancing technologies such as improved and high-yielding seed varieties, climate-resilient farming techniques, and precision farming methods. Studies have shown that Malawian smallholder farmers face challenges in accessing and utilising these technologies, which can hinder productivity growth (Machira *et al*. 2023; Pangapanga-Phiri *et al*. 2024). Our findings suggest that promoting the adoption of these technologies could be crucial for improving agricultural productivity in Malawi. TEC, however, improved by 29.3%, primarily due to an increase of 22.6% in scale efficiency. On the other hand, household farmers overall demonstrated a slight improvement in technical efficiency and a notable improvement in scale efficiency. Although the analysis utilises data from 2016 to 2019, it provides a valuable baseline understanding of productivity trends and determinants in Malawi's agricultural sector. We therefore argue that these findings remain relevant for informing policy discussions and guiding further investigation.

The table reveals notable regional differences in productivity growth. The Northern region exhibits resilience, with a 13.5% increase in total factor productivity (TFP) driven by improved TEC and contributions from pure efficiency change (PEC) and scale efficiency change (SEC). In contrast, the Central region faces challenges, with a 10.6% decline in TFP, despite significant gains in scale efficiency. The Southern region demonstrates strong productivity growth, with a 19.6% increase in TFP driven by an 18.5% rise in technical change, as well as stable TEC and SEC.

Given the challenges of low and declining agricultural productivity growth, largely driven by the limited adoption and utilisation of productivity-enhancing technologies, as well as regional disparities in productivity growth and access to support services, we recommend prioritising funds for a number of projects. These include strengthening Malawi's ailing agricultural extension services, revamping the country's dilapidated agricultural research stations to effectively promote technological adoption, adaptation and demonstration, and developing targeted support programmes to enhance smallholder farmers' access to improved seed varieties, climate-resilient farming practices, and other productivity-enhancing technologies.

3.3 Analysis of determinants

3.3.1 Tobit regression analysis

The tobit regression model identified the determinants of technical change among smallholder household farmers, shedding light on factors influencing Malawi's decline in agricultural productivity. The model specification was consistent throughout the years, ensuring comparability. Diagnostic tests confirmed no multicollinearity (VIF analysis), and a satisfactory model fit for 2019 (log-likelihood, LR test, and AIC/BIC values). We also conducted a bootstrap analysis for 2019, which yielded consistent results with our main tobit model estimates.

Table 4: Tobit model results for national and rural smallholder farming households

	2016			2019			2019 Rural		
Pseudo R^2	**0.10**			**0.616**			**-3.7**		
	Coefficient	**P-value**	**T-stat**	**Coefficient**	**P-value**	**T-stat**	**Coefficient**	**P-value**	**T-stat**
Rural residence	-0.25	0.06	-1.67	-0.09	0.07	-1.83	-	-	
Region									
Centre	0.25	0.86	018	0.12	0.00	2.93	0.71	0.08	1.78
South	0.06	0.64	0.47	0.16	0.00	3.57	0.11	0.02	2.41
Distance to boma	0.01	0.38	0.88	0.01	0.03	2.14	0.01	0.07	1.80
Illiteracy	0.09	0.19	1.33	-0.16	0.58	-0.55	-0.02	0.52	-0.65
Education	-0.95	0.42	-0.81	-0.03	0.38	-0.88	-0.02	0.56	-0.58
Sex									
Female	-0.16	0.03	-2.18	0.61	0.04	2.06	0.06	0.03	2.16
Age									
Between 35 and 54	0.02	0.79	0.26	-0.04	0.18	-1.36	-0.00	0.06	-0.87
Over 55	0.04	0.67	0.43	-0.06	0.07	-1.81	0.61	0.08	-1.78
Access to loans	-0.07	0.71	-0.37	0.01	0.82	-0.23	0.01	0.82	0.23
Wealth	-0.00	0.90	-0.13	-0.01	0.17	-1.37	0.01	0.78	-0.29
Terrain (garden is flat)	-0.07	0.29	-1.04	-0.60	0.02	-2.36	-0.39	0.12	-1.55
Plot has erosion	-0.08	0.19	-1.30	-0.06	0.00	-2.62	-0.05	0.04	-2.05
Soil quality is good	0.12	0.04	2.07	-0.03	0.29	1.06	0.02	0.44	0.83

Table 4 presents the results examining the determinants of technical change. A separate model is estimated for rural areas in 2019 to capture the unique challenges and opportunities faced by rural households.

As expected, the plot attributes significantly influence technical change. Terrain, a key geographical feature in Malawi's remote areas, plays a crucial role. According to the 2019 data, flat gardens have a negative relationship ($\beta = -0.6$, $p = 0.02$) with the influence of terrain, contradicting the common perception that flat areas should have improved soil fertility and water-retention properties. In contrast, slopy plots may boost productivity, potentially due to higher crop suitability and water retention properties, especially with irrigation and climate-smart practices. This is observable in Malawi's agricultural landscape, where innovative farms on slopy ground cultivate crops like Irish potatoes, onions and tomatoes.

This study reveals a deeper relationship between location and technical efficiency among smallholder farmers. Contrary to expectations, our analysis reveals that farmers living further away from the boma, the district administrative centre – typically a hub of activity with access to infrastructure, services and markets – tend to have higher technical efficiency, suggesting that districts may not be functioning as optimally as expected in terms of providing support services. Specifically, the results show a positive association between distance to the boma and technical efficiency in 2019 (coefficient = 0.01, $p = 0.03$, $t = 2.14$). This finding suggests that the relationship between proximity to Boma and technical efficiency may be more complex than initially thought and warrants further investigation. Notably, a similar pattern is observed in the rural model (coefficient = 0.01, $p = 0.07$, $t = 1.80$), suggesting that this relationship may be robust across different contexts.

Given the unexpected nature of this finding, we conducted additional analyses to better understand the relationship between distance to the boma and technical efficiency. These included spline, piecewise and stepwise regressions to determine if there is a more complex and/or non-linear relationship (see Section 3.3.2).

We found that farmers in rural areas are less efficient in their farming practices compared to those in urban or more developed areas. Our analysis confirms this trend, showing a consistent negative association between rural residence and technical efficiency over the period from 2016 to 2019, with marginally significant coefficients ($p = 0.06$ in 2016 and $p = 0.07$ in 2019). This could be due to various factors, such as limited access to resources, markets or information. This might mean that rural farmers face more challenges getting the inputs they need, accessing markets to sell their produce, or getting the latest farming techniques, which can affect their productivity and efficiency. Our analysis furthermore shows that being female is positively associated with technical change in 2019 (coefficient = 0.61, $p = 0.04$)

The relationship between plot attributes and technical change reveals an interesting pattern. Good soil quality was positively associated with technical change in 2016 ($\beta = 0.12$, $t = 2.07$, $p = 0.04$), meaning farmers with good soil quality tended to have better productivity or efficiency. In 2019, the relationship between good soil quality and technical change was negative, but not statistically significant ($\beta = -0.03$, $t = -1.06$, $p = 0.29$). In contrast, soil erosion consistently showed a negative relationship with technical change, meaning that areas with more soil erosion tended to have poorer productivity or efficiency. This was particularly evident in 2019 ($\beta = -0.06$, $t = -2.62$, $p = 0.00$), while the relationship was weaker in 2016 ($\beta = -0.08$, $t = -1.30$, $p = 0.19$).

3.3.2 Spline and piecewise analysis

Figure 1 presents the results of a spline regression analysis, revealing a complex relationship between the distance of smallholder household farmers to the nearest boma (a central government point) and technical change in agricultural productivity and practices. Employing a cubic basis function with predefined knots at five, 50, 80 and 100 km, the spline regression model (Harrell 2001) detects potential non-linear associations between proximity to a boma and the adoption of new technologies, farming practices, and overall productivity growth. The exploratory linear polynomial smoothing plotline suggests a non-linear relationship, underscoring the limitations of assuming a straightforward linear association between household farmers' distances from a boma and their ability to access the information, resources and support that drive technical change. The spline regression plot deviates significantly from a simple linear relationship between distance and technical change, highlighting the importance of accounting for non-linearity in understanding how geographical proximity to a boma influences smallholder farmers' capacity for innovation and growth. Although the coefficients for the spline terms (distance2_spline1, distance2_spline2, and distance2_spline3) indicate a complex interplay, the lack of statistical significance for individual terms warrants cautious interpretation in the context of smallholder farmers' diverse experiences and challenges.

Figure 2 presents a plotline based on scatter plots from a piecewise regression analysis, revealing three distinct relationships between the distance of smallholder household farmers to the nearest boma and technical change in agricultural productivity and practices. Specifically, the analysis shows that proximity to a boma (≤ 5 km) has a positive effect on technical change, suggesting that farmers closer to the government central point are more likely to adopt new technologies and practices, leading to improved productivity. In contrast, the relationship becomes slightly negative between eight to 60 km, indicating a gradual decline in technical change as the distance from the boma increases. Beyond 60 km, the decline in technical change becomes more pronounced, highlighting the challenges faced by farmers in remote areas in accessing information, resources and support. This piecewise relationship reveals an intriguing pattern, where the benefits of proximity to a boma are evident in the immediate vicinity, but diminish and eventually turn negative as distance increases, underscoring the need for targeted interventions to support smallholder farmers in diverse geographical contexts.

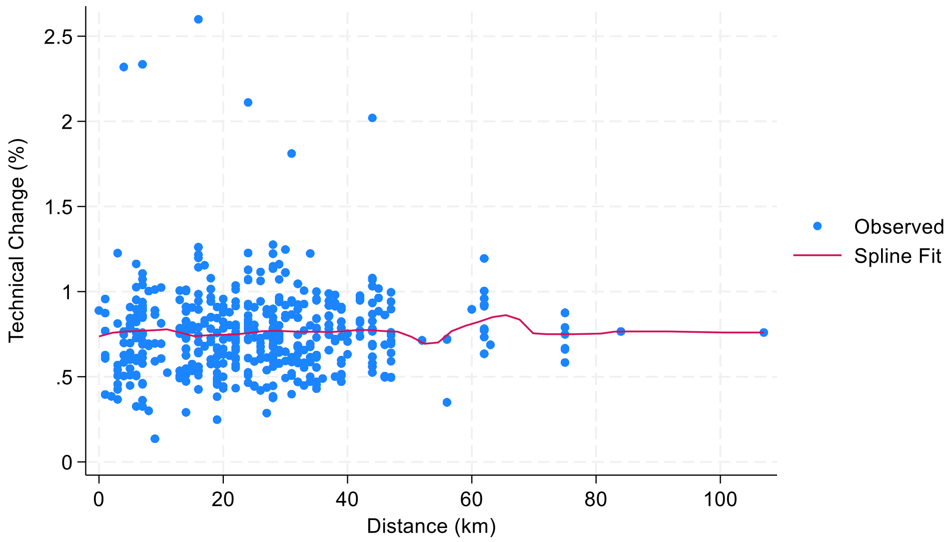

Figure 1: Spline plot – Technical change and distance to boma

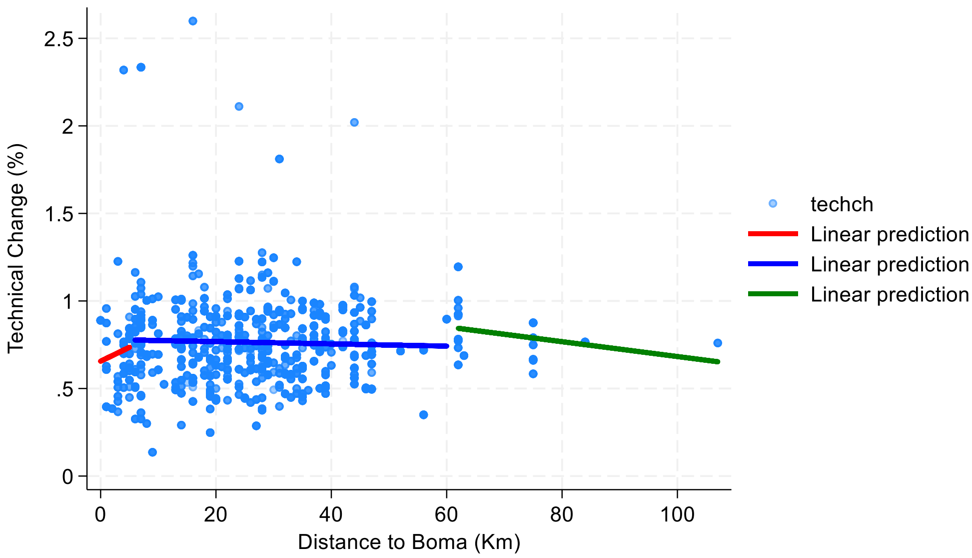

Figure 2: Piecewise plot – Technical change and distance to boma

The spline and piecewise regressions indicate a non-linear relationship, with different patterns emerging at different distance ranges. These findings highlight the need for targeted policies that address the unique challenges faced by farmers at different distances from district centres.

4. Conclusion

Our DEA analysis revealed a decline in productivity among smallholder farmers between 2016 and 2019, characterised by a significant drop in yield and decreases in input usage (labour, capital and fertiliser). These trends suggest potential productivity challenges facing smallholder farmers, warranting further investigation of the underlying factors. Technical change (TC) also declined, reflecting productivity challenges. To better understand the factors behind this decline, particularly the impact of distance and isolation, we used technical change as a proxy for productivity in our tobit analysis. This allowed for a deeper examination of how remoteness affects smallholder farmers' productivity, given the specific context of Malawi's rural landscape, where many farmers live in remote areas.

From the tobit analysis, we noted that remoteness, characterised by rural isolation and distance to weekly rural markets (where farmers sell their produce on designated market days, often without formal structures or storage facilities) and other markets (including input markets for agricultural produce) in Malawi's rural areas, significantly impedes Malawi's smallholder farmers. Specifically, our results show that rural residence is negatively associated with technical efficiency, with marginally significant coefficients in 2016 ($p = 0.06$) and 2019 ($p = 0.07$). Furthermore, distance to the boma (district administrative centre) had a positive association with technical efficiency in 2019 (coefficient = 0.01, $p = 0.03$), suggesting a complex relationship between access to services expected to be available in these places and technical efficiency. Overall, limited access to extension services, a lack of credit facilities and the absence of suitably functional markets for farmers' outputs exacerbate these challenges. This aligns with Fujita *et al*.'s (1999) concepts of spatial economy, highlighting that geographical factors play a role in technical progress and productivity in Malawi's agricultural sector.

5. Recommendations

Our analysis suggests that remoteness profoundly compounds the difficulties of the technological adoption and knowledge of inputs, and hence productivity growth, especially for smallholder household farmers living in rural areas where access to vital extension services and urban benefits is limited. To effectively address this, policymakers should prioritise innovative, context-specific rural development initiatives. Consistent with our findings on the impact of remoteness on productivity, traditional extension service delivery methods require enhancement through novel, adaptable approaches to surmount the challenges of remoteness, including formidable terrain and financial constraints faced by governments.

Building on our findings on the challenges posed by remoteness, we suggest exploring the potential of electronic platforms and digital villages, and revamping agriculture research stations to enhance agricultural innovation. These initiatives could help bridge the research-to-practice gap and provide remote access to extension services, addressing some of the limitations of traditional methods. Furthermore, such digital initiatives could also help mitigate the challenges arising from the collapse of the Agricultural Development and Marketing Corporation's (ADMARC) market system. ADMARC was a state-owned enterprise that historically played a critical role in stabilising agricultural marketing systems, including providing input supplies and other marketing services. These digital initiatives could play a role by providing farmers with digital price information, protecting them from exploitative traders and enhancing their bargaining power such as through organised groups like cooperatives. To support these efforts, Malawi's government might consider redirecting funding from its ballooning financing of input subsidy programmes toward extension services, digital infrastructure and innovation hubs.

Future research should prioritise updating data through facilitated group discussions, and examining the moderation effects among variables based on farmer characteristics, plot features and remoteness on agriculture productivity. In addition, subsequent studies could focus on developing and refining strategies to operationalise, scale and sustain digital village platforms and e-extension services, thereby effectively bridging the rural-urban divide.

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