Differential Financial Access and Entrepreneurial Breakthrough in Developing Nations: A Case of South African Rural Small Businesses

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Outline of the presentation

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Introduction

- Small and medium-sized enterprises (SMEs) are considered the backbone of the economy of many countries.

- SMEs significantly contribute to economic growth by creating jobs, alleviating poverty, distributing income, and promoting innovation (Maneesha, 2020).

- Tanwar and Bhardwaj (2022) state that rural entrepreneurship can help develop rural areas through the sound management of local resources and creating employment opportunities.

- Mukwarami et al. (2020) reported in their study in South Africa that small businesses are critical to improving economic development in rural areas of South Africa.

- Tanwar and Bhardwaj (2022) state that rural entrepreneurship can help develop rural areas through the sound management of local resources and the creation of employment opportunities

- Governments globally are increasingly emphasizing the success of small business entrepreneurs and providing increased support resources because entrepreneurial finance has been judged to positively influence the success and growth of SMEs (Kanayo et al. 2021).

Financial inclusion/access vs. segmentation theory

- While financial inclusion provides a framework for financial access, the segmentation theory explains the dynamics of class that may affect desired outcomes.

- Segmentation theory suggests that a population's farming and non-farming small businesses can be classified into distinct, unobserved subgroups based on shared characteristics or behaviors (Birkenmaier & Fu 2020).

- This implies that small businesses and smallholder farmers do not constitute homogeneous groups but instead exhibit varying financial behaviours, challenges, and outcomes attributed to differences in access to financial services, institutional barriers, and socioeconomic factors.

- Segmentation theory suggests that financial outcomes are not uniform but depend on specific latent characteristics that distinguish different classes within the population.

- This study contributes to the literature in two ways. Firstly, it identified factors impeding access to finance peculiar to smallholder farmers in the Eastern Cape province of South Africa. Secondly, the study categorised how these factors influence the farmers' needs for finance in different ways.

- Where specific factors that affect the financial access of a certain group of farmers can be identified based on their business lifecycle, personalised intervention can be provided.

Brief Literature review

- Extant literature has paid much attention to factors limiting access to finance by SMEs.

- Moscalu et al. (2020) found that economic activity and the presence of financial institutions often vary by region, affecting SMEs’ access to finance.

- The preceding studies identified various factors that constrain small businesses, including smallholder farmers, from accessing finance.

- However, the problem is the differential impact of financial access factors on South African smallholder farmers and small businesses.

- Extant literature tends to assume that these groups face similar challenges, resulting in generalised interventions that may not address their distinct needs (Moscalu et al., 2020).

- Assuming these factors affect them similarly may be misleading and hinder appropriate intervention.

Methods and Model specification

- This study collected data from 283 smallholder farmers and small businesses in the Eastern Cape province of South Africa.

- It was targeted at the rural settlers of the agrarian areas of the grasslands (Mthatha), savanna (East London) and the Karoo (Queenstown), which constitute the three agricultural areas in the province.

- This study categorises small farm holders as those who primarily rely on rainfall for agricultural production, cultivate less than five acres of land and have limited access to market opportunities.

- In contrast, subsistence businesses are small enterprises that operate solely for survival purposes and are unlikely to expand beyond their current size and generate employment opportunities.

- The participants were selected using simple random and snowball sampling techniques.

- The latter approach, which relied on the recommendations of known contacts to facilitate the recruitment of additional participants, proved particularly advantageous given the unknown nature of the study population, highlighting the importance of personal networks in research (Atiku et al., 2020).

- Descriptive statistics were fixed for the social and economic characteristics of the response. The coding indicated 1 for any factors that affected their ability to access finance and 0 if otherwise.

- This Latent Class Analysis (LCA) model was used to implement the objective of this study. LCA is a statistical technique that identifies unobservable or latent classes within a population based on observed variables

Model specification

- The parameters and the logistic or multinomial logistic regression coefficients can be estimated using the expectation-maximization algorithm, which iteratively updates the estimates until convergence.

- To evaluate the model fit and determine the optimal number of latent classes, goodness-of-fit indices such as the Bayesian information criterion (BIC), the Akaike information criterion (AIC), and the Vuong-Lo-Mendell-Rubin likelihood ratio test (VLMR-LRT) were used.

The LCA model (Collins & Lanza, 2009) for factors influencing financial literacy is presented as follows:

$Let\, Y = (Y_1,\ Y_2, \dots Y_\rho)$ be a set of ρ observed variables, where Y_j represents the jth variable. (These variables represent the financial support factors presented in Table 1.) Assume there are K latent classes in the population and let $\eta = (\eta_{1,} \eta_2, \dots, \eta_{k,})$ be the probabilities of class membership, where η_k is the probability of an individual belonging to the kth class, and $\sum \eta_k = 1$. Fixing a logistic regression, $X = (X_{1,} X_{2,} \dots, X_q)$ for a set of q covariates help to predict the probability of belonging to a specific latent class. The logistic regression model for the binary latent class membership $(K\ =\ n)$ can be written as:

$$log(Pr(C_n = n|X = n)) = \left(\frac{exp(\alpha_{nn})}{1 + exp(\alpha_{nn})}\right)$$

Where C is the variables and X the categories for estimating the intercept affecting each variable. The probability of a farmer belonging to each class is modelled in the following multinomial logistic regression:

$$log(Pr(C = n)) = \left(\frac{\epsilon^{X_n}}{\sum^{C} \epsilon^{X_C}}\right)$$

The LCA model estimates the conditional probabilities of each observed variable given the latent class membership. Let $\Pi_{jk} = P(Y_j = 1|C = k)$ be the probability of the jth variable being equal to 1 given the kth latent class. The joint probability distribution of the observed variables given the latent class membership can be written as:

$$P(Y|C = k) = \prod\left[\left(\pi_{jk}^{Y_j}\right) * (1 - \pi_{jk})^{Y_j}\right]$$

Results & Discussion

Table 1 group the factors most impactful to a particular class of smallholder farmers and small businesses in accessing the finance needed for the sustainability of their operations

The profile of the participants revealed that out of the participants, 210 were women, 160 were categorized as being above the youthful age, 192 had completed up to Grade 12 education, and the remaining participants had tertiary education.

Additionally, 220 participants obtained their financing from commercial banks. The participants owned either a small farm or a subsistence business in a ratio of 40:60.

Table 1. Financial access factor variables.

Variable Name	Yes	No	Variable label	References
MA	89	198	My area	Ono & Uesugi (2014); De la Torre et al. (2010)
MPI	125	158	My personal income	Cole (2013); Kwong (2010)
MBR	91	192	My business revenue	Fatoki (2014); Levenson & Willard (2000)
AFI	65	218	Availability of financial institutions	Han et al. (2009); Beck et al. (2009)
MFI	95	188	My financial literacy	Lusardi et al. (2015); Lusardi & Mitchell (2014)
MR	56	227	My race	Cavalluzzo et al. (2002)
SMB	117	166	Size of my business	Beck & Demirgüç-Kunt (2006); Fairlie & Robb (2007)
SOMB	125	158	State of my business	Casey & O'Toole (2014), Michaelas et al. (1999)
IR	50	233	Interest rate	Beck et al. (2008)

Source: Survey responses, 2022

Result & discussion

Table 2 contains the data for 10 randomly selected participants, arranged in the order they were surveyed.

It shows the likelihood of a single business being part of each sub-class by applying the posterior probability of class membership predictions.

The analysis revealed that all the listed participants had a more than 90% chance of being categorized as LIF, MIF, or VIF, except for the third and sixth participants.

Their probabilities stood at 58% and 87%, respectively, which indicated the model's aptness.

Table 2. Predicted probability of finance access factors in a class.

participant	cpr1	cpr2	cpr3	maxpr	predclass
1.	0.999653	5.03e-09	0.000347	0.999653	1
2.	8.81e-30	5.25e-17	1	1	3
3.	8.16e-06	0.4167418	0.58325	0.58325	3
4.	0.9113131	0.0794297	0.0092572	0.9113131	1
5.	0.9904739	0.0095091	0.0000171	0.9904739	1
6.	1.40e-06	0.134948	0.8650506	0.8650506	3
7.	1.54e-09	3.96e-17	1	1	3
8.	3.50e-24	0.0005872	0.9994128	0.9994128	3
9.	2.02e-16	0.0305315	0.9694685	0.9694685	3
10.	4.15e-16	0.0006109	0.9993891	0.9993891	3

Result & discussion

Table 3 shows the class prediction probability, demonstrating that our model could effectively differentiate participants into their sub-classes.

The results showed a 99% probability of accurately categorizing the participants as part of, for instance, LIF, with only roughly 0.9% and under 0.2% chances that the same participant could be mistakenly identified as part of MIF and VIF, respectively.

This trend was similarly observed for the second and third sub-classes, with a 98% and 99% probability that businesses falling under these sub-classes would be correctly classified.

Table 3. Class prediction

predclass	Class1pr	Class2pr	Class3pr
1	0.9886716	0.0090361	0.0022922
2	1.60e-06	0.9847025	0.0152959
3	0.0002453	0.0066204	0.9931343
Total	0.3948631	0.2253206	0.3798164

Result & discussion

Figure 1

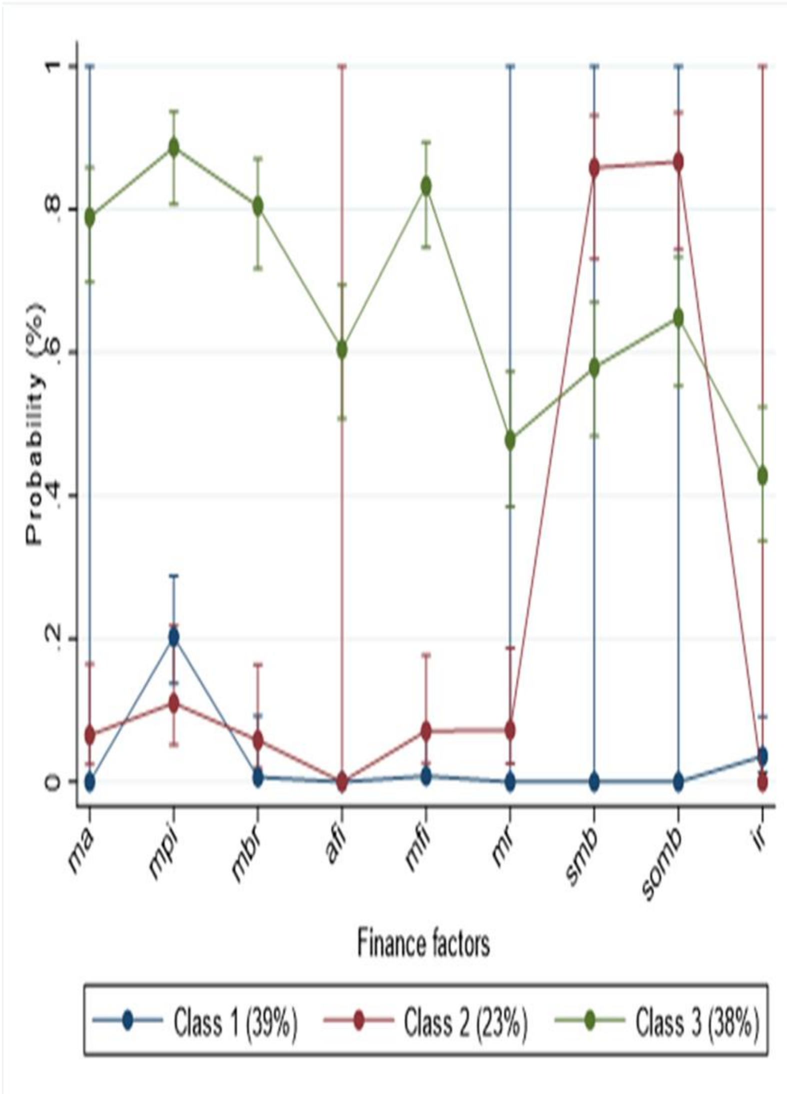

Table 4. Classification of factors affecting financial access.

Profile	Indicators	Margin	Delta method std. err.	[95% conf. interval]	
Class 1	MA	6.30e-08	0.0000265	0	1
	MPI	0.2026664	0.0383692	0.1376327	0.2881613
	MBR	0.0067911	0.0093002	0.0004582	0.0925527
	AFI	1.52e-08	.	.	.
	MFI	0.0083768	0.0091786	0.0009677	0.068614
	MR	1.33e-07	0.0000514	0	1
	SMB	1.00e-07	0.0000408	0	1
	SOMB	9.98e-07	0.0002521	1.1e-221	1
	IR	0.0357863	0.0175801	0.0134887	0.0915234
Class 2	MA	0.065309	0.0322363	0.0242187	0.1643711
	MPI	0.1101491	0.0407594	0.0519435	0.2185424
	MBR	0.0582965	0.0322697	0.0191853	0.1638225
	AFI	1.76e-08	0.0000168	0	1
	MFI	0.0712292	0.0347188	0.0266862	0.1766285
	MR	0.0725535	0.0370265	0.0259171	0.1869991
	SMB	0.85835	0.0498642	0.7306332	0.9312126
	SOMB	0.8667366	0.0473047	0.744541	0.9355418
	IR	1.95e-08	0.0000178	0	1
Class 3	MA	0.7892649	0.0407451	0.698542	0.8582263
	MPI	0.88691	0.032248	0.8068086	0.9364169
	MBR	0.8049631	0.039041	0.7171194	0.8704561
	AFI	0.6047328	0.0480591	0.5077889	0.6940858
	MFI	0.832857	0.0372298	0.7468407	0.8938032
	MR	0.4779457	0.0486635	0.3844901	0.5729712
	SMB	0.5792057	0.0481889	0.4830054	0.6697451
	SOMB	0.6487323	0.0465105	0.5531582	0.7337053
	IR	0.427978	0.0481724	0.3372056	0.5238721

- **Table 4 is** graphically represented by **Figure 1** and presents the actual predicted probability of financial access factors in terms of how they are likely to affect the ability of the target group to have access to finance, given the logistic regression model.

- The result indicated that only personal income at 20% and interest rate at 4% were the factors that mattered to the participants in the class when seeking to access finance from banks or other financial institutions, for instance.

- **Table 4** indicates the probability of farmers and businesses in this category as 39% of the surveyed sample. Authors such as Cole (2013) and Kwong (2010) agree on the potential for low personal income to impede businesses' access to finance.

- This suggests that providing the much-needed collateral in securing loans from finance providers is a challenge to this class (Klinger et al., 2013).

- Unlike the small businesses (small farmers and businesses) in class 1, the size and the business's state constituted the most important factors for financial access in class 2, categorized as MIF and VIF at 87% and 86%, respectively.

- This was followed by personal income accounting for 11%, the area where they live, financial literacy, and race each accounting for 7%, while business revenue sat at 6%.

- More specifically, farmers whose race had a 7% impact on determining their access to finance, for instance, had 87% and 86% chances that the size and the state of the businesses constituted impediments.

- Access to finance by small businesses (small farms and businesses) in class 3 displayed the same pattern: personal income and financial institutions are categorized as MIF and VIF at 88% and 84%, respectively.

- Specifically, race and interest rate accounted for 44% and 42% of the f financial access for small businesses in class 3.

Conclusion

LCA model identified and classified financial access factors fundamental to the different categories of smallholder farmers and small businesses in the South African Eastern Cape province.

Several factors were identified in the literature that impact SMEs' ability to access various forms of finance, especially from financial institutions.

While these factors apply even to the categories of SMEs considered in this study, our study found that the factors impacted the businesses differently.

The model classified smallholder farmers and small businesses into three classes impacted by varying numbers of financial access factors.

The findings suggest that the evaluated factors were prevalent for 38% of the surveyed respondents. However, these factors had a low to moderate influence on 39% and 23% of the farmers.

Recommendation

- The findings inform policies encouraging financial institutions to offer tailored products and services that address different groups' specific financial access issues, leading to more inclusive financial systems.

- It could assist in formulating guidelines for more nuanced credit risk assessments, allowing for more precise lending and risk management.

- Furthermore, the local and provincial governments in the Eastern Cape of South Africa could upscale the study and use the findings to design and implement targeted interventions, such as grants or subsidies, that address specific financial access issues different groups face.

- The results could guide the creation of educational programmes designed to improve financial literacy and management skills among smallholder farmers and small businesses, enabling them to navigate financial access issues better.

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Limitation and Future Research

- This study acknowledges the limitations posed by our small sample size, which hinders generalization and comprehensive coverage for policy formulation.

- Despite this, our findings highlight the need for a targeted approach to enhance financial inclusion, particularly in rural development, given the government’s efforts in this area.

- Therefore, efforts should focus on appropriately profiling these smallholder farmers and small businesses to identify their specific challenges for potential support.

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