Agrekon

Agricultural Economics Research, Policy and Practice in Southern Africa

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/ragr20

Examining the impact of human capital and innovation on farm productivity in the KwaZulu-Natal North Coast, South Africa

Lloyd J. S. Baiyegunhi

To cite this article: Lloyd J. S. Baiyegunhi (2024) Examining the impact of human capital and innovation on farm productivity in the KwaZulu-Natal North Coast, South Africa, Agrekon, 63:1-2, 51-64, DOI: 10.1080/03031853.2024.2357072

To link to this article: https://doi.org/10.1080/03031853.2024.2357072

AGREKON
2024, VOL. 63, NOS. 1–2, 51–64
https://doi.org/10.1080/03031853.2024.2357072

Examining the impact of human capital and innovation on farm productivity in the KwaZulu-Natal North Coast, South Africa

Lloyd J. S. Baiyegunhi

Discipline of Agricultural Economics, School of Agricultural, Earth and Environmental Studies, University of KwaZulu-Natal, Pietermaritzburg, South Africa

ABSTRACT
Human capital development is considered the primary source of knowledge and skills in the innovation process. Despite this, there is evidence of a lack of technical and managerial knowledge among emerging sugarcane farmers who are beneficiaries of South Africa's land reform programme, thus, limiting their full potential in terms of innovation and productivity which is detrimental to their competitiveness. This paper employs the Crépon, Duguet, and Mairesse (CDM) approach, correcting for endogeneity problems, to estimate the causal impact of on-the-job training expenditure, used as a proxy for human capital development, on innovation, and innovation on farm productivity. It is based on a case study of 35 emerging sugarcane farmers in the KwaZulu-Natal north coast, South Africa. The results from the CDM model confirm the causal relationships between human capital (on-the-job training) and the innovation behaviour of the farmers, which positively impact the farm's productivity. This result underscores the relevance of human capital development in boosting innovation and productivity in the agricultural sector.

ARTICLE HISTORY
Received 16 February 2024
Accepted 14 May 2024

KEYWORDS
Human capital; agricultural innovation; productivity; emerging farmers; sugarcane industry

JEL CLASSIFICATIONS
D25; I25; O13; O15; O31; Q15; Q16

1 Introduction and background of the study

Innovation has been widely acclaimed as the primary source of productivity for firms and a crucial factor influencing a firm's competitive advantage and performance across industries, regions and countries, contributing to the long-term economic growth of a nation (Ganotakis 2012; Slaper et al. 2011). A firm's capacity to innovate largely depends on its intangible resources, expertise and how these assets are utilised (Subramaniam and Youndt 2005; Custódio, Ferreira, and Matos 2019; Sun, Li, and Ghozal 2020). Consequently, spurring innovation has become a pressing issue for entrepreneur and policy makers alike. However, according to Hewitt-Dundas (2006), it is the accumulation of human capital that enables technical progress and change (i.e., innovations), thereby making growth and productivity in the agricultural sector more sustainable. Human capital provides firms with a competitive advantage in the form of abilities, talents, knowledge and a disposition to work. It embodies the creative capital found in employees, skills, and knowledge, which is cultivated through learning and improved health conditions. In the recent years, human capital has been widely recognised as the central source of skills and knowledge in the innovation process (Gallego, Gutierrez, and Rodrigo

CONTACT Lloyd JS Baiyegunhi Baiyegunhil@ukzn.ac.za Discipline of Agricultural Economics, School of Agricultural, Earth and Environmental Studies, University of KwaZulu-Natal, Pietermaritzburg Campus, Private Bag X01, Scottsville 3201 Pietermaritzburg, South Africa

2015; Crowley and McCann 2018). In the endogenous growth theory, human capital is acknowledged as the most crucial input in innovation at a macro level, emphasising that it is the combination of human capital and R&D that drives innovation (Romer 1990).

High levels of human capital capacity signify greater learning capability, thereby increasing a firm's capacity to innovate. Thus, a firm-level approach is desirable for a clear understanding of the link between human capital and innovation (Schneider *et al.,* 2010). Increased agricultural production and development require the enhancement of human capital at basic levels, such as the farm level. At a most fundamental level, agriculture relies on farmers' labour and their knowledge of crops and livestock, and their ability to efficiently utilise inputs and farming systems. Knowledge is, therefore, a critical resource for human capital development, necessitating access to information, technologies and the basic learning that produces novel inputs or innovative methods of utilising them (Agriculture for Impact 2013).

The significance of human capital in association with innovation and productivity remains evident. The structure of employee skills has been identified as a major determinant of the level of innovation in an economy. Well educated personnel increase a company's knowledge wealth through their daily work performance, accelerating contact with external knowledge linkages due to interactions with individuals possessing related capabilities outside the firm (Vinding 2006). Absorptive capacity has also been recognised as crucial in determining a firm's capacity to obtain, integrate, and effectively utilise new knowledge to enhance its innovation capabilities (Cokburn and Henderson 1998). Moreso, employee skill acquisition enhances the likelihood of innovation, as it improves a firm's ability to leverage external technological spillovers.

Human capital and innovation efforts have been identified as crucial factors driving productivity growth and competitiveness in the agricultural sector over time (Ramírez, Gallego, and Tamayo 2020; Aboal, Mondelli, and Vairo 2019). The development and production concerns in agriculture have underscored the importance of technical progress in increasing productivity to meet growing food demands. Technological advancements necessitate skilled workers to operate new technologies effectively (AgriSETA 2011; Reardon and Barrett 2000). Thus, farmers require education and analytical skills to enhance their farm output and contribute to innovation and research. Additionally, human capital plays a crucial role in determining the quality of employee engaged in farm innovation endeavours. Knowledgeable and skilled farmworkers are more likely to identify potential innovations, challenge existing current systems, and possess the understanding to develop novel solutions (Dakhli and De Clercq 2004). This highlights that productivity results not only from technology adoption but also from the capacity to produce and incorporate innovations in agrarian systems (EU SCAR 2012). Higher levels of human capital may lead to an increase in the number of innovative entrepreneurial farmers and products, thereby driving productivity and economic development through the innovation channel (Diebolt and Hippe 2019).

An increase in human capital aids in managing routine agricultural challenges such as drought, pests, diseases and soil degradation (Pretty, Bharucha, and Garba 2014). In this context, innovation is viewed as a process whereby a firm accumulates knowledge and technical competencies to enhanced productivity, reduce costs, develop new products and improve the quality of existing products (Fagerberg et al., 2010; 2012). Effective innovation relies on a firm's ability to develop the knowledge embodied in its employees through education and information sharing (Jensen et al. 2007; Fitjar and Rodriguez-Pose 2013). However, there has been inadequate focus on technological skill advancement in the sector.

Technological progress is associated with a decreasing need for unskilled labour while increasing the demand for highly skilled labour (Reardon and Barrett 2000). Farmers face pressure to produce greater volumes of food to sustain food security, meet specific production certification demands and remain competitive in a globalised market (Moyo 2010; Raynolds and Ngcwangu 2010). Agricultural firms must invest in human resource capacity to meet new production needs, necessitating targeted skills development initiatives (AgriSETA 2011; Reardon and Barrett 2000). Therefore, to remain globally competitive, skill training in agriculture must keep pace with technological progress.

In South Africa, agriculture is largely dominated by the minority white population, limiting access to skills development for the black population before the advent of democratic governance in 1994 (Horwitz et al. 2002). This lack of skills acquisition has hindered business development and perpetuated traditional, non-commercial subsistence agricultural activities among the previously disadvantaged (Mampholo and Botha 2004; Mayer and Altman 2005). Emerging farmers in South Africa are particularly vulnerable in terms of skill levels and development opportunities (Horwitz et al. 2002; Mayer and Altman 2005; Silolo and Oladele 2012). The lack of technological, managerial, and marketing assistance to emerging commercial farmers has been recognised as a strategic issue following land reform in South Africa (James and Woodhouse 2017). The South African government aims to transfer 30% of agricultural land to black ownership by 2025, necessitating beneficiaries to have the skills and capacity to utilise the land effectively for sustainable production and food security (Minkley 2012). However, success to date has been limited, with no substantial increase in productivity and economic growth attributed to beneficiaries' lack of essential production skills and industry expertise (AgriSETA 2018). An inadequate skill source is likely to increase the time needed for innovation, as it requires extensive knowledge and trialling to mitigate associated risks (Abadi-Ghadim, Pannell, and Burton 2005).

South Africa's sugar production industry is one of the most significant sectors of the economy. It is a cost-competitive industry that ranks amongst the top 15 of the 120 world's high-quality sugar producers; yielding an estimated average of 20 million tons of sugarcane each season and a yearly average of 2.3 million tons of sugar, thus, making up almost 50 percent of field crop gross agricultural income within the Mpumalanga and KwaZulu-Natal provinces (SASA 2019). In addition, about 75 percent of the sugar produced is marketed in the Southern African Customs Union (SACU) region, that generates an average yearly income of R12 billion from SACU regional sales and export and provision of sustainable employment for about 2 percent of South Africa's population (DAFF, 2016). Yet no study to date has explored the industry's productivity advancements based on the interrelationship between human capital, farm innovation activities, and productivity. Therefore, understanding South Africa's access to human capital and skills development initiatives is essential for sustaining viable agribusiness enterprises and associated rural farmers. While empirical evidence exists for human capital and innovation improving productivity in the manufacturing industry (Hall 2011; Mohnen and Hall 2013), research on innovation in the agricultural sector has primarily focused on its determinants, adoption and diffusion of technology or innovation (e.g., Baiyegunhi et al. 2019; Sinyolo 2020; Baiyegunhi 2023; Chao et al. 2024), neglecting firm or farm-level studies evaluating the link between human capital expenditures, innovation, and productivity at individual farm levels.

Leiponen (2005), argues that firms with appropriate skills benefit more from innovation due possessing complementary competencies or absorptive capacity (Cohen and Levinthal 1990). This study aims to contribute to literature by examining the links between investments in human capital, innovative activities, and farm-level productivity on emerging sugarcane farms in the KwaZulu-Natal North Coast. The study is critical given the imperative for emerging black farmers in South Africa to respond quickly to new market opportunities created by policy changes. This paper aims to enhance existing knowledge in innovation literature by examining the impact of human capital and innovation on sugarcane productivity in the KwaZulu-Natal North Coast. The major contribution of this study is addressing the endogeneity problem that may arise when human capital, in the form of on-the-job training, is included in the CDM Model. An endogeneity problem arises due to the simultaneity existing when on-the-job training is included in the knowledge production (innovation) estimation and subsequently in the farm productivity outcome estimation. The CDM approach corrects this problem by including predicted values from the initial stages of the estimation procedure. This study also contributes to literature by developing an agricultural innovation index that goes beyond measuring innovation through adopted technologies.

This paper is structured as follows: Section 2 presents the research methods, including the study area description, sampling, data collection techniques, the conceptual framework, and the empirical estimation model employed. Section 3 presents the empirical results and discussions, while Section 4 presents the conclusion and policy implications of the study.

2. Research methods

2.1 Description of the study area

This study was conducted in the north coast sugarcane supply region, encompassing the Darnall and Gledhow regions in the Ilembe District Municipality, and the Maidstone region in the eThekwini District Municipality, located in the KwaZulu-Natal province of South Africa. These municipalities, the Ilembe and eThekwini District Municipalities, are densely populated and situated around the Port of Durban and the Port of Richards Bay, two of Africa's busiest ports. They are also in close proximity to the King Shaka International Airport and Dube Trade Port, making them key players in the KwaZulu-Natal provincial commercial development landscape and well-positioned to access both local and international markets (Beires and Lincoln 2017).

The main economic activities in eThekwini include manufacturing, financial services, retail, tourism, construction, ports, transport and logistics related activities, and some agricultural activities, particularly cane growing and milling (Maidstone mill) (eThekwini District Municipality 2013). In Ilembe, economic activities comprise commercial agriculture (primarily sugar, some forestry, and emerging mixed farming), allied milling industry (Gledhow and Darnell mills), Sappi Paper mill at Mandeni, and tourism (iLembe District Municipality 2014). Approximately 63% of land holdings in the Ilembe District are controlled by customary institutions, jointly held by the State and Ingonyama Trust, with 31% contributing to commercial farming and mainly consisting of privately-owned sugarcane farms. Sugarcane is the primary commercial crop in the district, although some farmers are

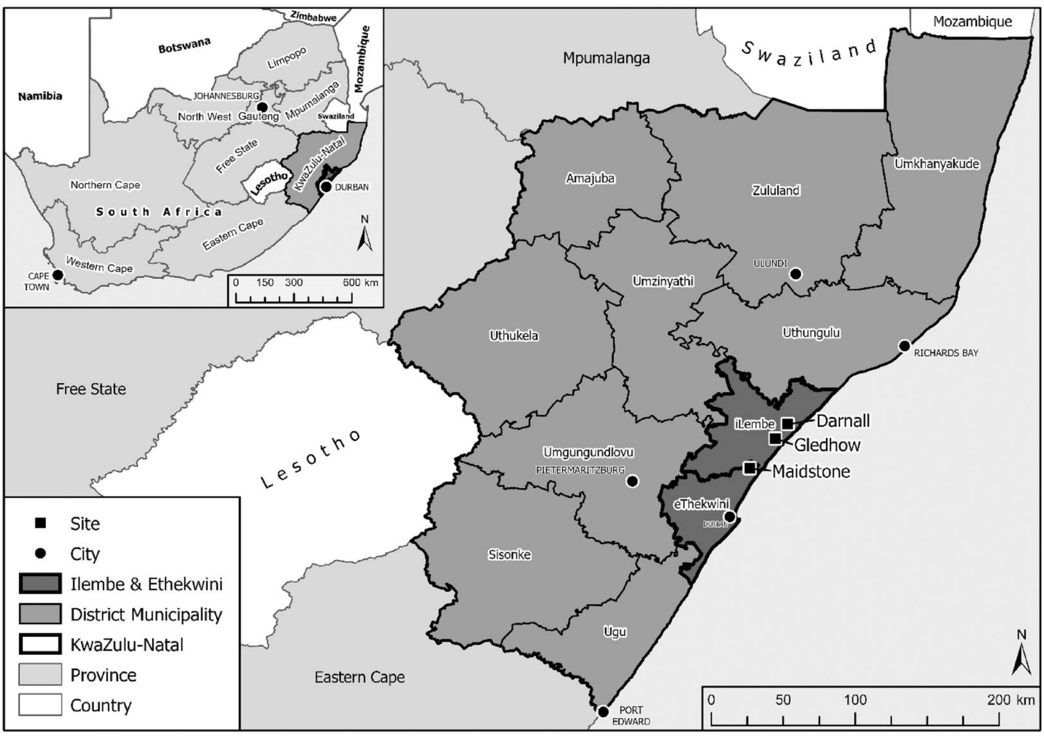

Figure 1. Map of KwaZulu-Natal province showing the study areas (Darnall, Gledhow and Maidstone). Source: UKZN Geography Department Cartographic Unit (2020).

diversifying into other sub-tropical fruits and macadamia nut crops, with limited livestock farming. Figure 1 depicts a map of the KwaZulu-Natal province, showing the study area of Darnall, Gledhow, and Maidstone.

2.2 Sampling and data collection method

Data for this study was obtained using a two-staged sampling method. In the first stage, a list of registered emerging cane growers, who are land reform beneficiaries in the North Coast sugarcane supply region, was obtained from the South African Cane Growers Association (SACGA). The list comprised 126 emerging cane growers, with 60 from the Darnall region, 37 from Gledhow, and 29 from Maidstone. In the second stage, convenience and snowball sampling techniques were used to identify and select 17, 10, and 8 respondent farmers from the Darnall, Gledhow, and Maidstone regions, respectively. This approach was necessitated by the COVID-19 pandemic lockdown in 2020. These farmers were easily accessible, available, and willing to participate in the study, also providing a platform for learning and networking for entrepreneurship advancement and support. Therefore, the 35 sampled emerging farmers in this study are regarded as a case study rather than a representative sample. The case study method helps in understanding the dynamics present within a specific situation and is valued for detecting ranges where a system is at its primary or determinative stages (Cepeda and Martin 2005).

Background information on emerging sugarcane farmers was obtained through key informant interviews. This information aided in the design of a structured questionnaire used to obtain quantitative primary data through face-to-face interviews. The structured questionnaire comprised both open-ended and closed-ended questions aimed at gathering information on emerging sugarcane farmers' socio-economic characteristics, human capital investments, innovation activities, farm productivity, and other institutional factors. Probing questions were employed to allow respondents to further clarify and expand on their answers (Saunders, Lewis, and Thornhill 2009), ensuring a comprehensive understanding of their viewpoints. Trained enumerators administered the questionnaires to farm managers during interview sessions. Farm managers play significant roles in farm-level innovation, including decision-making, resource allocations, priority setting, cost and expenditure controls, and idea screening (Herrmann, Tomczak, and Befurt 2006; Leiva, Culbertson, and Pritchard 2011).

2.3 Conceptual framework

Empirically studying the linkage between on-the-job training (proxy for human capital) and innovation, and innovation to productivity involves several challenges, such as measuring knowledge capital and correcting for latent unobserved farm heterogeneity when evaluating innovation activities, outputs, and productivity measures. Crépon, Duguet, and Mairesse (1998) proposed a structural CDM model, named after them, to address these challenges. The CDM model is an approach to deal with two econometric problems: self-selection and endogeneity. The self-selection problem arises because some farmers report positive on-the-job training expenditure, indicating non-random selection. These farmers might systematically differ from those who do not report on-the-job training, affecting parameter estimates due to sample selection bias. To address this, the Heckman approach was employed.

Furthermore, an endogeneity problem arises due to simultaneity when on-the-job training is included in the knowledge production (innovation) estimation and subsequently in the farm productivity outcome estimation. The CDM approach corrects this problem by including predicted values from the initial stages.

On-the-job training is included as a variable in the CDM model because it is vital for increasing firm productivity and driving innovation. The model comprises four stages: The first step is the on-the-job training equation, where firms decide on whether to invest in on-the-job training;

while the second step deals with on-the-job training expenditure (i.e., intensity), representing the on-the-job training investment equation. The third step focuses on innovation output, as innovation is produced as an outcome of on-the-job training investments and the final step focuses on productivity, with innovation as an input in the productivity equation.

2.4 Specification of the empirical estimation model

The CDM model used in this empirical study adopts a four-step analytical technique to estimate the relationships between on job-training (proxy for human capital) to innovation and innovation to productivity.

The first step is based on whether an emerging sugarcane farmer reports on-the-job training (decision) and the level of on-the-job training investment or expenditure (intensity). It is assumed that the likelihood of on-the-job training decision by a farmer is determined by a causal latent variable that embraces the farmers' true characteristics. The causal latent variable D^*_{OJT} is specified by:

$$D^*_{OJT} = \delta' z_i + \varepsilon_i \tag{1}$$

Estimating Equation (1) based on the actual observed on-the-job training investments will result in potential selection bias. To effectively correct this concern, the following selection equation describing if a farm is investing on on-the-job training related activities or not (see Griffith et al. 2006). D^*_{OJT} is a latent level of utility the farmers get from on-the-job training investments, $\varepsilon_i \sim N(0, 1)$ and,

$$\begin{aligned} D_{OJT} &= 1 \text{ if } D^*_{OJT} > 0 \\ D_{OJT} &= 0 \text{ if } D^*_{OJT} \leq 0 \end{aligned} \tag{2}$$

with D_{OJT} as the observed binary endogenous variable taking the value 1 if the marginal utility a farmer i get from on-the-job training investments is > 0, and 0 if otherwise. A probit model of on-the-job training investments that follows a random utility (Wooldridge 2003) is expressed by:

$$\Pr(D_{OJT} = 1 | z_i, \delta) = \Phi(h(z_i, \delta)) + \varepsilon_i \cdot \mu_i \sim N(0, \sigma^2) \tag{3}$$

where D_{OJT} is an indicator variable equal to 1 for farmers reporting on-the-job training activities on their farms; z_i is a vector of independent variables; δ is a vector of parameter estimates; .. is the standard normal cumulative distribution function; ε_i is a stochastic error term assumed to be independent and normally distributed as $\mu_i \sim N(0, \sigma^2)$ i.e., with zero mean and unit variance $\sigma^{2.}$

The second step, which is the on-the-job training investment, is conditional on the first stage, i.e., if the farm is reporting on-the-job training activities. In the second step, the Inverse of Mills Ratio (IMR) is added as a regressor in the on-the-job training investment equation in order to correct for potential selection bias, and is given by:

$$\Lambda(\Gamma_i | D_{OJT} = 1) = f(x_i, \beta) + \gamma\lambda \tag{4}$$

where Λ is the expectation operator; Γ_i is the total on-the-job training expenditure;x_i is a vector of independent variables; β is the vector of the resultant parameters to be estimated; λ is the IMR to account for sample selection in the on-the-job investment analysis; γ is the related parameter estimates.

The IMR is estimated as $\lambda = \frac{\varphi(h(z_i, \alpha'))}{\Phi(z_i\alpha')}$, where, $\varphi(\cdot)$ and Φ represents the normal probability density function and the cumulative distribution function respectively. Hence, Γ_i is specified as:

$$\Gamma^*_i = \beta' x_i + \gamma \overset{\hat{i}}{\lambda} + \mu_i, \quad \mu_i \sim N(0, \sigma^2) \tag{5}$$

where μ_i is a random error term with zero mean and variance σ^2. Γ^*_i is only observed for farmers reporting on-the-job training ($D_{OJT} = 1$), in which case $\Gamma_i = \Gamma^*_i$. OLS estimation of Equation (4), inclusive of λ, produces consistent estimates, eliminating selectivity bias (Greene 2012).

The subsequent two steps in the model are considered as a standard CDM model, which are expressed by (6) and (7). Equation (6) is the knowledge production (innovation) equation and is estimated as a probit model, expressed as:

$$Inn_i = \overset{\hat{\phi}}{\Gamma_i^*} + x_i^{'}\delta + \varepsilon_i \quad (6)$$

where $\hat{\Gamma}_i^*$ is the predicted value of on-the-job training investment Γ_i^* estimated from Equation (5) and x_i is a vector of explanatory variables relevant for innovation (see Crespi and Zuniga 2012). The farm productivity Equation (7) is estimated by an OLS regression model, and is expressed as:

$$\Pr od_i = j_i^{'}\pi + \overset{\hat{\vartheta}}{Inn_i} + \mu_i \quad (7)$$

where $\Pr od_i$ is the logarithm of productivity of firm i, j_i is a vector of variables that are related to productivity, and .. is the predicted value of Inn_i estimated from Equation (6).

2.4.1 Definition and measurement of the main associated factors in the CDM model

The definitions, measurements, assumptions and justifications for the three major associated factors in the analysis (on-the-job training, innovation and productivity) whose interrelationship was estimated in the CDM model are discussed in this section.

i. ***On-the-job training –*** Technical progress does not happen instantaneously or by chance but is an outcome of ambitious investments in human capital and research and development (R&D). Firms and individuals make choices about innovation, investment in human capital and R&D. According to Cohen and Levinthal (1990), firms' learning capacity is dependent on their internal capacities, which can be determined by the share of researchers in the R&D division, and is likely to affect the firms' innovation outcomes. As most of the agricultural firms in this study do not undertake formal R&D, the role of human resources management, and more specifically the human capital stock in the firm, is measured by manager and farm workers' on-the-job training. Firms expect on-the-job training to bring them efficiency gains and better adaptation to technical change. Thus, on-the-job training becomes an investment in the same way as R&D. Therefore, it is assumed that a firm that undertake more employee training will increase its innovative capacity.
ii. ***Firm's Innovation Output –*** The innovation index is used to embrace and reveal the complex nature of innovation in agriculture. Given that innovation in agriculture is influenced by the farmers' behaviour, it is imperative to value their efforts towards innovation. The innovation index is related to the common agreement in the literature that agricultural innovation is a practice that encompasses a dynamic reciprocity between farmers, economic and social agents, alongside supply networks and policy environments (Klerkx, van Mierlo, and Leeuwis 2012; Lamprinopoulou et al. 2014). Therefore, following Läpple, Renwick, and Thorne (2015), this study embraces the opinion that innovation is an extensive array of compatible approaches (OECD 2013). Innovation was measured by three indicators (i) innovation adoption, which deals with the application of new or considerably improved practice/product (ii) acquisition of knowledge, which refers to essential innovation learning processes, and is proxied by whether a farmer has sought out extension advisory services or not and (iii) continuous innovation, which highlights the necessity for continuous update or appraisal of existing innovation or practices. An indication of whether a farmer has changed or introduced some farm equipment in the previous two years is used as a proxy for continuous innovation. The three indicators were then given expert weights to capture their comparative significance for innovation. Adoption of innovation was considered the most imperative element and assigned a weight of 0.45, while knowledge acquisition and continuous innovation indicators were assigned weights of

0.40 and 0.15, respectively. Thus, the firm's innovation index assumes a value that ranges between 0 and 1, with higher values signifying a higher degree of innovation outputs/activities.

iii. ***Farm* Productivity** – Productivity of the farm is the total sugarcane output, measured in tons per hectare.

3. Empirical results and discussions

The empirical results and discussions emanating from the analysis of the link between human capital (on-the-job training), innovation and productivity of emerging sugarcane farmers are presented in this section.

3.1 Descriptive statistics of the emerging farmer's characteristics

The descriptive statistics of the independent variables and test of significance of difference between farms reporting on-the-job training and those who do not are presented in Table 1.

From the statistics in Table 1, it can be observed that about 66% of the sampled emerging sugarcane farmers provide on-the-job training to farm workers. Farmers reporting on-the-job training activities have invested an average of ZAR 3208 per employee in on-the-job training in the last season. There is a statistically significant difference in the innovation activities for farms reporting on-the-job training activities and those who do not. Firms reporting on-the-job training have an average innovation index of 0.98, compared to 0.44 for those farms not reporting on-the-job training. Overall, the average innovation index among the sampled emerging sugarcane farmers is 0.63, with a standard deviation of 0.28. Furthermore, Table 1 shows that farms reporting on-the-job training statistically differ from those who do not. Farms reporting on-the-job training have more farm workers, larger farm size, and higher farm productivity compared to those who do not. In addition, farmers reporting on-the-job training seem to be more educated, with more industry specific experience; they own and operate their farms as a family business enterprise. While farmers who do not report on-the-job training seem to be older compared to those who do report on-the-job training. There is, however, no observed statistically significant difference between farms reporting on-the-job training and those who do not in terms of public financial support, access to institutional credit, established links with markets/buyers, membership in informal networks (such as farmers based organisation/associations), and access to agricultural extension advisory services.

Table 1. Descriptive Statistics of the emerging farmers' characteristics.

	On-the-job training decision = 1 *(n = 23)*		On-the-job training decision = 0 *(n = 12)*		*t*-value
Variables	Mean	SD	Mean	SD	
On- job training expenditure	3208	1751	-	-	−243.32[a]
Innovation index	0.98	0.15	0.44	0.47	11.04[a]
Land productivity	67.8	16.4	55.1	22.5	3.02[a]
Number of farm worker	6.71	5.12	5.12	4.87	2.81[a]
Farm size	10.31	16.82	6.34	4.10	1.66[c]
Farm ownership	0.93	0.02	0.69	0.06	4.608[a]
Age of farmer	40.36	14.47	43.53	13.51	4.34[a]
Farmers' education	16.21	4.67	12.32	3.76	3.65[b]
Industry specific experience	7.78	0.47	6.73	0.35	1.72[c]
Public financial support	0.38	0.03	0.35	0.03	0.77
Access to institutional credit	0.51	0.45	0.49	0.50	0.42
Link with markets/buyers	0.86	0.34	0.87	0.34	0.05
Link in informal networks	0.97	0.09	0.98	0.09	0.12
Advisory services (extension)	0.98	0.46	0.99	0.48	1.50

[a,b,c]Denote significance levels at 1%, 5% and 10% respectively.

3.2 The CDM model result of the impact of human capital and innovation on farm productivity

The CDM Model result of the impact of human capital (on-the-job training) and innovation on farm productivity is presented in Table 2. The first and the second steps (the Heckmann's model Equation (3)) report the estimates of the determinants of on-the-job training and the intensity, i.e., the level or amount invested in on-the-job training. The third step (Equation (6)) presents the estimates of the determinants of innovation or knowledge production, and the fourth step (Equation (7)) provides the estimates of the factors influencing farm productivity.

The results presented in Table 2 reveal that the farmer's age, his educational level, industry specific experience, the number of farm employee, farm size as well as the farm being operated as a family business enterprise and access to agricultural extension advisory services are statistically significant determinants of emerging sugarcane farmers' on-the-job training decision. The level of investment in on-the-job training is influenced by statistically significant factors such as the farm managers' educational level, industry specific experience, number of farm employees, farm size, and the farm being operated as a family business enterprise. The results of the innovation production function (step 3, Equation (6)) show that farmers' educational level, farm size, farm operated as family business, industry specific experience, access to agricultural extension advisory services, link in informal networks and employee involvement in decision making, as well as on-the-job training investments (predicted) are statistically significant factors explaining innovation production by emerging sugarcane farmers.

The estimates of the productivity function (step 4, Equation (7)) shows that productivity is largely determined by statistically significant variables such as the farmers' educational level, farm size, farm operated as family business, industry specific experience, access to agricultural extension advisory services, link with market/buyers, as well as innovation (predicted) and physical capital, i.e., the total amount spent on productive inputs such as labour, fertilisers and herbicides.

Table 2. The CDM Model results of the impact of human capital and innovation on farm productivity.

	First & Second Step (Heckmann's Model)				Third Step		Fourth Step	
	Equation (3)		Equation (5)		Equation (6)		Equation (7)	
	On-the-Job Training Decision		On-the-Job Training Investments		Innovation Production		Farm Productivity	
Explanatory Variables	Coefficient	Robust SE	Coefficient	Robust SE	Coefficient	Robust SE	Coefficient	Robust SE
Age of farm manager	0.180[a]	0.028	0.132	0.404	0.018	0.012	0.022	0.043
Farmers' educational level	2.986[a]	0.440	0.143[a]	0.009	0.441[b]	1.982	0.363[a]	0.105
Number of farm employee	0.403[c]	0.175	0.0712[c]	0.062	0.037	0.038	0.024	0.054
Farm size	1.133[a]	0.295	0.114[b]	0.016	0.401[b]	2.613	0.857[a]	0.123
Family operated business	2.365[b]	0.826	0.167[b]	0.033	0.480[a]	3.002	0.173[c]	0.101
Industry specific experience	1.988[a]	0.299	0.167[b]	0.033	0.398[a]	3.532	0.172[a]	0.054
Advisory services (extension)	1.255[b]	0.413	− 0.139	0.173	0.227[c]	1.913	0.140[b]	0.058
Public financial support	− 0.467	0.409	0.016	0.630	0.084	0.076	0.115	0.103
Access to institutional credit	− 0.530	0.385	0.262	0.930	0.057	0.074	0.070	0.093
Link with markets/buyers	0.559	1.127	0.041	1.274	0.016	0.011	0.046[a]	0.014
Link in informal networks	0.645	1.263	0.033	0.672	0.227[c]	1.914	0.099	0.062
Employee involvement at work					0.180[a]	3.101		
On-the-Job Training Expenditure (Predicted)					0.044[a]	0.016		
Innovation (Predicted)							0.062[a]	0.023
Physical capital							0.297[a]	0.102
Constant	−1.806[a]	0.298	−1.237[a]	0.286			−2.712[a]	0.781

[a,b,c]Denote significance levels at 1%, 5% and 10% respectively.

These are statistically significant factors explaining the productivity (output) of emerging sugarcane farmers.

From the result presented in Table 2, age is found to be statistically significant and positively related to on-the-job training decision at the firm level. This is probably because as a farmer gets older, they might consider on-the-job training as essential for themselves and their employees in order improve the specific knowledge associated with sugarcane farming. The firm's capacity to generate innovation and collaborate with other farmers or institutions in knowledge generation seems to increase with age, perhaps because over time, firms can form durable partnerships and employees can expand their proven technical capabilities to exploit and build upon (Capozza and Divella 2019).

Farmer's educational level and industry specific experience were found to be statistically significant in influencing on-the-job training decision as well as the level of investments in employee on-the-job training. Both variables were also significant in influencing innovation production as well as firm productivity. This finding is consistent with those of earlier studies (Cohen and Soto 2007; Ganotakis 2012; Criaco et al. 2014), that show educational level attainment and industry specific experience are key drivers for innovation production and firm productivity.

Similarly, farm size was found to be statistically significant in influencing on-the-job training decision, the level of investments in employee on-the-job training, as well as in innovation or knowledge production and firm productivity. This result agrees with Sauer and Zilberman (2012) and Aboal, Mondelli, and Vairo (2019), who found that size is positively linked to innovation performance and is a relevant element for innovation decisions.

Farms operated as family business enterprise were found to be more favourable disposed to making positive on-the-job training decisions and investing more in on-the-job training activities. The results further show that family farms are more innovative and more productive. This is possibly because family businesses are an essential organisational form of economic activity worldwide, especially in emerging economies. This result is also similar to that of Aiello, Mannarino, and Pupo (2020), who found that family firms in Europe invested more in R&D than another firm.

Agricultural extension advisory services were found to be statistically significantly related to the on-the-job training decision and were significant in influencing innovation production and farm productivity. Several studies, such as Conley and Udry (2010), Mmbando et al. (2016); Baiyegunhi et al. (2019), among many others, have revealed the vital role of extension advisory services for decision-making and information sharing, particularly on new crop varieties and markets for products. Extension advisory services could also be a beneficial pointer of social interactions and contact with innovation opportunities (Pannell et al. 2006).

An established link with markets/buyers was found to be statistically significantly related to farm productivity. Aboal, Mondelli, and Vairo (2019) have shown in their study that established links with consumers enhance innovation production. Similarly, physical capital (i.e., the total amount spent on labour, fertilisers, and herbicides) was also observed to be statistically significantly related to farm productivity. This finding is consistent with Ramirez et al., (2020), who found physical capital to be significant for productivity in Colombian enterprises.

Link with informal networks and employee involvement in key decision-making on the farm were found to be statistically significant in knowledge or innovation production. Previous studies (Sunding and Zilberman 2001; Aboal, Mondelli, and Vairo 2019), have shown that farmers habitually innovate in reponse to ideas from their contemporaries.) In addition, allowing discretion on work procedures and responsibilities can embolden workers to employ their learning and intellect efficiently to develop a "creative effort" in performing their tasks. Consequently, they can be intensely associated with the firm's capacity to generate diverse types of innovation (Capozza and Divella 2019).

The predicted value of on-the-job training investments was found to be statistically significant in determining innovation, while the predicted value of innovation was found to be statistically significant in explaining productivity. The hypothesis of the study that on-the-job training investments are important to build farm innovation capacity, and innovation is imperative for farm productivity, are supported by these results and is therefore validated and accepted.

4. Conclusion and policy implications of the study

The delicate link between human capital (on-the-job training), innovation and firm productivity was explored in this study employing the CDM approach. The analysis was carried out in different stages, and the results have pointed to the various factors influencing on-the-job training decision as well as the level of on-the-job training investments in the first and second stages using the Heckmann's model to control for selection bias. The causal relationships between human capital (on-the-job training), innovation, and firm productivity were also established. Thus, it can be concluded that on-the-job training investments have a causal effect on the innovation production behaviour of farmers, while innovation activity had a significant impact on farm productivity. In general, human capital in the form of on-the-job training plays a significant role in knowledge and innovation creation and consequently farm productivity.

After establishing the underlying influence of human capital acquired through on-the-job training on innovation, and innovation on productivity at the farm level, the results emanating from this study are imperative for policy and decision makers as they support the creation of key human capital management policies irrespective of the extent of investment by a farm. Even though all types of human capital are important, on-the-job training for productivity improvement, especially in South African's agricultural sector where there are skills shortages, is indispensable and crucial for farm's a competitive advantage and national economic development. On-the-job training plays a central role in the knowledge creation process as it fosters the development of human capital within the industry.

Farm managers and policymakers could use these findings to stimulate further investments in formal on-the-job training for farm workers because this may be more valuable for innovation creation than policies directed towards R&D investments. This implies that policies should not focus solely on R&D but must also incorporate the human capital aspects of innovation. Therefore, effective policies for innovation must include strengthening the skills, knowledge, and experience of farm workers and increasing the incentives for farm management to innovate. Furthermore, policymakers and managers should consider the portfolio of factors that have a beneficial relationship with innovation and are thus important for innovation creation and productivity, and introduce them in combination with some elements of human capital that are more favourable to the farm. This implies that policies should aim at specific combinations of significant factors that affect innovation and productivity in the agricultural sectors and not be too generic.

The supply of skilled labour in the agricultural sector has been limited by several training issues such as poor engagement in vocational learning and training and higher education training. Further partnership between government and the agricultural sector may be beneficial in meeting the sector's various learning and training requirements. Additional investment in on-the-job training and education should be accompanied by improved access to novel information and technologies. Public and private extension services continue to be central in knowledge and information sharing with farmers. Improving the effectiveness of extension advisory services are expected to increase farmer's capacity for innovation and consequently farm productivity.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Data availability statement

Data available on request due to ethical restrictions, i.e., privacy.

Informed consent statement

Informed consent was obtained from all subjects involved in the survey before their participation.

ORCID

Lloyd J. S. Baiyegunhi http://orcid.org/0000-0001-7717-3610

References

Abadi-Ghadim, A.K., D.J. Pannell, and M.P. Burton. 2005. Risk, uncertainty, and learning in adoption of a crop innovation. *Agricultural Economics* 33, no. 1: 1–9.

Aboal, D., M. Mondelli, and M. Vairo. 2019. Innovation and productivity in agricultural firms: Evidence from a country-wide farm-level innovation survey. *Economics of Innovation and New Technology* 28, no. 6: 616–34.

Agriculture for Impact. 2013. Sustainable intensification: A new paradigm for African agriculture. A Montpellier Panel Report, London.

AgriSETA. 2011. *Agricultural sector strategic skills plan: 2011–2016. Agricultural sector education and training authority*. Pretoria: Department of Higher Education and Training.

AgriSETA. 2018. *Agricultural sector skills plan: 2018-2019. Agricultural sector education and training authority*. Pretoria: Department of Higher Education and Training.

Aiello, F., L. Mannarino, and V. Pupo. 2020. Innovation and productivity in family firms: Evidence from a sample of European firms. *Economics of Innovation and New Technology* 29, no. 4: 394–416.

Baiyegunhi, L.J.S., M.B. Hassan, G. Danso-Abbeam, and G.F. Ortmann. 2019. Diffusion and adoption of Integrated Striga Management (ISM) technologies among smallholder maize farmers in rural northern Nigeria. *Technology in Society* 56, no. 2019: 109–15.

Baiyegunhi, L.J.S. 2023. Examining the determinants of agricultural innovation activities: A case study of emerging sugarcane farmers in South Africa. *Agrekon* 62, no. 3-4: 241–57.

Beires, L., and G.M. Lincoln. 2017. Smart regional planning: unlocking innovative resource use and economic competitiveness - a look at biomass energy infrastructure provision at local municipal scale in eThekwini and iLembe, South Africa. Paper presented at 25th European Biomass Conference and Exhibition, 12–15 June 2017, Stockholm, Sweden.

Capozza, C., and M. Divella. 2019. Human capital and firms' innovation: Evidence from emerging economies. *Economics of Innovation and New Technology* 28, no. 7: 741–57.

Cepeda, G., and D. Martin. 2005. A review of case studies publishing in management decision 2003–2004. *Management Decision* 43, no. 6: 851–76.

Chao, J., T. Li, H. Yin, and Z. Wang. 2024. Adoption of multiple sustainable agricultural practices among farmers in northwest, China. *Cogent Food & Agriculture* 10, no. 1: 2300189.

Cohen, D., and M. Soto. 2007. Growth and human capital: Good data, good results. *Journal of Economic Growth* 12: 51–76.

Cohen, W.M., and D.A. Levinthal. 1990. Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly* 35, no. 1: 128–52.

Cokburn, I.M., and R.M. Henderson. 1998. Absorptive capacity, coauthoring behavior, and the organization of research in drug discovery. *The Journal of Industrial Economics* 46, no. 2: 157–82.

Conley, T.G., and C.R. Udry. 2010. Learning about a new technology: Pineapple in Ghana. *American Economic Review* 100: 35–69.

Crépon, B., E. Duguet, and J. Mairesse. 1998. Research, innovation and productivity: An econometric analysis at the firm level. *Economics of Innovation and New Technology* 7, no. 2: 115–58.

Crespi, G., and P. Zuniga. 2012. Innovation and productivity: Evidence from six Latin American countries. *World Development* 40, no. 2: 273–90.

Criaco, G., T. Minola, P. Migliorini, and C. Serarols-Tarrés. 2014. "To have and have not": Founders' human capital and university start-up survival. *The Journal of Technology Transfer* 39: 567–93.

Crowley, F., and P. McCann. 2018. Firm innovation and productivity in Europe: Evidence from innovation-driven and transition-driven economies. *Applied Economics* 50, no. 11: 1203–21.

Custódio, C., M.A. Ferreira, and P. Matos. 2019. Do general managerial skills spur innovation? *Management Science* 65, no. 2: 459–76.

DAFF. 2016. A profile of the South African sugar market value chain. Department of Agriculture, Forestry and Fisheries. Pretoria. Available at: http://www.nda.agric.za/doaDev/sideMenu/Marketing/Annualand20Publications/Commodityand20Profiles/fieldand20crops/Sugarand20Marketand20Valueand20Chainand20Profileand202016.pdf. Assessed on 09/06/2021.

Dakhli, M., and D. De Clercq. 2004. Human capital, social capital, and innovation: A multi-country study. *Entrepreneurship & Regional Development* 16: 107–28.

Diebolt, C., and R. Hippe. 2019. The long-run impact of human capital on innovation and economic development in the regions of Europe. *Applied Economics* 51, no. 5: 542–63.

eThekwini District Municipality. 2013. eThekwini Municipality Integrated Development Plan 5 Year Plan: 2012/13 to 2016/17 Annual Review 2013/2014. 2013: Durban, South Africa.

EU SCAR. 2012. *Agricultural knowledge and innovation systems in transition – a reflection paper*. Brussels: European Union's Standing Committee on Agricultural Research.
Fagerberg, J., M. Fosaas, and K. Sapprasert. 2012. Innovation: Exploring the knowledge base. *Research Policy* 41: 1132–53.
Fagerberg, J., Srholec, M. and Verspagen, B. 2010. The role of innovation in development. Review of Economics and Institutions, 1: 1–29.
Fitjar, R., and A. Rodriguez-Pose. 2013. Firm collaboration and modes of innovation in Norway. *Research Policy* 42, no. 1: 128–38.
Gallego, J.M., L.H. Gutierrez, and T. Rodrigo. 2015. Innovation and productivity in the Colombian service and manufacturing industries. *Emerging Markets Finance and Trade* 51: 612–34.
Ganotakis, P. 2012. Founders' human capital and the performance of UK new technology based firms. *Small Business Economics* 39: 495–515.
Greene, W. 2012. *Econometric analysis*, 7th ed. London: Prentice Hall.
Griffith, R., E. Huergo, J. Mairesse, and B. Peters. 2006. Innovation and productivity across four European countries. *Oxford Review of Economic Policy* 22, no. 4: 483–98.
Hall, B. 2011. Innovation and productivity. NBER Working Papers 17178.
Herrmann, A., T. Tomczak, and R. Befurt. 2006. Determinants of radical product innovations. *European Journal of Innovation Management* 9: 20–43.
Hewitt-Dundas, N. 2006. Resource and capability constraints to innovation in small and large plants. *Small Business Economics* 26: 257–77.
Horwitz, F.M., V. Browning, H. Jain, and A.J. Steenkamp. 2002. Human resource practices and discrimination in South Africa: Overcoming the apartheid legacy. *The International Journal of Human Resource Management* 13, no. 7: 1105–18.
iLembe District Municipality. 2014. iLembe District Municipality Integrated Development Plan 2014/2015 Review. 2014. iLembe District Municipality, KwaZulu-Natal Province, South Africa.
James, P., and P. Woodhouse. 2017. Crisis and differentiation among small-scale sugar cane growers in nkomazi, South Africa. *Journal of Southern African Studies* 43, no. 3: 535–49.
Jensen, M.B., B. Johnson, E. Lorenz, and B.A. Lundvall. 2007. Forms of knowledge and modes of innovation. *Research Policy* 36, no. 5: 680–93.
Klerkx, L., B. van Mierlo, and C. Leeuwis. 2012. Evolution of systems approaches to agricultural innovation: concepts, analysis and interventions. In *Farming systems research into the 21st century: The New dynamic*, eds. I. Darnhofer, D. Gibbon, and B. Dedieu, 457–83. Dordrecht: Springer Science + Business Media.
Lamprinopoulou, C., A. Renwick, L. Klerkx, F. Hermans, and D. Roep. 2014. Application of an integrated systemic framework for analysing agricultural innovation systems and informing innovation policies: Comparing the Dutch and Scottish agrifood sectors. *Agricultural Systems* 129: 40–54.
Läpple, D., A. Renwick, and F. Thorne. 2015. Measuring and understanding the drivers of agricultural innovation: evidence from Ireland. *Food Policy* 51: 1–8.
Leiponen, A. 2005. Skills and innovation. *International Journal of Industrial Organization* 23, no. 5-6: 303–23.
Leiva, P.I., S.S. Culbertson, and R.D. Pritchard. 2011. An empirical test of an innovation implementation model. *The Psychologist-Manager Journal* 14: 265–81.
Mampholo, R.K., and J.J. Botha. 2004. Impact of previously disadvantaged land-users on sustainable agricultural practices. *South African Journal of Agricultural Extension* 33: 108–27.
Mayer, M., and M. Altman. 2005. South Africa's economic development trajectory: Implications for skills development. *Journal of Education and Work* 18, no. 1: 33–56.
Minkley, G. 2012. Rainwater harvesting, homestead food farming, social change and communities of interests in the Eastern Cape, South Africa. *Irrigation and Drainage* 61, no. S2: 106–18.
Mmbando, F.E., E.Z. Wale, L.J.S. Baiyegunhi, and M.A.G. Darroch. 2016. The choice of marketing channel by maize and Pigeonpea smallholder farmers: Evidence from the northern and eastern zones of Tanzania. *Agrekon* 55, no. 3: 254–77.
Mohnen, P., and B.H. Hall. 2013. Innovation and productivity: An update. *Eurasian Business Review* 3: 47–65.
Moyo, S. 2010. The agrarian question and the developmental state in Southern Africa. In *constructing a democratic developmental state in South Africa: potentials and challenges*, ed. pp. 285–314. A. Edigheji. Cape Town: Human Sciences Research Council.
OECD. 2013. Agricultural Innovation Systems: a framework for analyzing the role of the government. Paris: OECD Publishing. Available at: https://doi.org/10.1787/9789264200593-en. Accessed on 20 May 2020.
Pannell, D.J., G.R. Marshall, N. Barr, A. Curtis, F. Vanclay, and R. Wilkinson. 2006. Understanding and promoting adoption of conservation practices by rural landholders. *Australian Journal of Experimental Agriculture* 46, no. 11: 1407–24.
Pretty, J., Z.P. Bharucha, and M.H. Garba. 2014. *Foresight and African agriculture: Innovations and policy opportunities. Foresight*. London.: UK Government Office for Science.
Ramírez, S., J. Gallego, and M. Tamayo. 2020. Human capital, innovation and productivity in Colombian enterprises: A structural approach using instrumental variables. *Economics of Innovation and New Technology* 29, no. 6: 625–42.

Raynolds, L.T., and S.U. Ngcwangu. 2010. Fair trade Rooibos tea: Connecting South African producers and American consumer markets. *Geoforum; Journal of Physical, Human, and Regional Geosciences* 41, no. 1: 74–83.

Reardon, T., and C.B. Barrett. 2000. Agro-industrialization, globalization and international development: An overview of issues, patterns and determinants. *Agricultural Economics* 23, no. 3: 195–205.

Romer, P.M. 1990. Endogenous technological change. *Journal of Political Economy* 98, no. 5: S71–S102.

SASA. 2019. South African sugar industry directory 2019/2020. South African Sugar Association. Assessed on 09/06/2020. Available at https://sasa.org.za/custom_content/downloads/SASA-ID-2019-20.pdf.

Sauer, J., and D. Zilberman. 2012. Sequential technology implementation, network externalities, and risk: The case of automatic milking systems. *Agricultural Economics* 43: 233–52.

Saunders, M., P. Lewis, and A. Thornhill. 2009. *Research methods for business students*. New York: Prentice Hall.

Schneider, L., Günther, J. and Brandenburg, B. 2010. Innovation and skills from a sectoral perspective: a linked employer-employee analysis. *Economics of Innovation and New Technology*, 19: 185–202.

Silolo, M.D., and O.I. Oladele. 2012. Socio-economic and job characteristics among farm workers in Mafikeng municipality South Africa. *Life Science Journal* 9, no. 4: 1453–9.

Sinyolo, S. 2020. Technology adoption and household food security among rural households in South Africa: The role of improved maize varieties. *Technology in Society* 60, no. 2020: 101214.

Slaper, T.F., N.R. Hart, T.J. Hall, and M.F. Thompson. 2011. The index of innovation: A new tool for regional analysis. *Economic Development Quarterly* 25: 36–53.

Subramaniam, M., and M.A. Youndt. 2005. The influence of intellectual capital on the types of innovative capabilities. *Academy of Management Journal* 48, no. 3: 450–63.

Sun, X., H. Li, and V. Ghozal. 2020. Firm-level human capital and innovation: Evidence from China. *China Economic Review* 59, no. 2020: 101388.

Sunding, D., and D. Zilberman. 2001. The agricultural innovation process: Research and technology adoption in a changing agricultural sector. In *Handbook of agricultural economics*, eds. BL Gardner and GC Rausser, 1st ed., 207–61. Amsterdam: Elsevier.

UKZN Geography Department Cartographic Unit. 2020. Map of KwaZulu-Natal province showing Darnall, Gledhow and Maidstone.

Vinding, A.L. 2006. Absorptive capacity and innovative performance: A human capital approach. *Economics of Innovation and New Technology* 15, no. 4–5: 507–17.

Wooldridge, J.W. 2003. *Econometric analysis of cross section and panel data*. MIT Press.