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Private extension delivers productivity growth in pasture-based dairy farming in the Eastern Cape, 2012–2018

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ABSTRACT

This study presents a novel way to measure the contribution of private extension to farm productivity for club data. Club data refers to any convenience sample obtained from a study group, consulting firm, cooperative or producer organisation. The study develops a stochastic frontier production function model with the inefficiency effects of pasture-based dairy farming in the Eastern Cape, South Africa. The analysis for 2012–2018 involves 49 adopter farms, and controls for inter-calf period, nutrient use efficiency and the amount of extension contact. Results are robust to functional form specification and there is no evidence of frontier-shifting technical progress for the Cobb Douglas or translog model, but there is a clear productivity benefit to engaging with the private extension service provider working locally (adoption). Productivity rises at 0.91–1.06% p.a. over time and by 1.54–1.62% p.a. with each extra year of the extension. Large farms close to the private extension provider's base of operations benefit most from being in the group. This case study is important because it documents productivity growth in the period since 2010 and puts the effect of extension on productivity growth back on the local research agenda.

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1. Introduction

In 2012 we were warned that the total factor productivity (TFP) growth of South African agriculture came to a halt during the period 1989–2010 (Liebenberg and Pardey 2012). This is a disaster since agricultural productivity growth is the main way to offset the industry's weakening terms of trade with the rest of the economy and to meet the food requirements of a growing population. The industry's failure to thrive has been blamed on institutional inefficiencies within the Department of Agriculture (Liebenberg and Pardey 2011) and on limited public R&D expenditure (Chaminuka et al. 2019). Declining public funding appears to be a common problem in Sub-Saharan Africa (Piesse and Thirtle 2010), yet beyond South Africa, the lack of funding did not prevent TFP growth (Nin Pratt and Yu 2008). In the Western Cape, TFP growth correlates with natural resource endowments (Conradie et al. 2009) and drilling down to the farm-level, productivity differences are explained by public vs. private extension delivery (Conradie 2016). This literature suggests that examples of above average TFP growth are likely to be found in industries with adequate private R&D and extension in high rainfall or irrigated areas. Pasture-based dairy is such an example, and since it is the only recent example of an industry achieving positive TFP growth, it is worthy of further study.

Commercial dairy farming is the only intensive livestock industry in South Africa to have had productivity measured recently. Mkhabela et al. (2010) employed a Cobb–Douglas stochastic frontier production function to derive farm-level efficiencies for a balanced panel of 37 farms in KZN and

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Galloway, Conradie, Esler, et al. (2018) studied the productivity of 43 Eastern Cape dairy producers using non-parametric methods. Over an eight-year period, Mkhabela et al. (2010) recorded growth associated with a shorter inter-calf period and larger herds, while Galloway et al. (2018) found access to irrigation, nutrient use efficiency and stocking density to correlate with differences in productivity. The coverage of the Galloway study was too short to permit meaning measurement of technical progress, but this data source has now expanded enough to allow parametric measurement of productivity growth.

The main contribution of our study is to measure the effect of extension input on farm productivity in cases where the nature of the dataset precludes the introduction of a simple control for extension contact. A recent review of thirty TFP studies that included some measure of extension in its inefficiency sub-model indicated that extension input is best captured with a dummy variable for exposure (Conradie 2020), but this can only be done if the sample also includes non-participating farms, which is usually not the case for datasets obtained from private firms or producer organisations. Our main hypothesis is that extension input takes several years to mature, and therefore that farms that have participated in an extension programme for longer, would be more productive that farms that have just joined it. This idea is tested in Section 3.4.

The private extension programme under consideration in this study is operated by Trace & Save, a private consulting company to the dairy industry whose promise is to deliver cost savings by means of improved feed conversion efficiency (Galloway 2017). The company serves family farms across the size spectrum (100–2000 cows) that are highly specialised in dairy production, and the firm has been building this client base since 2012/3. Trace & Save monitors nutrient balances, carbon footprints, water use efficiency and, lately also financial performance. Data is collected during in-depth interviews once a year as well as regular field visits, which provides opportunities for informal advising. There are also regular group meetings where growing conditions and specific aspects of the dairy production system are discussed in depth.

The Trace & Save dataset offers an almost complete set of input and output data suitable for fitting production functions and one of the richest sets of explanatory variables with which to populate an inefficiency sub-model, and the version used in this study is an unbalanced panel for 2012–2018 (this is in Table 1). The downside of this data source is that farmers self-select into the club at a considerable fee and since the club does not have any data on non-members, it is not possible to control for membership. This study offers a solution to this measurement problem.

The next section specifies a translog stochastic frontier production function with inefficiency effects and discusses the dataset in more detail. Section 3 – Results and Discussion – covers functional form tests in subsection 3.1, presents the main econometric results in subsection 3.2, analyses and contextualises the efficiency growth rates in subsection 3.3 and presents a marginal extension impact in subsection 3.4. The paper ends with brief conclusions.

Table 1. Descriptive statistics of the Trace & Save panel dataset after seven waves.

	2012	2013	2014	2015	2016	2017	2018
Observations	4	14	22	19	29	26	11
				Sample means			
Milk ECM megalitres	4.69	5.44	5.00	5.85	5.45	5.81	7.77
Cows in milk	692	815	732	856	798	812	1063
Concentrates R million*	7.91	8.09	7.45	8.52	7.62	7.83	10.94
*Roughage R million **	*1.67*	*1.47*	*1.26*	*2.21*	*2.34*	*4.00*	*6.95*
Fertiliser R million *	1.13	2.31	1.49	2.32	1.55	1.65	1.79
% dry cows	13	15	16	16	15	15	16
Time in group years	*1*	*1.14*	*1.54*	*1.95*	*2.31*	*3.35*	*3.36*
% nutrient use efficiency	26	26	26	30	29	24	28
Rainfall mm	*1057*	*790*	*845*	*724*	*530*	*535*	*375*

*Cost data are in constant 2018 prices.
Rows highlighted in italics if differences from year to year were significant.

2. Methods, dataset and study area

This study derives and explains farm-level TFP scores with Battese and Coelli's (1995) technical efficiency effects stochastic frontier production function model. The software was FRONT 4.1, whose maximum likelihood routine assumes the most flexible truncated normal distribution on the inefficiency term. This model jointly estimates the parameters in Equations 1 and 2 (Coelli 1996). The model consists of a frontier (Equation 1) and an inefficiency sub-model (Equation 2) and the functional form of the frontier is translog.

$$\ln Y_{it} = \alpha_0 + \sum\nolimits_{k=1}^{K} \alpha_k \ln x_{it} + \sum\nolimits_{k=1}^{K} \sum\nolimits_{j=1}^{J} \alpha_{jk} \ln x_{it} \cdot \ln x_{it} + \alpha_t t + v_{it} - u_{it}. \tag{1}$$

$$-u_{it} = \delta_0 + \sum_{m=1}^{M} \delta_m z_{it} + w_{it} \tag{2}$$

In Equation (1), Y_{it} is the output of farm i in period t and x_{it} is the amount of input k applied by farm i in period t. The variable t is a simple time trend to capture the possibility of frontier-shifting Hicks-neutral technical progress and as usual the error term is decomposed into an independently and identically normally distributed error term, v_{it}, and an inefficiency component, $-u_{it}$. As indicated in Equation (1), all inputs and outputs are in natural logarithms. The variance of the inefficiency term is measured by $\gamma = \sigma_\mu^2/(\sigma_\mu^2 + \sigma_v^2)$ (Battese and Corra 1977). If $\gamma = 0$, a mean response function is an adequate representation of the data. However, if $\gamma > 0$, a stochastic frontier model is more appropriate, in which case Equation (2) regresses a vector of farm characteristics, z_{it}, on the inefficiency terms from Equation (1) and w_{it} is an independently and identically distributed error term. The coefficients α_k, δ_m are to be estimated and γ is calculated from the estimated variances. A generalised likelihood ratio (LR) test can determine if γ and the δ_m coefficients are jointly zero. The test statistic, which is given by $LR = -2(\ln LH_{restr.} - \ln LH_{unrestr.})$, follows a mixed chi-squared distribution (e.g., Kodde and Palm 1986) with degrees of freedom equal to the number of restrictions (γ and all the δs, including the intercept of the inefficiency sub-model). A further LR test can confirm if the $\alpha_{jk} = 0$; if rejected, the translog functional form is favoured over the Cobb Douglas. The presence of frontier-shifting Hicks-neutral technical progress is examined by introducing and removing a time trend in Equation (1) and refinements of the inefficiency sub-model can be made by evaluating a series of additional LR tests conducted across nested models. The results of these tests are presented in Table 2 and discussed in Section 3.

Productivity analysis is conducted at the farm-level, and the data is organised as an unbalanced panel dataset of 125 observations compiled from $i = 49$ cross sections over $t = 7$ time periods. The number of observations per period reported at the top of Table 1 tracks the growth of this dataset over time. The small number of observations in the terminal period is due to incomplete data collection for the 2018 production year at the time at which the dataset was released to us. All farms in the sample are specialised in dairy and raise their own heifers, although this is not a universal practice in the area. Most farms are located along the Eastern Cape coast, between Tsitsikamma in the west and Alexandria in the east, with a small number situated inland along with the Great Fish and Gamtoos Rivers, where pasture production is irrigated. On the coast, pasture production is predominantly rain-

Table 2. Results of LR tests to determine the optimal specification for the dairy production frontier.

	Likelihood ratio tests				
	1	2	3	4a	4b
Hypothesis	$\delta_{rain} = 0$	$\alpha_t = 0$	$\alpha_{jk} = 0$	$\gamma = \delta_m = 0$	$\gamma = \delta_m = 0$
ln $LH_{restricted}$	102.763	102.763	102.763	74.935	85.983
ln $LH_{unrestricted}$	102.781	102.764	110.840	102.763	110.840
LR test statistic	0.036	0.002	16.154	55.655	49.713
Degrees of freedom	1	1	10	5	5
Critical value	2.706	2.706	17.670	10.371	10.371

fed. The coastal regions receive non-seasonal rainfall while summer rainfall dominates in the inland areas. Pastures are a grass-clover mixture with chicory and herds are either pure Jersey, pure Holstein Friesian, or, more commonly, a crossbreed of these two types.

When a production function is fitted, it is customary to include land and land enhancing – as well as labour and labour-enhancing factors of production to explain output, and to quality-adjust output. While quality adjusting usually replaces physical output with real values on farms that produce different crops, in this case, milk is the only significant output, and it is easily quality adjusted by applying a trusted formula to convert raw litres into energy corrected milk (ECM) (Renner 2021). According to Table 1, the mean of quality-adjusted milk output of 5.7 million litres of energy-corrected milk per farm per year did not vary significantly during the study period.

The Trace & Save dataset does not include labour or machinery, and therefore the production function presented here had to be assumed to be functionally separable in land and labour, and their substitutes. Cows in milk was used as a proxy for land, while feed was partitioned into concentrates and roughage, which are usually complements in milk production. Pasture production as a substitute for purchased feed (mainly roughage) was proxied by fertiliser use. Feed and fertiliser inputs were measured as real expenditure on the item with nominal costs inflated to constant 2018 Rand by applying the price indices for feed and fertiliser from the Abstract of Agricultural Statistics (DALRRD 2021). Descriptive statistics revealed that the real expenditure on roughage increased sharply over time, and Spearman's rank coefficient indicated that this increase was due to lower-than-expected rainfall in the period since 2016 (Spearman's $\rho = -0.2791$, $prob \geq 0.0016$). Rainfall decreased at 16.8% p.a. for 2012–2018, but cows in milk, concentrates and fertiliser did not vary from year to year during the study period, which is remarkable. The average farm had 820 cows in milk and spent R8.6 million on concentrates and R1.8 million on fertiliser in any year.

All inputs in the production function are expected to generate positive coefficients that are significant at least at the probability level $p \leq 0.05$, unless the input makes a negligible contribution to output, in which case the coefficient should still be positive but may no longer be significant. Coefficients on the translog interaction terms indicate complementarity if positive and substitutability if negative, and the signs on the square terms reveal if output increases at an increasing or decreasing rate with more of a specific input.

An inefficiency sub-model is usually populated with farmer characteristics like education, experience, gender and labour market participation and farm characteristics like resource endowments, technology proxies, extension input, farm size and structural breaks in the policy environment. For example, Mkhabela et al. (2010) used herd size, percentage dry cows and the capital value of the milking parlour to explain observed inefficiencies. The Trace & Save dataset includes no farmer characteristics, and we know very little about individual farms, except which region they are from. Between 2012 and 2018, there were no major changes to the macroeconomic, policy or disease environment to account for. Inter-calf period, an important partial productivity measure in dairy farming, can be inferred from the proportion of dry cows in the herd, and this variable has been shown to explain inefficiency (Mkhabela et al. 2010). In this sample, the percentage dry cows in the herd did not vary significantly over time around its mean level of 15%.

As explained above, when a farm becomes a Trace & Save client, it joins a well-developed private extension programme to monitor and optimise pasture production to produce milk at minimum cost. Evidenced-based advice takes a while to formulate and implement, and the speed with which the recommended changes can be made depends on a farm's financial reserves, which might be a function of its size and location. Therefore, there is a lag between joining the programme and reaping the efficiency benefits that it offers, and productivity is expected to rise with time in the group.

A recent review of how to incorporate measures of extension input into productivity models concluded that a dummy variable for contact, in general, performs just as well as the number visits, and that ideally, the quality of extension input should be tracked by also including measures of adoption of key recommendations (Conradie 2020). The innovation in this study was to proxy extension contact with years of programme membership. Each farm was assigned a *time-in-group* value of one the first time its unique farm identifier shows up in the dataset, and the series grew by one unit for each additional year. A gap in the series was interpreted as no contact for that year. While it is not uncommon for farmers to consult with several specialists in different fields at the same time, there is no public extension provider active in the area to provide a similar service and so it is not necessary to worry about substitution between different extension sources. As expected, the mean value of the *time-in-group* variable increased significantly between 2012 and 2018.

Nutrient use efficiency is a function of time in the group and the farm's specific circumstances, for example, its dominant soil type, but Table 1 reveals that there was no change in nutrient use efficiency by year during the study. This means that as time went on, the low nutrient use efficiency of new entrants offset the gains made by the higher efficiency of those who have been in the group the longest.

Rainfall sometimes belongs in the production frontier and sometimes helps to explain efficiency differences. Since the official rainfall series of the study area contains many interruptions, we chose to rely on farm-measured rainfall data, which has a higher level of spatial disaggregation and seemed to be of good quality. Gaps in farm-level rainfall series were plugged with averages for the location. A single variable analysis of variance with a series of Bonferroni pair-wise correlations revealed that annual rainfall was significantly lower from 2012 to 2015 than from 2016 to 2018. Some of this variation is due to changes in group composition, but most of it is due to a widespread drought that prevailed across the Eastern Cape during this time. It is suspected that rising temperatures are affecting cow and pasture performance too, but so far, the available temperature data has been inadequate to document clear impacts (Renner 2021). There are other possibilities to investigate as the temperature series expands (Conradie et al. 2021).

3. Results and Discussion

3.1 Specification tests

The evaluation of model specification began with fitting three versions of the Cobb Douglas model. Version 1 included four frontier inputs (cows, roughage, concentrates and fertiliser) and four variables in the inefficiency sub-model (% dry cows, nutrient use efficiency, time in group and rainfall). Of these eight, only rainfall explained nothing, and since the first LR test reported in Table 2 failed to reject the hypothesis that the coefficient on rainfall was zero, the rainfall variable was omitted from subsequent formulations. This does not mean that rainfall is not an important factor in pasture production, but simply that in this sample's rainfall data was either too inaccurately measured or varied too little to explain of the variation in observed efficiency. Version 3 of the Cobb Douglas model inserted a time trend in the frontier to examine the possibility of Hicks-neutral, frontier-shifting technical progress and the result of test 2 in Table 2 failed to reject the hypothesis of zero technical progress. Therefore, the time trend is dropped from subsequent models. As in Battese and Coelli (1995), there is clearly a degree of collinearity between technical progress and technical efficiency gains in this dataset.

A generalised translog functional form introduces squared terms and cross products of the Cobb Douglas inputs into the frontier sub-model. In this case, the four Cobb Douglas inputs produced ten squared terms and cross productions, and LR test 3 investigated the possibility that these extra coefficients were all simultaneously equal to zero. The test statistic of LR = 16.154 on LR test 3 is marginally smaller than the critical value for ten degrees of freedom of 17.670, which formally fails to reject the Cobb Douglas restriction. However, the main statistical results that are presented in Table 3 reveal that although none of the individual squared terms and cross products were significant at probability $prob \leq 0.05$, adding the extra translog terms improves the performance of both the inefficiency sub-model and the four basic frontier inputs, and therefore both sets of results are retained in the rest of the analysis, and their efficiency scores are compared in Figure 1. The fourth LR test in Table 2 investigated the performance of the inefficiency model, first for the best Cobb Douglas

Table 3. The main stochastic frontier statistical results, dependent variable energy corrected milk.

	Translog specification			Cobb Douglas specification		
Variable name	Coefficient	SE	z-ratio	Coefficient	SE	z-ratio
Frontier intercept	0.134 **	0.032	4.22	6.495 **	0.418	15.55
Cows in milk	0.696 **	0.051	13.75	0.730 **	0.049	14.89
Roughage	0.023 **	0.009	2.63	0.004	0.003	1.42
Concentrates	0.126 **	0.045	2.78	0.140 **	0.041	3.41
Fertiliser	0.146 **	0.022	6.58	0.141 **	0.020	7.00
Cows^2	0.062	0.158	0.39			
Cows × roughage	0.021	0.014	1.51			
Cows × concentrates	−0.252	0.280	−0.90			
Cows × fertiliser	0.060	0.086	0.69			
Roughage^2	0.001	0.001	1.54			
Roughage × concent.	0.000	0.014	0.00			
Roughage × fertiliser	−0.010	0.006	−1.65			
Concentrates^2	0.169	0.146	1.16			
Conc. × fertiliser	−0.083	0.085	−0.98			
Fertiliser^2	0.010	0.026	0.37			
Inefficiency intercept	0.446 **	0.072	6.19	0.488 **	0.076	6.40
Dry cows (%)	0.515 **	0.262	1.97	0.430	0.255	1.69
NUE (%)	−1.236 **	0.261	−4.73	−1.411 **	0.268	−5.26
Time in group	−0.025 **	0.012	−2.12	−0.027 **	0.012	−2.29
σ^2	0.012 \ast \ast	0.003	4.50	0.013 **	0.002	5.27
γ	0.500	0.301	1.66	0.413	0.255	1.62
Log likelihood statistic	110.840			102.763		
Observations	125			125		

Note: ** indicates $p \leq .05$.

(4a) specification and then for the corresponding translog formulation (4b), and the test statistics indicate that the inefficiency sub-models worked adequately for both functional forms.

3.2 Stochastic frontier results

The main statistical results are presented in Table 3, with the translog model fitted on mean-centred data to simplify the calculation of the returns to scale. There are only minor differences between the

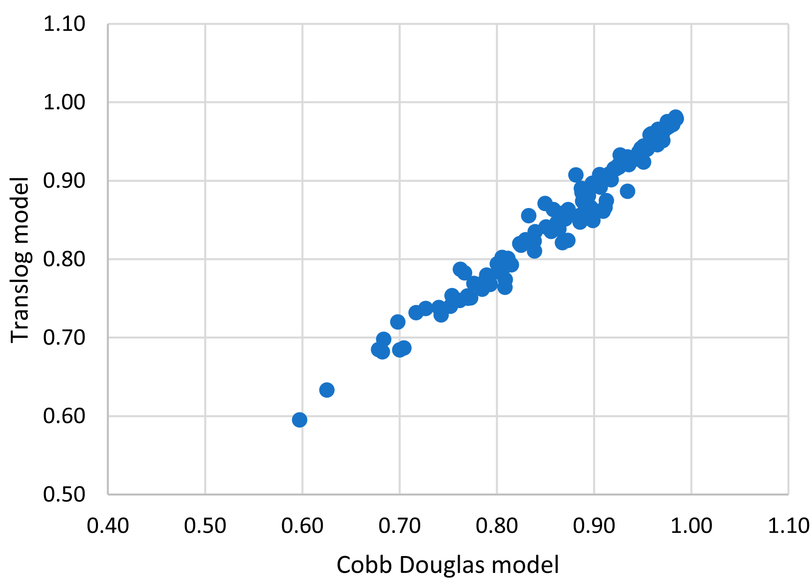

Figure 1. Farm-level efficiency scores produced by Cobb Douglas and translog functional forms in this study.

two sets of results, and little grounds for choosing between them. It was already reported the LR test 3 favours Cobb Douglas, but the coefficient on roughage is significant in the translog, which clearly favours the translog. The other coefficients are positive and significant and vary little across functional forms, and both sets of results indicate constant returns to scale. It is possible that the size differences are due to Trace & Save taking on certain management functions for very small and/or very large farms, which enhances the performance of both types, but further investigation of this intriguing possibility lies beyond the scope of the current analysis.

The signs on the interaction terms reveal that there is at best weak complementarity or substitutability between these inputs and no evidence or increasing or decreasing returns to any input. If one is willing to relax the significance level on the one-tailed t-test to $p \leq 0.10$, three interaction coefficients are significant. They indicate that cows and roughage are complements, fertiliser and roughage are substitutes and that milk production increases at an increasing rate in roughage. The complementarity of the herd and its feed is reasonable, and it is gratifying to confirm that home produced roughage is a substitute for purchased roughage, but it was a surprise that quality adjusted milk output increases at an increasing rate with the expenditure on purchased roughage. Trace & Save is probably so focussed on cost saving and optimal pasture production that the company might be underplaying the importance of buying in roughage during shortfalls.

The main difference in specifications of the inefficiency sub-model is the coefficient on percentage dry cows, where the estimate increased by 20% and became significant in the translog. In addition, the marginal extension impact was 7% smaller, and the effect of nutrient efficiency decreased by 12.5% in the translog. It is worth repeating that despite the importance of rainfall to pasture production and the limited irrigation on these farms, efficiency was uncorrelated with rainfall.

3.3 Annual efficiency growth rates

These dairy farms are highly productive and made significant progress to even greater productivity during the study. The translog functional form produced a sample mean efficiency of 84.5% in 2012, which rose to 90% in 2018, an increase of 0.9% p.a. over the study. For Cobb Douglas, the mean score was 85% in 2012 and it rose to 92% by 2018 at an average growth rate of 1.06% p.a. over the study. Figure 1 shows how little the two sets of scores differ, with Spearman's rho at a value of $\rho = 0.9837$ on the correlation.

It is usually not wise to compare efficiency scores across studies since efficiency estimates are highly sensitive to sample size and model specification, but arguably this study is similar enough to Mkhabela et al. (2010) at least to be able to compare productivity growth rates. For this study, the annual growth rate was computed by regressing individual scores on time, and for Mkhabela et al. (2010), we regressed the published annual sample means on time, which produced a figure of 1.3% p.a. for the preferred specification. The higher Mkhabela growth rate is because it came off a lower base, of just 70% efficiency in year 1. Despite the severe cost-price squeeze operating on dairy farms, some farmers have found a way to cope with rising input costs and the role of private R&D and extension in this phenomenon remains an open question. However, neither study can answer this question because both rely on club data which does not include a control group. This prevents the results from being generalised to the whole of dairy industry, and it is a major limitation to most productivity studies that have been conducted in South African agriculture over the last twenty years.

The available productivity growth rates for South African agriculture were summarised in Table 4. Dairy is the only example of intensive livestock and on the extensive side we only have an estimate for Karoo sheep, where productivity deteriorated by −3.19 to −5.59% p.a. during the drought of 2016–2021, depending on the model type and precipitation (Conradie 2019; 2019). For field crops, there is a non-significant estimate of 0.57–1.00% p.a. from the 1970s based on regional Maize Board data (Van Zyl 2000) and a recent estimate of −1.13% p.a. for mixed farming in the

Table 4. Recent productivity growth rates from panel data studies conducted on South African agriculture since 2000.

Industry	Period	Annual TFP growth	Source
Dairy Eastern Cape	2012–2018	0.91*–1.06**	This study
Dairy KZN	2000–2007	1.04***–1.34 ***	Mkhabela et al. 2010
Extensive sheep	2012–2014	−3.19**	Conradie et al. 2019a
Extensive sheep	2012–2015	−5.59***	Conradie 2019
Medium crop farms	1970s	0.57^{ns}	Van Zyl 2000
Small crop farms		1.00^{ns}	
Mixed farming	2009–2018	−1.13**	Conradie & Genis 2020
Crop trial Western Cape	2002–2015	3.34***–3.42***	Conradie et al. 2021
Wine industry	2005–2015	−0.365*	Piesse et al. 2018
Stellenbosch, Paarl		-0.077^{ns}	
Rest of the industry		−0.934**	
Wine industry	2005–2015	-0.076^{ns}	Conradie et al. 2019b
Stellenbosch, Paarl		−0.292**	
Rest of the industry		0.216^{ns}	

Note: *** indicates $p \leq .01$; ** indicates $p \leq .05$; * indicates $p \leq .10$.

Southern Cape (Conradie & Genis 2020). The Maize Board data referred to reference farms, also a type of club, while data for the Southern Cape is from a small study group run by the local cooperative. Horticulture is limited to the wine industry, where a recent analysis of club data from VINPRO revealed strong productivity gains in the outline areas and zero growth in Stellenbosch and Paarl during the period 2005–2015 (Piesse et al. 2018). Industry-wide there was some growth. A second non-parametric study that focused on scale efficiency concluded that industry-wide, there was no growth while the Stellenbosch and Paarl core experienced decreasing productivity during the period 2005–2015 (Conradie, Piesse, Thirtle, et al. 2019).

3.4 Marginal extension impact

The last time that the contribution of extension to farming success was systematically investigated was when Khatri et al. (2000) fitted a short run dual profit function on aggregate accounts data to tease out extension's contribution to productivity growth. By Hotelling's lemma, the partial derivatives of the dual profit function give a system of (simultaneous) demand and supply equations that are non-decreasing in output prices P, non-increasing in input prices R, linearly homogenous in prices, twice continuously differentiable and convex in prices. If the equations are in logarithms, the partial derivatives of the demand and supply equations generate a set of price elasticities that capture supply response and input substitution possibilities. In Khatri et al. (2000) the system of equations controlled for farmer education, the cost of public extension, expenditure on public sector R&D and a patent count as a proxy for private R&D expenditure. Results revealed that investing more in extension increased horticulture and livestock output but had no effect on crop output and that it reduced the use of all variable inputs except animal feed significantly, thereby delivering improved productivity. Schimmelphennig et al. (2000) extended this analysis by calculating the shadow prices for these fixed conditioning variables from these elasticities and other parameters of the dual profit function. Both public and private research expenditure carried positive shadow prices, signalling that there was too little of it. The same analysis reported that the shadow prices on farmer education and public extension were negative, indicating that the government over-supplied these resources, a point of view shared by Ndoro et al. (2014), who complained about a lack of knowledge and accountability amongst public sector extension staff in KZN.

Ndoro et al. (2014) argued that to measure the impact of extension effectively, one must control for self-selection into programmes, and this can only be done for data obtained from representative farm surveys, which are currently sorely lacking in South Africa, especially in panel form. If only club data is available – as in this case – the second best is to calculate the marginal contribution of extension to productivity, and we did that by regressing pooled productivity scores on time in the group instead of the year of observation (this is in Figure 2). While there were previously only four observations in period 1 (2012), whose mean efficiency under the translog was 84.5%, the reorganised data has 49 observations for farms in their first year in the programme, and this group's mean score was 84.7% under the translog. Figure 2 shows a large degree of dispersal for new entrants. The coefficient of variation of the translog TFP scores was $CV_1 = \frac{std\ dev}{mean} = 0.113$. On the opposite side of the exposure distribution, farmers with five years of contact with Trace & Save exhibited much less variation in the efficiency. Their coefficient of variation was 50% lower at $CV_5 = 0.068$, than the new entrants' dispersal.

The increase in translog scores by time in the group illustrated in Figure 2 was a highly significant 1.54% p.a., and this coefficient represents the marginal extension impact of passing time. The Cobb Douglas produced similar results, with a marginal extension impact of 1.62% p.a. over the study.

Marginal extension impacts varied by farm size and location and these differences are reported in Table 5. Two dummy variables were constructed to partition the sample into nearby and distant farms as well as into large and small operations. Trace & Save's head office is in Jeffreys Bay, and nearby farms were defined as those within a 50 km radius, an area that includes Humansdorp, Oyster Bay and Tsitsikamma, while Cradock, Cookhouse and Alexandria were considered far away. The distance between Jeffreys Bay and Cradock is more than 300 km, while the distance to Alexandria 170 km. There were 74 observations for nearby dairies and 51 for more distant operations. A figure of a thousand cows in milk was used as an arbitrary cut-off between large and small dairies, and the sample contains 64 observations for small and 61 observations for large dairies. The data reported in Table 5 are the coefficients on a series of OLS models that regresses pooled TFP scores on time in the group variable for specific sub-groups. For example, the 74 nearby farms produced a significant marginal extension impact of 1.85% growth per year of contact for scores obtained from the translog model, while the corresponding scores of the 51 distant farms did not increase over time.

Line 1 of Table 5 indicates that the group as a whole is benefitting from extension since mean productivity rose during the study. Line 2 shows that this is especially the case for all nearby farms, while line 3 reports that the programme had less impact on distant farms where productivity did not increase during the study. Lines 4 and 5 report the differences in marginal extension impact for large and small operations; large farms clearly benefit from extra time in the group, while more

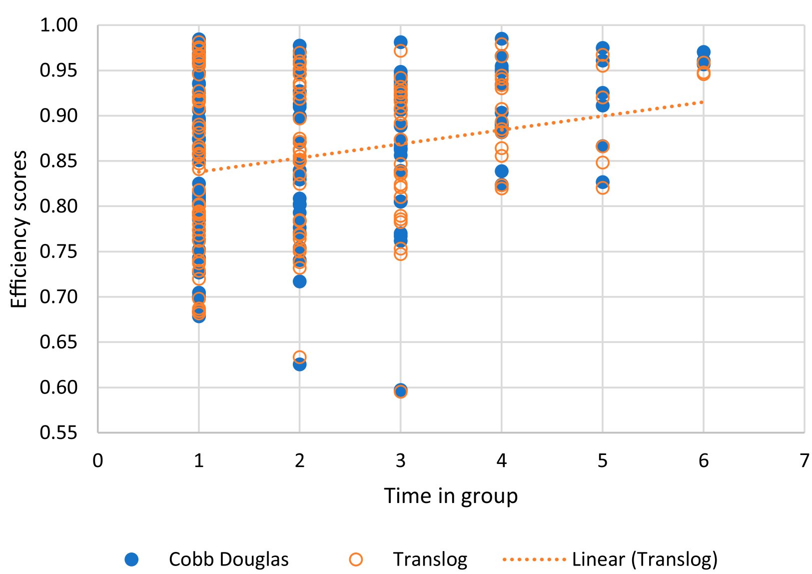

Figure 2. Improvement in farm efficiency with exposure to private extension input ($n = 125$).

Table 5. Marginal extension impact of time in the group for various subsamples.

Sub-group	*n*	From translog estimates	From Cobb Douglas estimates
Full sample	125	1.54***	1.62**
Nearby farms	74	1.85***	1.98***
Distant farms	51	0.37^{ns}	0.52^{ns}
Large farms (>1000 cows)	64	1.79***	1.95***
Small farms	61	0.12^{ns}	0.05^{ns}
Large, nearby farms	44	2.19***	2.51***
Small nearby farms and all distant farms	81	0.61^{ns}	0.68^{ns}

Note: *** indicates $p \leq .01$; ** indicates $p \leq .05$; * indicates $p \leq .10$

time in the group did not result in productivity gains for small farms. Lines 6 and 7 divided the sample into 44 large, nearby farms and the rest, a group comprising all distant farms as well as small, nearby farms. The marginal extension coefficients show that productivity on large nearby farms grows even more rapidly than on large distant farms, where together with all small farms where productivity gains have been negligible during the study period.

By our hypothesis, it is expected that the benefits of additional contact might still materialise in the more remote areas, since Trace & Save's client base grew organically into more distant areas during the study. A t-test of the difference in the average time in the group for nearby and distant farms revealed that the average nearby farm has with Trace & Save for 2.45 years while the average distant farm has been with Trace & Save 1.98 years. The test statistic of $t = -1.9337$ is significant at better than $p \leq 0.05$ on the one-tailed test. The implication is that if Trace & Save were to market aggressively further afield, it should take pains to ensure a sufficient presence in those new areas during the first three or four years of setting up shop in a new area. In terms of size, Trace & Save seems to find it more challenging to engage small scale producers as effectively as large farms, and this could simply be because small farms face additional cash flow constraints, which makes it difficult for small farms to adopt recommended improvements fully or timeously.

4. Conclusions

This study makes two important contributions to the local TFP literature. Firstly, it confirms the evidence of productivity growth in dairy farming reported in Mkhabela et al. (2010), which settles the dairy industry is one of the few points of hope in the wider agricultural sector and shows that South Africa conforms to the international patterns reported in Alvarez and Del Corral (2010). This study's second important contribution is to propose a way to measure extension impact in club data. It has been shown that most of the panel datasets that are suitable for farm-level productivity analysis derive from benchmark clubs or producer organisations. These data sources cannot control for the organisation or the club's input since they do not cover non-members. We demonstrated that panel data can be used to track the marginal contribution of a programme as farms spend more time in the group and found that programme effectiveness is a function of clients' size and location. This offers a valuable way forward while we are waiting for representative industry surveys to be put into place.

Although we can be confident of productivity gains inside these private extension clubs or study groups, the productivity trajectory of many farms outside these clubs is of greatest concern. It remains an open question if it is possible to stay competitive in the dairy industry if (1) a farm does not grow its own roughage or (2) if it only has access to public extension services or even worse to no extension at all. More work is needed on quantifying the extension input as well as measuring productivity in other sectors, and to do so meaningfully South African agriculture should embark on a widespread data collection campaign to supplement deteriorating public sector efforts. The effect of adverse weather on rain-fed pasture production in dairy production and other livestock industries also needs further work. Various papers have considered suitable proxies for heat and moisture stress, but these have not all be equally successful. Suitable temperature data is a major constraint.

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