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Farm size and productivity: smallholder dairy production in Eswatini

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ABSTRACT
In response to the 2015 paper by Henderson published In Journal of Agricultural Economics, this case study of dairy farmers in Eswatini, this case study of dairy farmers in Eswatini tests the explanatory power of two hypotheses to explain the inverse relationship between farm size and productivity. To this end, we fit a stochastic frontier production function with inefficiency effects. We find that dairy farmers who use hired labour are significantly less efficient than those who use own and family labour. This supports the labour market imperfections hypothesis. To test the technical efficiency hypothesis, we segment our sample into small, medium and large farmers based on the number of cows in milk. We find that small farmers are the most efficient (78.5%), followed by medium (75.9%) and large (75.1%) farmers, but the differences are not statistically significant. This supports Henderson's finding that differences in efficiency affect productivity but not enough to disqualify labour market imperfections as the principal explanation for the inverse relationship.

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1. Introduction

This paper contributes to the debate on what causes the inverse relationship between farm size and efficiency. While the existence of the inverse relationship is relatively well established, the same cannot be said for why it is observed. In a survey of the large body of theoretical and empirical literature explaining the inverse relationship, Henderson (2015) discerns five competing hypotheses: i) decreasing returns to scale, ii) heterogeneity in land quality, iii) farm size-specific differences in the responses to risk and uncertainty, iv) labour market imperfections and v) differences in technical and allocative farmer efficiency. Henderson notes that, at the time of writing (2015), hypotheses i), ii), and iii) had failed to gather substantive empirical and theoretical support, but that more support had been found for hypotheses iv) and v). The latter two are the focus of this study.

Hypothesis iv) postulates that the inverse relationship is the result of the imperfect substitutability between hired and own labour due to moral hazard (see, for example, et al., 2003). The substitutability is imperfect because hired labour in agriculture carries greater supervision costs since, unlike manufacturing, agricultural workers and machinery move about on the farm and are not confined to a factory (Brewster 1950). As a result, family farms, where the owners and their household provide most of their labour, are generally more efficient. The efficiency cost of hired labour can be substantial. Frisvold (1994), for example, found that a reduction in the intensity of worker supervision by owners of rice farms in India, or by their family members, resulted in an output loss of more than 10% in 40% of the farms studied. Similarly, Piesse et al. (2018) found that South African wine

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farms that spend more on supervision achieve higher levels of efficiency than those that spend less, and they also found that those employing a higher proportion of permanent workers do better than those that rely more on seasonal workers.

Hypothesis v) is closely related to iv) since it proposes that differences in technical and/or allocative efficiency across different farm sizes drive the inverse relationship (Henderson 2015). In this case, there is far less consensus of opinion. Yotopoulos and Lau (1973), for example, found that the smallest Indian farms in their sample were 20% more technically efficient than the larger ones. Bravo-Ureta and Pinheiro (1997), on the other hand, found that medium-sized farms in the Dominican Republic (operating on between 3.25 and 6.5 hectares) had a higher technical efficiency than small and large farms. And again differing, Helfand and Levine (2004) found a U-shaped relationship between farm size and technical efficiency for farms in the Centre-West of Brazil.

Henderson (2015) develops and deploys a four-stage empirical framework that simultaneously tests how well hypotheses iv) and v) explain the inverse relationship. For this purpose, he uses an LSMS-type[1] nationally representative panel of Nicaraguan farmers. He concludes that although differences in efficiency significantly affect productivity, their explanatory power is insufficient to disqualify labour market imperfections as the principal explanation for the inverse relationship.

In response to Henderson (2015), this study uses dairy farmers in Eswatini to test the explanatory power of hypotheses iv) and v). To this end, we fit a stochastic frontier production function with inefficiency effects, as described by Battese and Coelli (1995). To test hypothesis iv), we segment our sample of farmers based on whether they use hired labour and we do a t-test for statistically significant differences in the mean efficiency estimates of the groups. Similarly, we test hypothesis v) by segmenting our farmers into three groups – small, medium and large – based on their number of cows in milk (not the size of the farm in hectares) and do an ANOVA test on the mean efficiency estimates. As an extension of Henderson (2015), we also postulate a hypothesis to explain how farmers can overcome the inverse relationship. For this, we test whether the number of extension visits has a statistically significant effect on efficiency and consider how a change in the extension programme's content could improve efficiency. The contribution of this study is to test whether Henderson's (2015) explanation for the inverse relationship holds in a small-scale dairy farming context, and to propose a hypothesis for how farmers can overcome this relationship.

A note on terminology: the terms "efficiency" and "productivity" are used interchangeably in the literature. In this study we opt to use "productivity" since it enables us to make a clearer distinction between productivity and efficiency (technical) as the empirical technique we use in this study.

2. Dairy farming in Eswatini

The Kingdom of Eswatini (formerly Swaziland) is a small landlocked country semi-enclaved between South Africa and Mozambique, home to approximately 1.2 million people. It is one of the smallest countries in Africa, with a total area of 17 364 square kilometres (1.7 million ha), of which lakes, wetlands and estuaries cover 160 square kilometres. Despite its small size, Eswatini has a diverse climate and topography. It spans four agroecological regions: the Highveld, the Middleveld, the Lowveld, and the Lubombo Plateau Figure 1. Agriculture is the primary source of income, employment and food for the rural population, with over 70% of the population being entirely dependent on this sector for their livelihoods (WFP 2021).

About two-thirds of the country's surface, most of which is communally owned and managed through the Swazi Nation Land (SNL), is used for extensive livestock farming. A total area of 127 842 ha is under field crops, mostly maize (71 973 ha) and sugar cane (45 000 ha). Cultivated pastures, primarily used for dairy production, comprise 5% of the total field crop area. Despite increasing 2.6-fold between 2006 and 2021, dairy production in Eswatini supplied only 25% of local demand in 2021. However, the share of local supply has grown steadily from its lowest point of 14% in 2014 (Eswatini Dairy Board 2022).

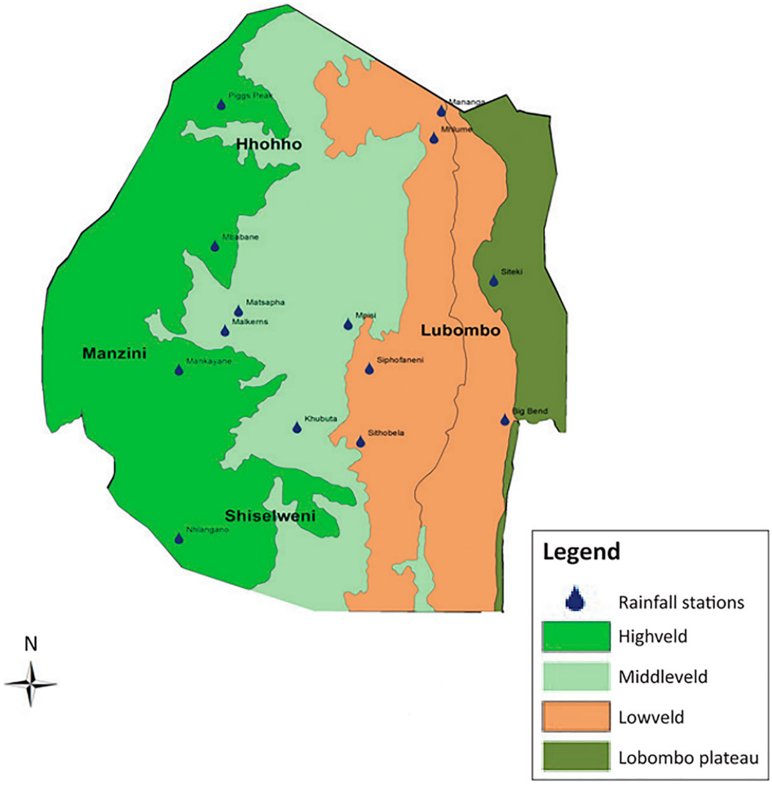

Figure 1. Agroecological zones of Eswatini. Source: Mlenga, Jordaan, and Mandebvu (2019).

The largest proportion of dairy cows (41%) is in the Manzini region, a mainly highveld agroecological zone. Nationally, the median number of cows in milk (cows being milked) per farmer is between four and five, and the average production is 10 litres per cow per day (Eswatini Dairy Board 2019). In South Africa, by comparison, small-scale dairy farmers produce an average of 13 litres per cow per day (Milk South Africa 2022), and the South African national average is 15.2 litres per cow per day (Milk South Africa 2022).

Most dairy farmers in Eswatini use a natural grazing-based production system supplemented by a concentrate which is fed while the cows are being milked. Some farmers have automated milking parlours but the majority milk by hand.

Dairy extension officers, provided by the veterinary department through the Eswatini Dairy Board and the government, are stationed in all regions of the country and regularly visit farmers in their areas. They provide an artificial insemination service, the use of which has grown significantly in the country in recent years, chiefly because the service is provided at a subsidised rate by the Eswatini Dairy Board. This breeding system has become popular because it accelerates genetic improvement and is more cost-efficient than using a bull.

3. Data and methods

3.1 Data

Of the 720 commercial dairy farmers in Eswatini, 88% (635) had fewer than ten cows in milk, 10% had 10–50 cows in milk and 2% had more than 50. We categorised these as small, medium and large. From these we purposively sampled 118 owners and operators of dairy farms and regionally stratified the sample to account for climatic and topographical differences. Farmers were randomly sampled from the Manzini, Shiselweni, Hhohho and Lubombo districts. The sample was not stratified by farm size. The data was collected using a structured questionnaire administered in person or through telephonic interviews. The questionnaire covered farm and farmer attributes and was limited to the 2019 production seasons. (See Appendix A for the questionnaire.)

3.2 Methods

This study derives farm-level effiency estimates using Battese and Coelli's (1995) stochastic frontier production function model with inefficiency effects. The parameters in Equation 1 (the frontier) and 2 (the inefficiency submodel) are jointly estimated. We considered both a Cobb-Douglas and a translog functional form and chose the latter on the grounds of the results of a generalised likelihood ratio test (see Section 5.1). All input variables are mean-centred, and all variables are logged as indicated. The translog terms were formed from mean-centred, logged data.

$$lnY_i = \alpha_0 + \sum_{k=1}^{K} \alpha_k lnx_{ki} + \frac{1}{2}\sum_{k=1}^{K}\sum_{j=1}^{J} \alpha_{jk} lnx_{ki}.lnx_{ji} + v_i - u_i \tag{1}$$

$$-u_i = \delta_0 + \sum_{m=1}^{M} \delta_m z_i + w_i \tag{2}$$

Equation 1 represents the translog specification of our model, Y_i represents the milk output of farm i and x_{ki} is the amount of input k applied by farm i. In the Cobb-Douglas variant of our model j and k are set to 0. The error term is decomposed into an independently and identically distributed error term v_i and inefficiency component u_i and follows a truncated normal distribution. The parameters to be estimated are represented by a_k and a_{jk}. The variance of the inefficiency term is measured by $\gamma = \sigma_\mu^2/(\sigma_\mu^2 + \sigma_v^2)$, which is the proportion of overall error variance captured by the inefficiency effect. In a stochastic frontier model with embedded inefficiency submodels, gamma takes values close to one, especially if farm fixed effects are considered.

Equation 2 accounts for the observed farm-level efficiencies with a set of z-variables that explain farm and farmer characteristics. This inefficiency submodel is achieved by regressing a vector of farm characteristics z_i on the efficiency estimate obtained through Equation 1. The final term, w_i, represents an independently and identically distributed error term. For a frontier to exist, γ must be significant, and the restrictions imposed by a mean response model (OLS) must pass a likelihood ratio test. The normal error variance σ_v^2captures measurement problems, resulting in low values for γ if there is deliberate or inadvertent misreporting.

Technical efficiency estimates are recovered by comparing actual output to output on the frontier, according to Equation 3 where Y^* is the frontier output that shares the same factor ratios as Y. The frontier analysis employed in this study was implemented in R using the "frontier" package developed by Coelli and Henningsen (2013).

$$TE_i = \frac{Y_i}{Y_i^*} \tag{3}$$

4. Summary statistics

The median dairy farmer in our sample had four cows in milk and, during the year, produced 11 567 litres of milk, spent 2 920 h of labour (own, family and hired) on dairy farming activities and fed 6 024 kg of concentrates (Table 1). Per cow per day, these translate to 9.6 litres of milk, two

Table 1. Summary statistics.

	Min	Median	Mean	Max	CV (%)
Number of cows	1.0	4.0	7.2	66.0	154.5
Milk, litres/year	1 171.2	11 567.8	24 512.3	232 951.5	165.4
Milk, litre/cow/day	2.6	9.6	9.7	21.5	39.4
Labour, hours/year	730.0	2 920.0	2 972.6	7 300.0	35.1
Labour, hours/cow/day	0.2	2.0	2.7	12.0	89.1
Concentrates, kg/year	608.3	6 024.5	12 630.2	129 461.4	173.3
Concentrates, kg/cow/day	0.6	4.2	4.5	14.2	47.6
Farmer age	25.0	54.0	53.8	77.0	16.7
Farmer education, years	3.0	12.0	12.5	17.0	30.4
Agricultural income share, %	5.0	60.0	54.1	90.0	36.2
Extension visits, number/year	0.0	1.0	1.3	4.0	64.4

hours of labour and 4.2 kg of concentrates. Our summary statistics are in line with those of the Eswatini Dairy Board (2016) and Mugambi et al. (2015). The Eswatini Dairy Board reported an average production of 10 litres per cow per day in 2016. Measuring an average of four cows in milk per dairy farm in Kenya, Mugambi et al. (2015) reported an average of between 2.1 and 2.6 labour hours per cow per day, and an average concentrate consumption of 2.2 kg/cow/ day, which is lower than our average of 4.5 kg/cow/day. However, the East Africa Dairy Development (EADD 2022) estimates that an average concentrate mix of 3 kg/cow/day should yield an average milk production of 5–10 litres per cow per day, and that more than 10 kg/cow/day could yield between 18 and 25 litres/cow/day.

The median age of the farmers in our sample was 54 years, their educational attainment was 12 years and 77.1% of our sample were male. The median farmers earned 60% of their income from dairy products, with the most and least dairy-dependent farmers relying on dairy products for 90% and 5% of their total income. Only 34% of our sample said they used hired labour during the year, which is to be expected since the median number of cows in milk was only four.

Farmers received between 0 and 4 extension visits, with the median being 1. The extension service covers eight topics: preparations for starting a dairy, fodder production, cattle feeding, cattle breeding, calf management, milking and hygiene, disease control and farm management. Since most extension officers are trained as animal scientists, their emphasis is typically on themes other than farm management. They offer an artificial insemination service at a subsidised cost, and the extension training is generally combined with such a farm visit. As a result, 79% of our sample use artificial insemination.

As part of the service, farmers are given herd management and milk production record sheets, and 60% of our sample said they used this or an alternative system. Farmers typically sell their milk locally and 81% of them process unsold milk into naturally fermented *maas* (sour milk). Only 52% do quality testing on their milk.

The correlation coefficient between Litres produced and Cows in milk is 0.95, indicating a strong positive correlation between the two variables, Table 2. Similarly, there is a strong positive correlation between Cows in milk and Concentrates (0.98) and between Litres produced and Concentrates (0.93). The correlation coefficient between Labour hours and the other variables is relatively low, ranging from 0.32–0.35, indicating a weaker relationship between Labour hours and the other variables Table 3.

Table 2. Correlation Matrix.

	Litres produced	Cows in milk	Labour hours	Concentrates
Litres produced	1.00	0.95	0.32	0.93
Cows in milk	0.95	1.00	0.35	0.98
Labour hours	0.32	0.35	1.00	0.35
Concentrates	0.93	0.98	0.35	1.00

Table 3. Results of LR tests.

	Likelihood ratio tests		
	1	2	3
Hypothesis	$\alpha_{jk} = 0$	$\gamma = \delta_m = \alpha_{jk} = 0$	$\gamma = \delta_m = 0$
Log (likelihood)	42.645	54.775	−42.645
Degrees of freedom	6	4	4
Pr (>chi sq)	0.0005 ***	0.0006 ***	0.0000 ***

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.

5. Results and discussion

5.1 Model specification

Table 4 summarises the five models specified, with total milk production in litres during 2019 being the dependent variable. All models include the same input variables: the average number of cows milked throughout the year, the total number of labour hours spent on dairy farming and the total kilograms of concentrates consumed by the cows being milked throughout the year.

Given our small sample of only 118, our modelling strategy needed to carefully consider degrees of freedom at every step of the process.[2] A typical production function includes land and land-enhancing inputs, as well as labour and labour-enhancing inputs. Because it is difficult to measure smallholder landholdings and landholdings in communal areas, and because herd sizes tend to be highly correlated with landholdings, we decided to omit land from the production function. The main land-enhancing inputs were livestock, which was not quality-adjusted, and the amount of feed concentrates consumed. For labour, we included the total number of hours spent during the year as the sum of hours worked by the owner, the family members and the hired labourers. While it was theoretically possible to include each type of labour as a separate input (see, for example, Frisvold 1994; Ali and Deininger 2015), the small sample size of 118 and the low uptake of hired labour (non-zero in 40 cases only) made it an undesirable strategy. However, in the inefficiency submodel we included a binary dummy variable for hired labour to test the Henderson hypothesis.

In addition to the hired labour dummy, we also included two other *z*-variables. The first is the number of extension visits received during the year, included so that we could comment on the literature on the efficiency impact of extension (see, for example, Conradie 2020; Dessie et al. 2020; Conradie, Galloway, and Renner 2022; Koye, Koye, and Mekie 2022). The second is whether the farmer was using the record-keeping system provided or an alternative, since record-keeping could serve as a proxy for good farm management practices. Several authors, such as Groenewald (1991) and van Zyl, Binswanger, and Thirtle (1995), have highlighted the importance of management in farm efficiency.

We tested six other possible determinants of technical efficiency: course attendance, aspirations, use of artificial insemination, processing, milk quality testing, and income.

The Dairy Board offers several courses to farmers, and we asked respondents which they attended. Since training and course attendance are closely related, we tested the total number of courses in the inefficiency submodel. We found that this reduced inefficiency as expected, but was not statistically significant.

Aspirations play a substantial role in shaping the activities and investments of smallholder farmers (Nandi and Nedumaran 2021). We measured aspirations by asking participants if they aimed to increase their number of cows in milk and, if so, by how much. We expressed their response as a percentage increase above their current number of cows in milk and included this in the inefficiency submodel. We hypothesised that farmers with higher aspirations would be more efficient. We found that was the case, but it was not statistically significant.

Artificial insemination, on farm milk processing processing and quality testing all proved to be statistically insignificant. We also tested the impact of a farmer's agricultural income share from

Table 4. Stochastic frontier statistical results, dependent variable annual milk production.

	Model 1		Model 2		Model 3		Model 4		Model 5	
	Cobb Douglas		Translog		Translog		Translog		Translog	
Variable name	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE
Frontier intercept	10.454 ***	0.068	10.433 ***	0.059	10.399 ***	0.064	10.383 ***	0.066	10.37 ***	0.060
Cows	0.858 ***	0.090	0.631 ***	0.174	0.564 **	0.181	0.566 **	0.179	0.511 **	0.175
Labour	0.285 **	0.106	0.333 .	0.175	0.235	0.164	0.206	0.166	0.378 *	0.170
Concentrates	0.045	0.073	0.305 .	0.168	0.356 *	0.177	0.347 *	0.174	0.411 *	0.170
Cows^2			−0.593 *	0.298	−0.721 *	0.281	−0.743 **	0.277	−0.744 **	0.263
Labour^2			0.682 *	0.346	0.524 .	0.311	0.453	0.299	0.773 *	0.337
Concentrates^2			−0.035	0.166	−0.036	0.159	−0.036	0.156	0.014	0.154
Cows x Labour			0.130	0.212	0.143	0.200	0.181	0.197	0.179	0.187
Cows x Concentrates			0.365 *	0.183	0.418 *	0.166	0.429 **	0.162	0.401 **	0.155
Labour x Concentrates			−0.275	0.168	−0.311 *	0.158	−0.351 *	0.159	−0.337 *	0.153
z-variables: Hired labour	0.638 .	0.341	0.333 .	0.181					1.001 **	0.334
z-variables: Extension	−0.254	0.238			−0.304	0.26			−0.361	0.260
z-variables: Records	−0.605 .	0.356					−0.652 .	0.348	−0.757 *	0.372
Sigma^2	0.504 **	0.154	0.312	0.06 ***	0.476 ***	0.139	0.451 ***	0.106	0.466 ***	0.139
Gamma	0.904 ***	0.054	0.903	0.056 ***	0.925 ***	0.042	0.917 ***	0.047	0.924 ***	0.039
Log likelihood statistic	− 54.775		− 49.195		− 48.958		− 47.335		− 42.645	
Observations	118		118		118		118		118	
Mean efficiency	69.13%		66.38%		69.31%		70.02%		71.08%	

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.

dairy farming on inefficiency since several studies have shown that part-time farmers are less efficient than full-time farmers (see, for example, Brummer 2001; Coelli, Rahman, and Thirtle 2002; Sabasi, Shumway, and Astill 2019). We found that farmer who earned a higher portion of their income from dairy farming increased efficiency, but this was not statistically significant.

The Cobb-Douglas specification (1) was accepted by the Wald test at the 1% significance level but rejected in favour of the translog specification (5) by the likelihood ratio test at the 1% level (see test 1 of Table 2). We proceeded with the translog specification for our analysis to reduce the chance of using a too restrictive functional form. In models 2, 3 and 4 we tested for the robustness of the efficiency effects by including them individually in each model and collectively in models 1 and 5. We did likelihood ratio tests on all models to confirm that they were stochastic frontiers. The results for the complete models (1 and 5) are summarised in tests 2 and 3 of Table 2. In all instances, the significance values were such that the OLS model could be rejected in favour of the stochastic frontier model; in other words, there is significant technical inefficiency. The first-order coefficients of all five models are monotone, which is to be expected with a production function.

As expected, the number of cows milked is a statistically significant input in all the models. The coefficients for labour and concentrates are not statistically significant in any of the models, but this is a function of sample size, and all signs are according to theoretical expectations. Although we sampled only 15% of the industry, model 5 produced a remarkably good fit for such a complex specification. The substantial differences in the coefficients of the Cobb-Douglas and translog specifications indicate non-trivial interactions between the variables included in our model. We used model 5 for the efficiency estimates used in subsequent sections since all the input coefficients are statistically significant and it includes all of the inefficiency variables.

Given our objective of comparing the explanatory power of hypotheses iv) and v) for the inverse relationship, the robustness of the inefficiency submodel (z-variables) of the models tested (1–5) is of greater importance for this study. The direction and the statistical significance of the inefficiency effect are stable in all of the models specified. This shows that using hired labour results in a statistically significant reduction in efficiency, and that the number of extension visits reduces inefficiency, but this indicator is not statistically significant in any of the models. Lastly, our results show that using a record-keeping system produces a statistically significant reduction in inefficiency.

5.2 Testing hypotheses iv) and v): hired labour use and number of cows in milk

Having finalised our model, we now consider how well our results support the explanatory power of hypotheses iv) and v).We segment our sample based on hired labour use to test hypothesis iv). We find that farmers who use hired labour have an average technical efficiency of 65.2% and those who do not use it have an average of 74.1%,. A t-test confirms that these differences are statistically significant ($p < 0.05$). Figure 2 shows the technical efficiency estimates segmented by labour type. It also shows more variability in technical efficiency for farmers who use hired labour than for those who do not: the first and third quartile technical efficiency estimates are 47.9 and83.5% for the former and 66.6 and 85.5% for the latter. It means that some employers are able to address moral hazard effectively through offering the right incentives, hiring the right workers (perhaps family members) and adequate supervision, while others are not.

Similarly, we test hypothesis v) by segmenting our farmers into three equal-sized groups classified as small, medium and large based on the number of cows they have in milk.[3] In line with Yotopoulos and Lau (1973), we find that the small farmers have a higher average technical efficiency (74.2%) than the medium (70.9%) and large (68.6%) farmers. However, mean efficiency estimates by group fail to show statistically significant differences between the groups when subjected to an ANOVA test. Figure 2*: Technical efficiency estimates summarised by labour type.*

Figure 3 again shows the efficiency estimates but now segmented according to farmer size. As with the hired labour use, we see more variability in technical efficiency in the groups with a lower average efficiency than in those with a higher average efficiency.

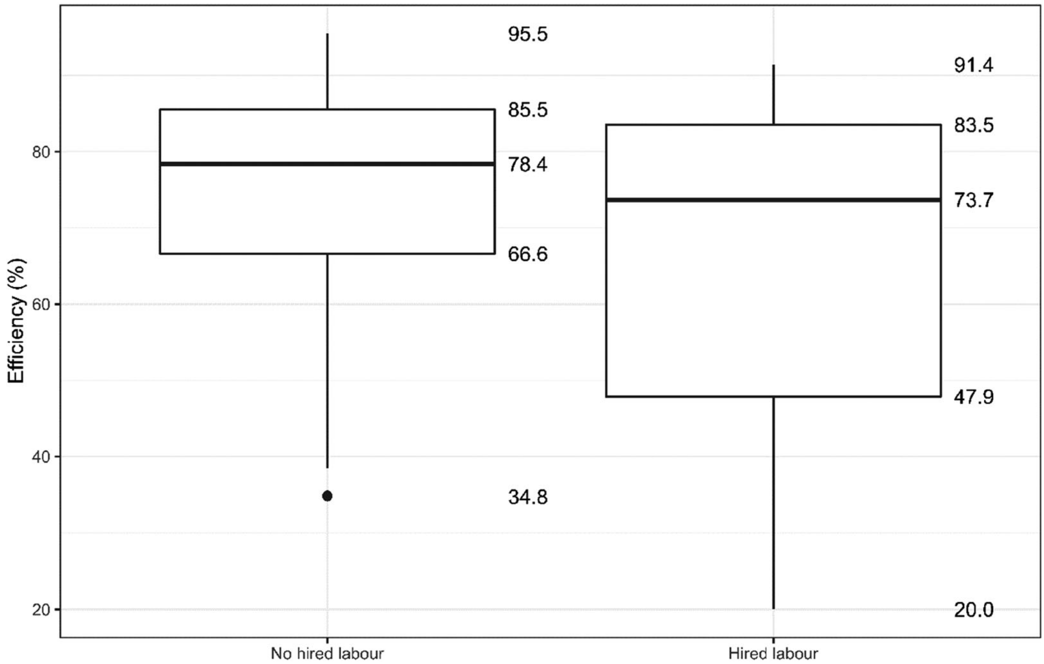

Figure 2. Technical efficiency estimates summarised by labour type.

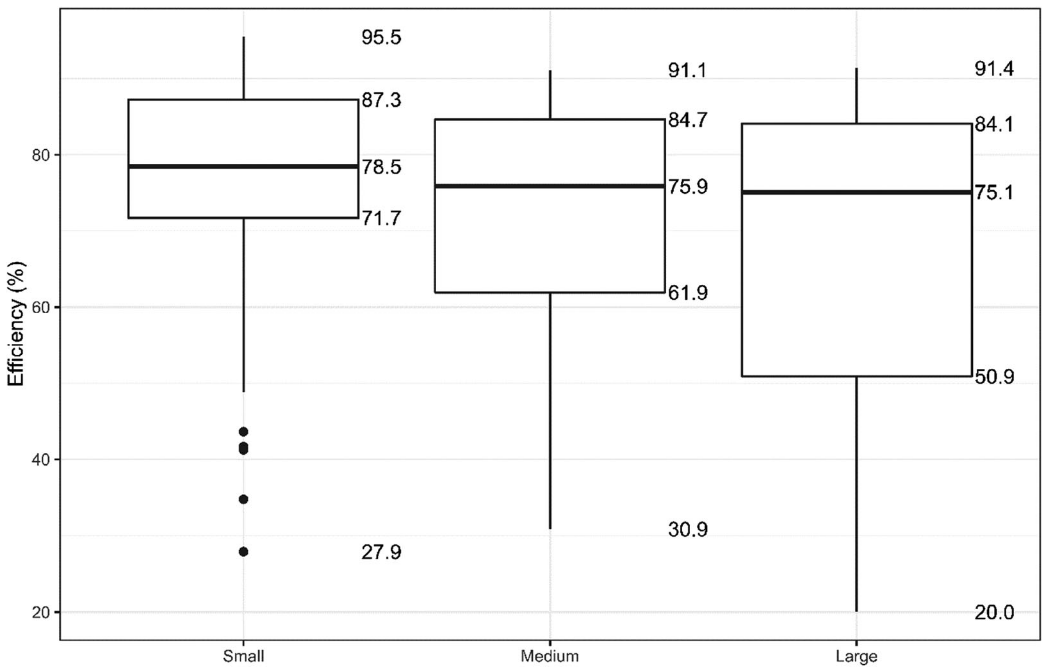

Figure 3. Technical efficiency estimates summarised by number of cows in milk.

5.3 Reducing inefficiency: extension content

We now shift our focus from explaining the cause of the inverse relationship to strategies that could be used to overcome it. A possible solution would be to provide improved farmer extension services. However, the impact of these services on farm efficiency has not been established conclusively. Some have found that they reduce farm inefficiencies (see, for example, O'Neill, Matthews, and Leavy 1999; Dessie et al. 2020), but others (for example Koye, Koye, and Mekie 2022) have failed to show that they have a statistically significant impact, and this has been our finding too. A possible shortcoming of other studies is that they test for the efficiency impact of the quantity of extension delivered and not the quality of the content.

Having shown that farmers who do not use hired labour are more efficient, we would expect that labour management would be one of the focus areas of the extension service. The reality is that of the eight topics covered, most address the practical aspects of dairy farming, starting a dairy, fodder production, cattle feeding and breeding, calf management, milking and hygiene, and disease control, and tend to neglect the farm management component. This neglect could offer a partial explanation for why we fail to find a statistically significant relationship between the number of extension visits and inefficiency. Ideally, we would like to quantify the efficiency impact of offering more labour management extension, but this would require additional data and possibly changing the extension curriculum. However, our data enables us to quantify the productivity impact of one component of the farm management topic: the record-keeping system provided to farmers. We find that farmers who use this record-keeping system have an average technical efficiency of 74.8%, while those who do not use it have an average of 65.5%. More importantly, these averages are statistically significantly distinct, with a t-test *p*-value of 0.007.

6. Limitations

A major limitation of this study is our small sample size. A larger sample stratified by farm size rather than number of cows in milk would have enabled us to explore the determinants of efficiency in more detail. Our questionnaire could also have included more detailed questions related to the use and management of hired labour use.

To test the effectiveness of the revised extension content on farmer productivity, the Eswatini Dairy Board should consider conducting a randomised controlled trial. Farmers should be randomly assigned to either a treatment group, which receives the revised content, or a control group, which receives the unrevised version. This will allow for a direct comparison of the impact of the revised content on productivity. An alternative strategy could be to evaluate the performance of specific extension staff members, and then train and transfer the skills of the more effective staff to their junior colleagues. This approach may help identify key areas of the extension curriculum that are most important and where improvements can be made.

7. Conclusion

In response to Henderson (2015), this study analysed dairy farmers in Eswatini as a case study to test the explanatory power of hypotheses iv) and v) for the inverse relationship. To this end, we fit a stochastic frontier production function with inefficiency effects and statistically compare the technical efficiencies estimated. We find that farmers who use hired labour are significantly less efficient than those who rely on own and family labour for their dairy operations, thus supporting the labour market imperfections hypothesis (iv). Our efficiency estimates show that farmers who do not use hired labour have a median efficiency of 78.4% compared to 73.7% for those who use hired labour.

To test hypothesis v), and to make our results comparable with the previous studies, we segment our farmers into three groups, small, medium, and large, based on the number of cows in milk. We find that, on average, the small farmers are more efficient (78.5%) than the medium farmers (75.9%)

and the large farmers (75.1%). However, our mean efficiency estimates by group fail to show statistically significant differences between the groups when subjected to an ANOVA test.

Considered collectively, our findings support those of Henderson (2015). We find that labour market imperfections explain the inverse relationship, but we do not find that this is true for farm size-related differences in technical efficiency.

We extend hypothesis v) by considering how farmers could mitigate the inefficiency impact of using hired labour. We find that the number of extension visits to farmers does not have a statistically significant impact on efficiency. A possible explanation for the programme's limited impact is that 87.5% of the content is devoted to teaching the practical skills required by dairy farming. We hypothesise that increasing the amount of farm management-related content would increase farm efficiency, especially if labour management is prioritised. Our hypothesis is supported by the fact that one component of the farm management-related extension content, a simple record-keeping system given to farmers, results in a statistically significant reduction in inefficiency. We also find statistically significant differences in the mean efficiency of farmers who do and do not use the record-keeping system provided, with the former being 9.3% higher than the latter.

Ideally, the Eswatini Diary Board should consider implementing a randomised controlled trial to test whether the revised extension content increases the productivity of farmers, especially those who use hired labour. Follow-up studies should randomly allocate farmers to a treatment and control group, with the former receiving the revised extension content and the latter the unrevised version.

Notes

1. Observations per sample year: 1998: 4209, 2001: 4191 and 2005: 6879.
2. A Breusch-Pagan test (Breusch and Pagan 1980) test was performed on the model and there is not enough evidence to reject the null hypothesis that the error term is homoskedastic.
3. The median and mean number of cows per group is as follows; small, 2.0 and 1.7; medium, 4.0 and 4.2; large 9.5 and 16.6.

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