The Impact of Debt Structure on the Production Efficiency of Broadcare Farms in Western Australia

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Abstract

Farming activities are often financed using debt yet empirical studies that investigate the relationship between farm debt structure and performance are still rare. In a ten years unbalanced panel (1995-2005) of Western Australia broadacre farms, we relate the impact of long-term debt, short-term debt and tax liability on farm performance measured by input-oriented technical efficiency and return on assets (ROA). To check for the robustness of our results, both data envelopment analysis (DEA) and stochastic frontier analysis (SFA) methods are employed. Results from both models are consistent: farm production efficiency is positively related to short-term debt, tax liability and investment and negative related to off-farm income activities. Long-term debt has no effect on production efficiency and ROA.

Key words: farm debt structure, return on assets, input-oriented technical efficiency, broadacre farming, Western Australia.

Introduction

In the farming business, reliance on external funding is often unavoidable and important to address farm financial needs or counter market fluctuations such as extreme weather conditions and disease outbreaks. Farmers' use of debt capital is widespread and funding level and availability does affect investment, financial and business planning decisions. Farm lenders also adjust cost availability and other terms of debt in response to a host of risk characteristics, business practices and financial performance indicators of agricultural producers (Barry 2006).

Therefore, the capital structure of a farm enterprise does affect its financial performance and production efficiency. For instance, lack of credit or credit rationing can impede the uptake of available technological processes and hinder productivity growth.

Traditionally, financial indicators such as the return on equity (ROE) and return on assets (ROA) have been used to investigate the relationship between farm debt structure and performance. However, as noted by Zhengfei and Lansink (2006), financial indicators may not fully signal management effort when studying the effect of debt because they depend on variables in the market environment, such as factor prices, that are beyond the control of management. Thus, the value of a farm that allocates its resources efficiently may still be affected by its profitability through revenue and cost structures. Alternatively, a measure that is independent of market prices, such as technical efficiency, can be used to study the relationship between farm debt structure and performance.

There are limited studies that address the impact of debt structure on farm performance. Zhao et al. (2008) analyzed the financial effects of signaling on farm's credit capacity and investment conditions on crop farms in Illinois. The results indicate that signaling does affect agricultural credit relationships between lenders and borrowers. High quality borrowers use their financial status to achieve greater credit capacity by providing lenders with valid signals such as their past cash flow and profitability. Davidova and Latruffe (2007) analyzed the relationship between farm debt structure and technical efficiency in Czech Republic during the transition to a market economy. The analysis detects substantial differences in the effect of financial exposure on technical efficiency between individual farms and corporate farms. Zhenghei and Lansink (2006) investigated the impact of capital structure on farm performance as measured by return on equity (ROE) and Malmquits productivity index. Using data from Dutch crop farms, the empirical results showed that long-term debt increases productivity growth while capital investment have no effect on productivity growth. Lambert and Bayda (2005) investigated the impact of farm structure on production efficiency of North Dakota crop farms. Farm technical efficiency was found to be influenced by debt structure, with a negative relation between efficiency and short-term debt and a positive relationship between efficiency and intermediate debt. Intermediate debt was also positively related with scale efficiency.

Empirical studies that address the impact of debt structure on farm performance fails to investigate other important issues. The health status of farm household is central to overall farm management. Health individuals have greater ability to learn new skills and become more productive in managing farm operations and resources, including farm debt structure. Off-farm income, largely earned from employment and business activities, is also important in alleviating liquity constraint that may influence production. Off-farm income generating activities also shape the way management allocates time and labor resources. However, convectional analyses of production efficiency at the farm level often neglect the linkages between farm and off-farm activities that characterize rural households.

The objective of this article is to investigate the impact of farm debt structure on production efficiency and financial performance of broadcare farms[1] in Western Australia. We investigate the impact of farm debt structure - long-term debt, short-term debt and tax liability - on performance while controlling for the effects of off-farm income, capital investment and health care expenditures. Recent empirical studies on this subject have used the nonparametric approach to measure production efficiency and productivity growth (Davidova and Latruffle 2007, Zhengfei and Lansink 2006, Lambert and Bayda 2005). Our analysis employs both the

[1] Broadcare farms comprise of cropping, mixed cropping–livestock, sheep, beef and mixed livestock producers.

parametric and nonparametric approaches to check for the robustness of our results. In the parametric approach, a translog stochastic production frontier and a technical inefficiency model are estimated simultaneously. A two-stage approach is used with the nonparametric approach. In the first stage, production efficiency scores are computed with data envelopment analysis (DEA) while accounting for sampling variation by using a bootstrapping procedure. In the second stage, regression analyses are applied to investigate the factors that influence variation in technical efficiency and returns to assets (ROA).

Western Australian farms receive very little government support relative to farms in the U.S and European Union. Therefore, unlike previous studies that focused on U.S. and Dutch farms, this study would be of interest to policy makers interested in understanding the impact of debt structure on performance of farms that receive little government support[2]. This has important implications for ongoing structural adjustment[3] and the overall performance in Australian agriculture, especially the ability of farmers to adapt to a changing production environment. The connection of farm debt structure, health care expenditure, and off-farm income generating activities has important implications not only on production efficiency, but also for the rural labor market and farm households.

The next section provides a brief overview of finance theories that explain the relationship between firm capital structure and performance. This is followed by explanation theoretical and empirical approaches for estimating production frontiers, a section on data description, empirical results discussion and finally, concluding remarks.

[2] The average producer support estimate (PSE) for Australia for the period 1994/1995 to 2004/2005 is 6%; the average for US is 18% and European Union is 35%. PSE is an indicator of the annual monetary value of gross transfers from consumers and taxpayers to agricultural producers, measured at the farmgate level (OECD 2009).

[3] Structural adjustment refers to changes in land, labour, capital and resource use in response to changes in technology, demand, climate, social values, policies and the global economy.

Theory of Finance and Farm Businesses

Farm debt structure does matter and influences performance. However, the theoretical and empirical literature on the relationship between farm debt structure and performance is still sparse. The *free cash flow*[4] *theory* explains the benefits of debt in motivating managers and their organizations to be efficient by hypothesizing a positive relationship between debt and production efficiency (Jensen 1986). The theory suggest that management tend to behave with laxness and even invest in projects that are less profitable when a firm is left with too much free cash flow and little debt. However, high debt levels and the burden of debt servicing motivate managers to become more efficient to meet their obligations. Applied to farm management, Nasr et al. (1998) and Giannakas et al. (2001) find support for this theory in their applications to farm samples in US and Canada. Zhengfei and Lansink (2006) also find a strong disciplinary effect of debt on the productivity growth of Dutch arable farms.

On the contrary, the *agency theory* postulates an inverse relationship between debt and production efficiency (Jensen and Meckling 1976). Agency problems arise when the objectives of the principal and agent are different and when the existence of asymmetric information makes it difficult for the principal to monitor the agent's actions. Those problems exist for the relationship between borrower and lender. When establishing a borrowing contract, the borrower often has more information than the lender. Most farms tend to be family controlled because they are legally constituted as sole proprietorships or partnerships between family members. The monitoring costs of such farms are higher because they are not subject to market discipline (Boland et al., 2008). Therefore, due to the potential of adverse selection and moral hazard, the

[4] Free cash flow is cash flow in excess of that required to fund all of a firm's projects

lender charges the borrower extra premium to meet the cost of monitoring. Thus, borrowers with higher debt incur higher costs that reduce the value of their firms. Those costs reduce the production efficiency and performance of highly indebted firms compared to those that use less external funds[5]. Applied to farm management, Davidova and Latruffle (2007) observe that highly indebted farms may not have access to credit for working capital and therefore cannot apply technological processes that improve efficiency.

Agricultural lenders are normally concerned with the borrower's credit risk. Lenders often use credit-scoring and risk-rating models to assess the borrower's financial data, and along with the other relevant information, to reach a valid assessment of the borrower's creditworthiness. A third approach, the *credit evaluation theory*, hypothesizes a negative relationship between production efficiency and debt of a firm. According to this approach, lenders evaluate loan applications according to the applicants' probability of repayment and prefer financing borrowers who are low risk. Production efficiency, as reflected in managerial actions and repayment capacity, might be among the variables taken into considerations. Therefore, the preferences of the lender, as expressed by the interest rate charged and non-interest rate terms of the loan contract, have an impact on the performance and optimal resource allocation of a firm (Barry et al., 1981). Applied to agriculture, Barry et al (1981) tested for how credit risk influences farmers' debt use. The authors observe that use of stringent risk measures for credit risk assessment generally leads to lower use of debt by farmers. Lenders often constrain capital credit more than operating credit but reduction in operating credit may trigger other adjustments, such as reduction in operating inputs or changes in enterprises, to sustain farm's operations. This suggests that credit evaluation approach may imply a positive

[5] Agency theory suggests that the value of a firm will decline when an owner-manager allows outside equity to enter the firm and its governance structure (Demsetz 1983).

relationship between long-term credit financial leverage and technical efficient and weak relationship with short-term debt.

Theoretical Modeling

The relationship between debt structure and farm performance is investigated using two approaches: (1) a two-stage method that estimate technical efficiency using data envelopment analysis (DEA) and later regress the computed efficiency scores against several explanatory variables related to debt structure, and (2) the stochastic frontier analysis method where the production frontier and factors influencing technical inefficiency are estimated simultaneously. This second approach is flexible and consistent compared to the first approach that assumes a deterministic production function. The farms are assumed to have access to the same technology for transforming inputs (*x*) into outputs (*y*):

$$\Psi = \left\{ (x, y) \in \mathbb{R}_{+}^{p+q} \mid x \in \mathbb{R}_{+}^{p} \text{ can produce } y \in \mathbb{R}_{+}^{q} \right\} \tag{1}$$

Data envelopment analysis (DEA) is a linear programming estimator that assumes the free disposability and the convexity of the production set Ψ. For a given set of outputs and inputs for farm i (X_i, Y_i), efficiency is measured relative to the boundary of the convex hull of inputs and outputs:

$$\widehat{\Psi}_{DEA} = \left\{ (x, y) \in \mathbb{R}_{+}^{p+q} \mid y \leq \sum_{i=1}^{n} \gamma_i Y_i ; x \geq \sum_{i=1}^{n} \gamma_i X_i , \text{for } (\gamma_i, ..., \gamma_n), \text{s.t. } \sum_{i=1}^{n} \gamma_i = 1; \gamma_i \geq 0, i = 1, ..., n \right\} \tag{2}$$

where $\widehat{\Psi}_{DEA}$ is the smallest free disposal convex set covering all the data and γ_i are the intensity variables over which optimization is made. Equation (2) assumes Variable Returns to Scale (VRS) but can be adapted to other returns to scale situations: Constant Returns to Scale (CRS) holds if the equality constrain , $\sum_{i=1}^{n} \gamma_i = 1$, is dropped; Non Increasing Returns to Scale holds if the equality constrain is $\sum_{i=1}^{n} \gamma_i \leq 1$; and Non Deceasing Returns to Scale (TEI) holds if the equality constrain is changed to $\sum_{i=1}^{n} \gamma_i \geq 1$.

A general stochastic frontier model can be given defined as

$$\ln y_{it} = f\left(\ln x_{it}\right) + v_{it} - \mu_{it} \tag{3}$$

where y_{it} is the output produced by farm *i* in time *t, x* is a vector of factor inputs, v_{it} is the stochastic terms and μ_{it} is the estimate of the technical inefficiency of farm *i*. The error term is assumed to be independently and identically distributed with variance σ_v^2. The inefficiency component can be estimated over a range of different distributional assumptions such as half normal, truncated normal, exponential and gamma distributions. Here we assume the inefficiency term has a truncated normal distribution with mean m_{it} given by

$$m_{it} = Z_{it}\delta + W_{it} \tag{4}$$

where Z is the vector of farm-specific variables that influence the farm's inefficiency, δ is the associated matrix of coefficients, and W_{it} is an i.i.d. random error term (Battese and Coelli 1995). Technical efficiency of the farm *i* is the relative measure of output of the farm as a proportion of the corresponding frontier and is given by $TE_{it} = e^{-\mu_{it}}$. The parameters of the stochastic frontier and those of the technical inefficiency effects are estimated simultaneously using the method of maximum likelihood.

Empirical Modeling

Data Envelopment Analysis (DEA) model

For a farm operating at levels (x_0, y_0), the input-oriented technical efficiency is obtained by solving the following linear program, assuming VRS:

$$\widehat{\theta}_{DEA}\left(x_{0,}y_0\right)=\left\{\theta \mid y_0 \le \sum_{i=1}^{n}\gamma_i Y_i;\theta x_0 \ge \sum_{i=1}^{n}\gamma_i X_i,\theta > 0;\ \sum_{i=1}^{n}\gamma_i = 1;\gamma_i \ge 0, i = 1,...,n\right\} \quad (5)$$

where $\widehat{\theta}_{DEA}\left(x_{0,}y_0\right)$ measures the radial distance between $\left(x_{0,}y_0\right)$ and the level of the inputs the unit should reach in order to be on the efficient boundary of the production set with the same level of output and same proportion of inputs. The estimated efficiency scores are bounded between zero and unity, with unity representing perfect technical efficiency score. However, the convectional DEA efficiency scores are deterministic and do not take into account sampling variation. Therefore, to account for sensitivity of efficiency scores to sampling variation, we use the smooth homogenous bootstrap procedure of Simar and Wilson (2000) to compute bias-corrected efficiency scores under VRS as well as standard errors and confidence intervals. Details of the DEA bootstrapping process are well documented in Simar and Wilson (1998; 2000).

For the second stage analyses, the following fixed effects regression equation is used to investigate factors that influence technical efficiency

$$TE_{it}^{bc} = \alpha + \beta_{LD}LD_{it} + \beta_{SD}SD_{it} + \beta_T T_{it} + \beta_{OFI}OFI_{it} + \beta_{INV}INV_{it} + \beta_{MD}MD_{it} + \varepsilon_{it} \quad (6)$$

TE^{bc} denotes the bias-corrected technical efficiency score under an input-orientation and VRS technology; *LD* denotes the ratio of long-term debt to asset; *SD* denotes the ratio of short-term debt to asset; T denotes the ratio of tax liability to asset; *OFI* denotes the ratio of off-farm income to total farm income; *INV* denotes ratio of long-term investments to asset, and *MD* is measure of medical expenditure. We also use the traditional financial indicator, the return on assets (ROA), as a second performance measure by estimating the following fixed effects regression equation:

$$ROA_{it} = \alpha + \beta_{LD}LD_{it} + \beta_{SD}SD_{it} + \beta_{T}T_{it} + \beta_{OFI}OFI_{it} + \beta_{INV}INV_{it} + \beta_{MD}MD_{it} + \varepsilon_{it} \qquad (7)$$

Long-term debt and short-term debt ratios measures the impact of financial leverage on efficiency and financial performance. Long-term debt is often associated with long-term projects while short-term debt is related to seasonality of farm production and liquidity needs. Empirical work has found both positive and negative relationships of those variables and production efficiency and performance. Off-farm income measures the impact of off-farm income generating activities on efficiency and financial performance. It is hypothesized that farm efficiency and performance will decline as allocation of family time and labor to off-farm income generating activities increases. Tax liability measures the proportion of debt obligation that is unfulfilled in order to increase liquidity to finance farm operations. We hypothesize that higher tax liability to asset ratio will increase technical efficiency. Medical expenses are a measure of the health status of farm families. We expect that poor health status, as reflected in high medical expenses, to reduce the quality of family labor and thus reduce technical efficiency. Investment is a measure of capital investment that may involve adoption of new production technologies. We also include a time trend to capture the direction of technical efficiency over time.

The bias-corrected efficiency scores and ROA are not restricted on the range [0, 1] and therefore ordinary least square estimates are consistent measures (Green 1993). To check for the robustness of our results, Tobit regression models are estimated with the convectional technical efficiency (TE) and scale efficiency (SE) scores as dependent variables:

$$y^{*}_{it} = \alpha + \beta_{LD}LD_{it} + \beta_{SD}SD_{it} + \beta_{T}T_{it} + \beta_{OFI}OFI_{it} + \beta_{INV}INV_{it} + \beta_{MD}MD_{it} + \varepsilon_{it}. \qquad (8)$$

The Tobit models are estimated using the maximum likelihood approach formulated as:

$y_{it} = \{y_{it}* \;\; if \;\; y_{it}*<100; \; 100 \;\; otherwise\}$. The dependent variable, y_{it}, is either technical efficiency (TE) or scale efficiency (SE) index of farm i at time t that is scaled between 0 and 100. The expected value from this model is computed as:

$$E(y/Z) = 1 - \Phi(b) \times 100 + \Phi(b) Z\beta - \sigma\phi(b), \qquad (9)$$

where $b = (100\text{-}Z\beta)/\sigma$ and Z is the vector of independent variables as described in equation (8), Φ is the cumulative normal function and ϕ is a normal density function. The marginal effect can be computed as:

$$\partial y E(y/z) / \partial z_k = \Phi(b)\beta_k \qquad (10)$$

Translog Stochastic of Production Frontier

A Translog production function is used to examine the relationship between output and inputs. The general form of the model can be expressed as

$$\ln Y_{it} = \beta_0 + \sum_i^n \beta_i \ln X_{it} + 0.5 \sum_i \sum_j \beta_{ij} \ln X_{it} \ln X_{jt} - \mu_{it} + v_{it} \qquad (11)$$

where Y_{it} is the value of output for farm i in period t (Farm Income) and X_{it} is the vector of inputs to the production process (Capital, Labor, Operating Expenses, and Land). The error term is separated into two components: v_{it} is the stochastic error term and μ_{it} is the estimate of the technical inefficiency. The technical inefficiency effects are defined by

$$U_{it} = \alpha + \beta_{LD} LD_{it} + \beta_{SD} SD_{it} + \beta_T T_{it} + \beta_{OFI} OFI_{it} + \beta_{INV} INV_{it} + \beta_{MD} MD_{it} + \varepsilon_{it} \qquad (12)$$

In this formulation, a negative sign of an element of estimated parameters indicates a variable with a positive influence of technical efficiency. Since the translog parameters are not directly interpreted, the output elasticities with respect to the inputs are computed as:

$$\partial \ln Y_{it} / \partial \ln X_{it} = \beta_0 + \sum_{i=1}^{n} \beta_i \ln X_{jt} \geq 0 \forall i \qquad (13)$$

All our empirical analysis are estimated using the Frontier package in R and Stata 11.

Data

This study used farm level panel data from BankWest for the period 1994/95 to 2004/2005. There are 2096 observations for 1096 farms. The panel is unbalanced and the average farm stays in the sample for about two years. One aggregate output and four inputs are used in the computation of the frontier. The output is measured as total farm income deflated with consumer price index. It is an aggregate of income from crops and livestock. Inputs include capital, labor, operational expenses and land. Capital is a measure of farm assets in monetary value and deflated by capital index. Labor is measured as total costs of labor deflated by the labor index. Operating expenses is measured in dollars and deflated by operating expenses index. This includes the costs of fertilizer, seeds, pesticides and farm utilities. Land is measures as acres of farmed land. Total farm income, capital, labor, and operational expenses are measured in 2005 prices obtained from the website of Australian Bureau of Agricultural and Resource Economics (ABARE). The initial data had 4000 farms for 10 years. After checking for consistency and cleaned, the resulting usable records are 2096 farms. All the observations for 1997 are dropped because of incompleteness. Summary statistics of data used in the estimation of production frontier together with factors that influence technical efficiency and ROA are reported in Table 1.

< Insert Table 1 >

Return on assets (ROA) is the ratio of net farm income to total assets; the average ROA is negative 4 %, suggesting poor financial performance[6]. The average off-farm income is about 23 % of total farm income and has been increasing over time. The long-term debt to asset ratio is about 9.2 % and short-term debt to asset ratio is 4 %. Tax liability to asset ratio is about 0.5 % and average capital investment[7] to total asset ratio is 0.15 %. Average annual medical expenses is AUS$6433.

Broadcare farming in WA is characterized by a trend of fewer but larger farms with fewer people employed directly in farming. Most farms are owner operated with minimal utilization of casual and contract labor. Most farms use labor-saving technologies due to continuing difficulties in gaining access to reliable and skilled labor. Wheat, lupins and barley are the main crops in the region. Other crops grown in smaller amounts include field peas, canola, faba beans, and chickpeas. Most farms include a sheep, beef and pig enterprise. Main challenges facing farm managers include cost and price volatility. Larger farms are more complex to run and require more sophisticated management and advisory services (John et al. 2005; Pannel and Kingwell 2009).

Empirical Results

Stochastic Frontier Estimation

The estimation results for the stochastic translog model specifications are presented in Table 2. We estimated two models, one with an interactive time variable (SFA 1) and another without (SFA 2). Model specification check using Likelihood Ratio Test rejects SFA 1 in favor of SFA 2.

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[6] This does not mean that farms are not profitable; it implies that net returns are less than value of assets held.

[7] This includes investment in vehicles, plant, machinery, buildings and farm improvement.

The hypothesis that the correct functional form of the model is Cobb-Douglas was also rejected in favor of the translog specification. Therefore, our discussion only focuses on SFA 2. For this model, eight out of the fifteen estimated parameters of the frontier are statistically significant. Specifically, capital and operation expenditure variables and their quadratic terms are significant. Labor and land are not statistically significant although the quadratic term of land is significant. Interactive terms between capital and land and capital and operation expenditure are significant as is the interactive terms between operation expenditure and land. The hypothesis regarding the insignificance of the variables that determine technical efficiency is rejected[8], thus the proposed determinants of technical efficiency have a significant impact on the estimated model.

Since the parameters of the estimated translog model are not directly interpretable, the production elasticities, reported in Table 3, are used to provide economic interpretation of the parameter estimates. The sign of all the elasticities evaluated at the sample mean are positive. The average elasticity of output with respect to operation expenditure is relatively high (0.599) compared to that of capital (0.256) and land (0.183) while labor has the lowest elasticity (0.001). This implies that operational expenditure is more limiting to production than capital and land. The low elasticity of labor could be a reflection of the capital-intensive nature of broadcare farming. The sum of those elasticities is slightly above one (1.039) indicating increasing returns to scale. This suggests that scale economies are likely to exist on the frontier.

The technical inefficiency model provides valuable information about the impact of the debt structure on the performance of individual farms. Long-term debt is negative and statistically insignificant. Short-term debt, tax liability and investment are negative and statistically significant. This implies that an increase in any of those variables would increase

[8] Likelihood ratio test for the null of no inefficiency, against the efficiency effects frontier, is rejected at 1 percent significance level. Therefore, the efficiency effects frontier model is used.

reduce inefficiency (increase efficiency). Off-farm income is positive and significant indicating that increase in off-farm activities would reduce increase inefficiency (reduce efficiency). Medical expenses are positive and significant but the coefficient is close to zero. The coefficient for the linear tend is insignificant suggesting that the direction of technical efficiency over time is indeterminate.

Technical Efficiency Scores

Table 3 presents results of the estimates of average technical efficiency from the parametric and nonparametric models by year. Columns 2 (SFA 1) and 3 (SFA 2) report the efficiency scores for the stochastic frontier models with time as an interactive term and without. Columns 4 to 6 are the DEA efficiency scores under VRS, CRS, and NIRS (TEV, TEC and TEI). Column 7 is scale efficiency measure (SE).

The estimated technical efficiency scores are comparable across the five models with the overall average efficiency scores ranging from 65% to 80%, with variations across the different models. On average, the SFA (2) has the highest efficiency scores while the TEC model has the lowest efficiency scores. Based on the DEA efficiency scores under VRS technology[9], the percentage of farms on the frontier ranged from a low of 7% in 1999 and 2001 to a high of 34% in 2002[10]. The stochastic frontier models indicate that average technical efficiency was high in 1995 while the DEA models indicate 2005. Except for the SFA (1), all other models indicate that

[9] Here we choose to use VRS technology because it is the least restrictive compared to NIRS or CRS technologies.

[10] In 1999, 40 out of 496 farms were on the frontier compared to 2001 when 36 out of 498 farms were on the frontier. In 2002, 15 out of 56 farms were on the frontier.

average technical efficiency was lowest in 2000. Average scale efficiency was 88% suggesting that pure technical inefficiency is the main factor hindering farms to operate at optimal scale.

< Insert Table 3 >

Table 4 presents the input-oriented bias-corrected technical efficiency scores, under VRS, derived from the bootstrapping procedure (Simar and Wilson 1998, 2000) with 2000 bootstrap replications. Overall, the bias-corrected scores are less that the point estimates, a clear indication that the point estimates overstates efficiency. The average bias-corrected technical efficiency is 67% and the confidence interval is wide, 63% to 73%, suggesting a high statistical variability of DEA efficiency estimates. The average estimated bias is about 5.88%. Overall, the technical efficiency analysis indicates that there are inefficiencies in broadcare farm production.

< Insert table 4 >

The ratios of technical efficiency under CRS (TECRS) to technical efficiency under VRS (TEVRS), and technical efficiency under CRS (TECRS) to technical efficiency under NIRS (TENIRS) can be used to indicate whether the scale inefficiency is due to a too small scale or a too large scale (i.e., SE1 = TECRS/TEVRS and SE2 = TECRS/TENIRS). Increasing returns to scale is inferred when SE2 = 1 given that SE1 < 1, and decreasing returns to scale when SE2 < 1 given that SE1 < 1. The analysis reveals that farms operated at a small scale 68% of times, compared to large scale at 27% and optimal scale at 5%. This lends support to the results from the parametric analysis that, on average, farms operated at increasing returns to scale.

Analysis of Determinant of Technical and Scale Efficiency

The goal of the second stage of the nonparametric analysis is to investigate the dependency of the efficiency scores (estimated in the first stage) on farm specific factors that relate to debt structure. We estimate two Tobit regression models with technical efficiency (TEV) and scale efficiency (SE) scores as dependent variables[11]. We also estimate two fixed-effects models with the bias-corrected efficiency score (BC-TEV) and return on assets (ROA) as dependent variables. Those results are presented in Table 5. For the sake of checking for robustness of our results, the results from the technical inefficiency model of the stochastic frontier model (i.e., SFA 2) are compared to those from the DEA stage-two regressions (TEV and BC-TEV) as reported in Tables 2 and 5.

Both fixed-effect and random-effects models were are estimated for TEV and ROA and the Haussman test was used to select the appropriate model. The test returned a $\chi 2$ of 14.54 (p=0.024) for the TEV model and $\chi 2$ of 198.80 (p=0.000) for the ROA model. Therefore, the null hypothesis of no correlation between the explanatory variables and the error terms are reject and that the fixed-effect models are preferred to the random-effects models. For each model, the Modified Wald test for groupwise heteroskedasticity in fixed-effect regression is used to test the null hypothesis of constant variance (homoskedasticity). In both cases, the constant variance hypothesis is rejected and we control for heteroskedasticity by running robust regressions. Estimated parameters are reported in Table 5.

< Insert table 5 >

The DEA stage-two results are consistent with those from the technical inefficiency model of the stochastic frontier analysis. Long-term debt is statistically insignificant across all the models. Short-term debt is statistically significant for the SFA 2 and TEV models but insignificant for the BC-TEV model. The negative sign in the SFA 2 model (positive for the TEV model) suggest that an increase in short-term debt would decrease technical inefficiency

[11] Longitudinal Tobit is used because the dependent variables are right censored; maximum technical and scale efficiency is one.

(increase technical efficiency). Tax liability, investment, and off-farm income are statistically significant across the three models and with consistent signs. Increase in tax liability would reduce technical inefficiency (increase technical efficiency); Increase in off-farm income would increase technical inefficiency (reduce technical efficiency); and increase in investment would reduce technical inefficiency (increase technical efficiency). Time trend is insignificant in the SFA 2 model but significant for the DEA stage two models (TEV and BC-TEV). The significant negative sign indicate that, on average, technical efficiency has declined over time. The coefficient of medical expenditure is insignificant for the BC-TEV model but significant and consistent for the other two models. Although the magnitude of this coefficient is close to zero, the significant sign suggest that medical expenses would increase technical inefficiency (reduce technical efficiency).

For the scale efficiency model (SE), only long-term debt is statistically insignificant. Except for off-farm income, all the other significant variables are positive. This suggests that off-farm income generating activities reduces the capacity of an average farm to operate at optimal scale. Increase in short-term debt, tax liability and investment drives an average farm towards optimal scale. On the contrary, off-farm activities reduce the capacity of farms to achieve optimal scale. The time trend variable suggests that average optimal scale of farms has been improving over time. Except for long-term debt and medical expenses, all the variables in the ROA model are statistically significant. The only positive and significant coefficient is tax, indicating that increase in tax liability would increase ROA. On the contrary, increases in short-term debt, investment and off-farm income would decrease ROA. The positive and significant time trend suggest that ROA had declined over time, suggesting persistent low-income returns relative to assets held.

Concluding Remarks

This paper provides one of the first analyses of the impact of debt structure on the financial performance and production efficiency of boadare farms in Western Australia. To check for robustness of our results, both parametric and nonparametric methods are employed. The bootstrap DEA procedure by Simar and Wilson (1998; 2000) is used to account for sampling variant in the DEA deterministic model.

We find evidence of farms lagging behind the best practice frontier and operating below optimal scale. The farms' short-term debt structure is found to have a positive relationship with technical and scale efficiency but a negative relationship with ROA. This could suggest that production efficiency can be improved by using short-term debt to purchase necessary farm inputs and maintain farm operations. Delaying tax payment to finance farm operations would also improve production efficiency. However, allocation of family time and labor to off-farm income generating activities would reduce production efficiency. Poor health status of farm families has the potential to reduce production efficiency. Tax liability is found to positively affect ROA while short-term debt and investment do not. The effects of long-term debt on farm efficieny and performance are insignificant.

Our results support the assertion by Zhengfei and Lansink (2006) that financial indicators may not fully signal management effort when studying the effect of debt on farms. In our case, the debt structure has a positive relationship with production efficiency and negative with ROA. This relationship implies lenders will provide soft loans to farmers who are efficient and with high returns on assets[12], presumably because of their low level of loan default. This observation can be explained with the free cash flow problem; the benefits of short-term debt may motivate

[12] Our data also indicate that farms that are technically efficient also have high returns on assets relative to those that are technically inefficient.

farm managers to be more efficient because of the higher interest rate the loans attract relative to long-term debt. Therefore, policies that enable farmers to have access to short-term debt would improve production efficiency in broadacre farms of Western Australia.

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Table 1. Summary Statistics of Western Australia Farms 1995-2005 (in 2005 Prices)

Variable	Units	N	Mean	Std.Dev
Output (Y)	AUS$	2909	5019.79	3545.83
Capital (K)	AUS$	2909	25102.19	16305.45
Labor (L)	AUS$	2909	169.13	242.47
Operating Expenses (OPEXP)	AUS$	2909	3296.66	2344.45
Land (LD)	Hectares	2909	2681.06	1726.12
Long-term debt (LD)	Ratio	2909	0.09	0.09
Short-term debt (SD)	Ratio	2909	0.04	0.05
Tax liability (T)	Ratio	2909	0.01	0.01
Long-term investments (INV)	Ratio	2909	0.02	0.03
Off-farm income ratio (OFI)	Ratio	2909	0.23	0.37
Medical expenses (MD)	AUS$	2909	6433.18	11235.61
Return on Assets (ROA)	Ratio	2909	-0.04	0.09

Table 2. Stochastic Production Frontier Models

	SFA (1)		SFA (2)	
	Estimate	Std. Error	Estimate	Std. Error
Constant	0.353	0.987	0.509	0.985
K	-0.273	0.199	-0.450	0.188*
L	0.034	0.047	0.035	0.046
OEXP	1.818	0.229***	1.788	0.227**
LD	-0.512	0.219*	-0.301	0.217
Time	-0.025	0.035		
K^2	0.089	0.028**	0.115	0.024***
K*L	0.005	0.007	0.003	0.006
K*OEXP	-0.179	0.032***	-0.151	0.031***
K*LD	0.130	0.030***	0.095	0.029***
K*Time	0.005	0.005		
L^2	0.001	0.003	0.001	0.003
L*OEXP	-0.004	0.008	-0.002	0.008
L*LD	-0.007	0.007	-0.007	0.007
L*Time	0.000	0.001		
$OEXP^2$	0.263	0.037***	0.271	0.035***
OEXP*LD	-0.195	0.035***	-0.235	0.033***
OEXP*Time	0.002	0.006		
LD^2	0.134	0.046**	0.183	0.045***
LD*Time	-0.015	0.006**		
$Time^2$	0.019	0.002***		
Technical Inefficiency Model				
Time	0.052	0.005***	0.003	0.005
LTDEBT	-0.153	0.112	-0.057	0.132
STDEBT	-1.080	0.242***	-1.312	0.327***
TAX	-7.240	1.486***	-21.926	4.176***
OFINC	0.302	0.021***	0.403	0.028***
INV	-2.627	0.429***	-4.563	0.890***
EXPMED	0.000	0.000***	0.000	0.000***
sigmaSq	0.093	0.005***	0.150	0.011***
gamma	0.753	0.028***	0.774	0.024***
Log Likelihood	-76.50		-168.54	

Legend: * $p<0.05$; ** $p<0.01$; *** $p<0.001$

Notes: Using the likelihood ratio test, SFA (2) is preferred to SFA (1). The Cobb-Douglas specification is rejected in favor of the translog specification.

Table 3. Production Elasticities Evaluated at the Sample Mean

	CAP	LAB	OEXP	LAND	Return to Scale
Mean	0.2466	0.0012	0.5993	0.1827	1.030
Standard error	0.0012	0.0001	0.0021	0.0016	

Note: Return to scale is the sum of production elasticities

Table 4. SFA and DEA Technical Efficiency Scores, 1995-2005

Year	SFA(1)	SFA(2)	TEV	TEC	TEI	SE
1995	0.860	0.881	0.8182	0.7322	0.8075	0.904
1996	0.822	0.845	0.8175	0.7364	0.7995	0.910
1998	0.765	0.796	0.7941	0.6779	0.7665	0.866
1999	0.770	0.800	0.7278	0.6398	0.7243	0.888
2000	0.674	0.727	0.6730	0.5675	0.6619	0.853
2001	0.753	0.817	0.6979	0.5880	0.6904	0.862
2002	0.683	0.793	0.7942	0.7366	0.7745	0.925
2003	0.672	0.812	0.6928	0.6402	0.6791	0.930
2004	0.579	0.781	0.7627	0.6746	0.7390	0.895
2005	0.518	0.793	0.8492	0.8114	0.8379	0.957
Average	**0.730**	**0.800**	**0.7349**	**0.6455**	**0.7228**	**0.888**

Notes: SFA (1) and SFA (2) are the average technical efficiency scores from the parametric models (1) and (2). TEV, TEC and TEI are the average technical efficiency scores from data envelopment analysis under Variable Returns to Scale, Constant Returns to Scale, and Nonincreasing Returns to Scale technical efficiency. SE is scale efficiency.

Table 5. Bootstrap DEA Efficiency Scores

Year	Efficiency Score	Bias-corrected Score	Bias	95% Lower Bound	95% Upper Bound
1995	0.8182	0.7705	0.0477	0.7223	0.8141
1996	0.8175	0.7632	0.0543	0.7115	0.8121
1998	0.7941	0.7394	0.0547	0.6900	0.7888
1999	0.7278	0.6742	0.0536	0.6377	0.7181
2000	0.6730	0.6081	0.0650	0.5667	0.6615
2001	0.6979	0.6483	0.0496	0.6097	0.6910
2002	0.7942	0.6953	0.0989	0.6136	0.7854
2003	0.6929	0.6268	0.0660	0.5844	0.6817
2004	0.7627	0.6838	0.0789	0.6215	0.7539
2005	0.8492	0.7774	0.0718	0.7078	0.8435
Average	**0.7350**	**0.6762**	**0.0588**	**0.6314**	**0.7266**

Notes: Reported values are bootstrapped efficiency scores under variable returns to scale with 2000 bootstrap replications.

Table 6. Results from Return on Assets and Technical Efficiency Models

Variable	TEV	BC-TEV	SE	ROA
Time	-0.0066***	-0.0066***	0.0038***	-0.0016**
Long-tern Debt	0.0537	-0.0183	0.0014	-0.0269
Short-term Debt	0.2047**	0.0081	0.3143***	-0.3211***
Tax Liability	3.6196***	3.0206***	1.0170***	0.3811**
Investment	0.6207***	0.3290*	0.3350***	-0.6359***
Off-farm Income	-0.0774***	-0.0616***	-0.0569***	-0.1071***
Medical Expenses	-0.0000**	-0.0000	0.0000***	-0.0000**
Constant	0.7639***	0.7116***	0.8503***	0.0174***
N	2909	2909	2909	2909
R^2		0.1055		0.3572
Adjusted R^2		0.1033		0.3557
Sigma_u	0.1271***		0.0972***	
Sigma_e	0.1633***		0.0992***	

Legend: * p<0.05; ** p<0.01; *** p<0.001

Notes: TEV and SE are censored regressions with technical efficiency and scale efficiency as dependent variables; reported values are marginal effects. BC-TEV and ROA are robust fixed-effects regression models with bias-corrected technical efficiency and return on assets as dependent variables. Those two equations are not censored.