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Impact of debt structure on production efficiency and financial performance of Broadacre farms in Western Australia

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Farming activities are often financed using debt, yet empirical studies investigating the relationship between farm debt structure and performance are still rare. Using a 10 year unbalanced panel of Broadacre farms in Western Australia, 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. We find farm technical efficiency is positively related to short-term debt, tax liability and capital investment, but negatively related to off-farm income generating activities. Long-term debt has no effect on production efficiency and return on assets. These results are robust to both parametric and nonparametric methods of estimation.

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

1. Introduction

Farming businesses often rely on external funding to finance their operations. Use of debt financing is widespread although funding levels and cost of such funding vary greatly among farms. This variation exists because lenders often adjust the cost of debt and other terms of credit in response to changes in various risk characteristics, for example changes in business practices or financial performance indicators (Barry and Robinson 2001). In some cases, farmers may be approved for loans that fall short of their desired amounts. Therefore, the capital structure of a farm business may affect its financial performance as well as its technical efficiency by affecting its ability to utilize the best available technology. For instance, lack of or insufficient credit can impede uptake of appropriate technology, leading to limited productivity growth.

Financial indicators such as return on equity (ROE) and return on assets (ROA) have long been used to investigate the relationship between farm debt structure and performance. However, Zhengfei and Lansink (2006) note that such indicators may not fully signal firm performance and management effort when studying the effect of debt; these measures depend on variables in the

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market environment, for example factor prices, that are beyond the control of management. Instead, a measure that is independent of market prices, such as technical efficiency, is more appropriate.

Only a limited number of studies have empirically investigated the impact of debt structure on farm performance. Zhao *et al*. (2008) analysed the financial effects of signalling on farm's credit capacity and investment conditions for crop farms in Illinois. Their results indicated that signalling affects agricultural credit relationships between lenders and borrowers. That is, borrowers with high credit ratings obtain more credit by providing lenders with valid signals such as positive cash flows and profitability histories. Davidova and Lafruffe (2007) analysed the relationship between farm debt structure and technical efficiency in the Czech Republic during its transition from a centrally planned to a market economy. They found substantial differences in the effect of long-term indebtedness on technical efficiency between individual farms and corporate farms because of differential treatment by lenders. Zhengfei and Lansink (2006) investigated the impact of capital structure on farm performance for Dutch crop farms using return on equity (ROE) and Malmquist productivity index as a measure of total factor productivity. They found that long-term debt has a positive effect on productivity growth, but no effect on ROE. This suggests that financial indicators, ROE in this case, may not fully signal management effort when studying the effect of debt. In a related study, Lambert and Bayda (2005) investigated the impact of debt structure on production efficiency of North Dakota crop farms. They found that intermediate debt was positively related with farm technical efficiency as well as scale efficiency.[1] However, short-term debt had a negative impact on technical efficiency.

Overall, empirical studies that address the impact of debt structure on farm performance fail to investigate the role of off-farm income which can also be important in alleviating liquidity constraints. For example, for a farm facing credit rationing, access to off-farm income can influence its productive capacity through timely access to farm inputs such as fertilizer.[2] Consequently, it can affect the farm's allocative efficiency.[3] Furthermore, off-farm activities also shape the way management allocates time and labour resources.

The objective of this article is to investigate the impact of farm debt structure on production efficiency and financial performance of Broadacre farms in Western Australia. Broadacre farms comprise of large-scale agricultural or pastoral enterprises (sheep and beef cattle). We investigate the impact of farm debt structure (long-term and short-term debt) and tax liability on performance of these farms while controlling for the effects of off-farm income and equity capital investment.

[1] Scale efficiency means that farms are of the appropriate size so that no reorganization will improve output or earnings.

[2] Off-farm income may depend on size, type of enterprise, age of operator and other nonfarm factors like employment and business opportunities.

[3] Allocative efficiency implies resource allocation decisions that minimize cost, maximize revenue or more generally maximize profit.

The current study differs from previous ones by using both parametric and nonparametric approaches to check for the robustness of results.[4] In the parametric approach, a translog stochastic production frontier and a technical inefficiency model are estimated in a one-step procedure. The two-step procedure was not used because it has been found to cause the effects of explanatory variables on technical inefficiency to be biased towards zero (Wang and Schmidt 2002). A two-stage method is used to implement the nonparametric approach. In the first stage, technical efficiency scores are computed via bootstrapping data envelopment analysis (DEA) to account for sampling variation sensitivity of the technical efficiency scores (Simar and Wilson 1998; Mugera and Langemeier 2011). In the second stage, regression analysis is used to investigate the factors that influence variation in technical efficiency and return on assets (ROA).

Western Australian farms receive limited government support relative to U.S. and EU farms. Therefore, this study would be relevant to policy makers interested in understanding the impact of debt structure on performance of farms that receive little or no government support.[5] Results from this study have important implications for ongoing structural adjustments[6] and the overall performance of Australian agriculture, especially the ability of farmers to adapt to a changing production environment. Understanding how farm debt structure and off-farm income generating activities affect farm level technical efficiency and financial performance is important for designing policies that promote the rural economy.

The rest of the paper is organized as follows: section 2 provides a brief overview of finance theories that explain the relationship between firm capital structure and performance; section 3 presents the analytical framework; section 4 describes the data used; section 5 presents the empirical results; and section 6 presents the concluding remarks and policy implications.

2. Theory of finance and farm businesses

Existing theoretical and empirical literature on the relationship between farm debt structure and performance is sparse. The *free cash flow*[7] *theory* explains the

[4] The parametric approach involves specifying and estimating a parametric production function that represents the best available technology. This method provides a convenient framework for conducting hypothesis testing, but the results can be sensitive to the functional form chosen. The nonparametric method estimates a piecewise linear best practice frontier using the mathematical programming approach.

[5] The average producer support estimate (PSE) for Australia for the period 1994/1995 to 2004/2005 is 6 percent; the average for the United States is 18 percent and for the EU, it is 35 percent during that period. PSE measures the annual monetary value of gross transfers from consumers and taxpayers to agricultural producers at farm-gate prices (OECD 2009).

[6] 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.

[7] Free cash flow is cash available for distribution to equity and debt holders (investors) after the business firm has made all investments in fixed assets and working capital necessary to sustain ongoing operations.

benefits of debt in motivating managers and their organizations to be efficient by hypothesizing a positive relationship between debt and technical efficiency (Jensen 1986). This theory suggests that management tends to act with laxity and may even invest in less profitable projects when a firm has a lot of free cash flow with little or no debt. In contrast, high debt levels and subsequent debt-servicing burden motivate managers to become more efficient. Defaulting on debt obligations is a greater financial risk than lower profits for equity holders when the firm has little or no debt. In a sense, debt serves as a 'disciplinarian' of managers. Empirical studies by Nasr *et al*. (1998) and Giannakas *et al*. (2001) have found support for this theory using data from farms in the United States and Canada. Zhengfei and Lansink (2006) also found evidence of a strong 'disciplinary' effect of debt on the productivity growth of Dutch farms.

Agency theory, on the other hand, postulates an inverse relationship between debt and technical efficiency (Jensen and Meckling 1976). This is the well-known principal-agent problem which occurs when asymmetric information makes it difficult for the principal to monitor the agent's actions. This problem is especially serious in borrower–lender relationships. When establishing a loan 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. Monitoring costs of such farms are higher because they are not subject to market discipline[8] (Boland *et al*. 2008). Therefore, due to the potential of adverse selection and moral hazard problems, lenders charge borrowers an extra premium to meet costs of monitoring. Hence, borrowers with higher debt incur higher costs which reduce the profitability of their firms. Agency theory avers that these costs also reduce the technical efficiency and financial performance of such firms.[9] Applied to farm management, Davidova and Lafruffe (2007) observe that highly indebted farms may not have access to credit for working capital and therefore may not apply technological processes that improve efficiency.

A third approach, the *credit evaluation theory*, hypothesizes a negative relationship between debt and technical efficiency. This theory posits that lenders evaluate loan applications according to the applicants' probability of repayment and prefer financing low-risk to high-risk borrowers. Therefore, lender's preferences, as expressed by the interest rate charged and non-interest rate terms of the loan contract, will have an impact on farm performance as well as optimal resource allocation (Barry *et al*. 1981). Applying this theory to agriculture, Barry *et al*. (1981) examined how credit risk may influence farmers' debt use in south-central and eastern Texas. They observed that use of

[8] A mechanism through which market participants monitor and influence the risk-taking behaviour of financial institutions by penalizing excessive risk-taking.

[9] Agency theory suggests that the value of a firm declines when an owner–manager allows outside equity to enter the firm and its governance structure (Demsetz 1983). In this case, the Modigliani and Miller (1958) capital structure irrelevance principle does not apply because of the existence of agency costs, taxes and asymmetric information.

stringent measures for credit risk assessment generally led to lower debt use. Even though lenders often constrain capital credit more than they do operating credit, any reduction in operating credit usually triggers other adjustments to sustain the farm's operations, for example reduction in operating inputs or changes in enterprise mix. The credit evaluation approach implies that there may be a positive relationship between long-term debt and technical efficiency, but a negative relationship with short-term debt.

In summary, we draw the following conclusions. First, based on the *free cash flow theory*, debt financing is positively related to technical efficiency and financial performance. Second, based on *agency theory*, debt financing has a negative impact on technical efficiency and financial performance. Last, based on the *credit evaluation theory*, long-term debt has a positive impact, while short-term debt has a negative effect on technical efficiency and financial performance. We use these theoretical underpinnings to give context to our interpretation of the results in this study.

3. Theoretical modelling

The relationship between debt structure and farm performance is investigated using two approaches: (i) a two-stage method that estimates technical efficiency using data envelopment analysis (DEA) and then regresses the computed efficiency scores against several explanatory variables related to debt structure and (ii) a stochastic frontier analysis method which simultaneously estimates the production frontier and factors influencing technical inefficiency. For a discussion of the weaknesses and strengths of these methods, see Biesebroeck (2007) and Cornwell and Schmidt (2008).

All farms are assumed to have access to the same technology for transforming inputs (x) into outputs (y):

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

Data envelopment analysis 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 as:

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

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 forms of returns to scale situations. Constant Returns to Scale (CRS) holds if the equality constraint, $\sum_{i=1}^{n}\gamma_i = 1$, is dropped, and Nonincreasing Returns to Scale holds if the inequality constraint is $\sum_{i=1}^{n}\gamma_i \leq 1$.

A general stochastic frontier model can be expressed as:

$$y_{it} = x_{it}\beta + v_{it} - \mu_{it} \tag{3}$$

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 error term and μ_{it} is the one-sided error ($\mu_{it} \geq 0$) capturing the shortfall of y_{it} from the frontier. The stochastic error term is assumed to be independently and identically distributed with variance σ_v^2. We assume that the inefficiency term has a truncated normal distribution[10] with mean m_{it} given as:

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

where Z is the matrix of farm-specific variables that influence the farm's inefficiency, δ is the associated vector of coefficients and W_{it} is an i.i.d. random error term (Battese and Coelli 1995). Technical efficiency for farm i is the relative measure of output as a proportion of the corresponding frontier given by $TE_{it} = \mathrm{e}^{-\mu_{it}}$. To estimate the parameters of the stochastic production frontier and the technical inefficiency effects, Equations (3) and (4) are simultaneously estimated using the maximum likelihood function:

$$\log L(\beta, \sigma, \lambda) = \sum_{I=1}^{N}\left[\frac{1}{2}\log\left(\frac{2}{\pi}\right) - \log\sigma - \frac{1}{2}(\varepsilon_i/\sigma)^2 + \log\phi(-\gamma\varepsilon_i/\sigma)\right] \tag{5}$$

where $\varepsilon_i = v_i - u_i$; $\lambda = \sigma_u/\sigma_v$; $\sigma = \sqrt{\sigma_v^2 + \sigma_u^2}$; and $\phi(.)$ is standard normal cdf.

3.1. Empirical modelling

3.1.1. 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:

[10] Other distributions that could be considered include half-normal, exponential and gamma. The choice of truncated normal here is for simplicity of estimation. As Kumbhakar and Lovell (2000) note, the choice of distribution to use is immaterial because ranking of decision-making units by their efficiency scores, or the composition of the top and bottom efficiency scores deciles, is not sensitive to distributional assumptions.

$$\widehat{\theta}_{DEA}(x_0,y_0) = \min\left\{\theta | y_0 \le \sum_{i=1}^{n} \gamma_i Y_i; \theta x_0 \ge \sum_{i=1}^{n} \gamma_i X_i, \theta > 0; \sum_{i=1}^{n} \gamma_i = 1; \gamma_i \ge 0, i = 1, \ldots, n\right\} \quad (6)$$

where $\widehat{\theta}_{DEA}(x_0,y_0)$ measures the radial distance between (x_0, y_0) and the level of the inputs the unit should reach 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 a perfect technical efficiency score. However, conventional DEA efficiency scores are deterministic and do not account for sampling variation. To correct for this problem, 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. See Simar and Wilson (1998, 2000) for detailed description of the DEA bootstrapping procedure.

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

$$TE_{it}^{bc} = \alpha + \beta_{LD}LD_{it} + \beta_{SD}SD_{it} + \beta_T T_{it} + \beta_{OFI}OFI_{it} + \beta_{INV}INV_{it} + \varepsilon_{it} \quad (7)$$

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 assets; *SD* denotes the ratio of short-term debt to asset; *T* denotes the ratio of tax liability to assets; *OFI* denotes the ratio of off-farm income to total farm income; and *INV* denotes ratio of long-term investments to assets. Long-term investment is taken to be any loan acquired to pay for machinery, vehicles and farm structures.

As an additional measure of performance, we use return on assets (ROA) as a regressand in the following fixed-effects regression equation:

$$ROA_{it} = \alpha + \beta_{LD}LD_{it} + \beta_{SD}SD_{it} + \beta_T T_{it} + \beta_{OFI}OFI_{it} + \beta_{INV}INV_{it} + \varepsilon_{it} \quad (8)$$

The right-hand side variables are the same as those in Equation (7). Long-term debt and short-term debt ratios are used to measure 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 between these variables and technical efficiency and performance.

The off-farm income variable measures the correlation between off-farm income generating activities and efficiency as well as financial performance.

We have no *a priori* expectation on the direction of the correlation.[11] Tax liability is measured as the ratio of outstanding tax to total assets. Except in cases where concessions allow for tax deferment, there is no theoretical underpinning on the effect of this variable. Hence, we have no *a priori* expectation of its impact. The investment variable is used as a measure of capital investment which may involve adoption of new production technologies. A time trend is also used as a regressor to investigate the direction of technical efficiency over time.

Because the bias-corrected efficiency scores and ROA are not restricted on the range [0, 1], ordinary least square estimates are consistent measures (Green 1993). To check for the robustness of our results, Tobit regression models are estimated using conventional technical efficiency (TE) and scale efficiency (SE) scores as dependent variables. Scale efficiency is the ratio of technical efficiency under CRS to VRS. The independent variables remain the same as in Equation (7). The Tobit models are estimated using the maximum likelihood method.

3.1.2. Translog stochastic 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:

$$\ln y_{it} = \beta_0 + \sum_{i}^{n} \beta_i \ln x_{it} + 0.5 \sum_{i} \sum_{j} \beta_{ij} \ln x_{it} \ln x_{jt} - \mu_{it} + v_{it} \qquad (9)$$

where y_{it} is the value of output for farm i in period t (farm income) and x_{it} is the matrix of inputs to the production process (capital, labour, 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 effect is defined as:

$$\mu_{it} = \alpha + \beta_{LD} LD_{it} + \beta_{SD} SD_{it} + \beta_T T_{it} + \beta_{OFI} OFI_{it} + \beta_{INV} INV_{it} + \varepsilon_{it} \qquad (10)$$

In this formulation, a negative sign on estimated parameters indicates that the corresponding variables have a positive influence on technical efficiency. Because the translog parameter estimates are not directly interpretable, we compute output elasticities with respect to the inputs which can be interpreted. The Frontier package in R (Coelli and Henningsen 2012) and Stata 11 are used for computation.

[11] Off-farm income may or may not come at an opportunity cost depending on whether the farmer or the farmer's partner works off-farm. However, it is important to include it in this study because it can impact the farm's debt repayment capacity, regardless of its source.

4. Data

We utilized data for Broadacre farms in Western Australia. These are mainly large farms, mostly owner-operated and highly mechanized with minimal utilization of casual and contract labour. Wheat, lupins and barley are the main crops grown although some farms have field peas, canola, soybeans and chickpeas. In addition, most farms have sheep, beef and pig enterprises. Besides facing cost and price volatility challenges, these farms are complex and require sophisticated management and advisory services (Pannell and Kingwell 2009).

The data were provided by one of the financial institutions in Western Australia for the period 1994/1995 to 2004/2005, with 2909 observations. The initial data set had 4000 farms, but about 27 percent of farms were excluded from the sample because of inconsistency and/or missing data. Furthermore, all of the 1997 data were excluded because of incompleteness. The resulting panel data are unbalanced, and a typical farm stays in the sample for about two years.[12] The data are based on comprehensive annual farm surveys about actual financial and production performance of Broadacre farm businesses. The sample is drawn from the Central Midlands, Great Southern, north-eastern Wheatbelt, northern Wheatbelt, south coast and south-eastern Wheatbelt regions. To estimate the production frontier, we use one aggregate output and four inputs. Output is measured as total real farm income by aggregating income from both crop and livestock enterprises. Inputs comprise of capital, labour, operational expenses and land. The monetary value of farm assets is used as a measure of capital, while labour is measured as total costs of labour. Operating expenses is the sum of costs of fertilizer, seeds, pesticides and farm utilities. Land is measured as the total number of acres farmed. Values related to total farm income, capital, labour and operational expenses were deflated by the consumer price index, capital index, labour index and operating expenses index with 1997/1998 as the base year; the price indices were obtained from the Australian Bureau of Agricultural and Resource Economics (ABARE) website.

Summary statistics of data used in estimation of the production frontier and factors that influence technical efficiency and return on assets (ROA) are reported in Table 1. The average ROA, calculated as the ratio of net farm income to total assets, is negative 4 percent. This suggests overall poor financial performance. Average off-farm income is about 23 percent of total farm household income, suggesting that off-farm activities are an important part of the farmers' portfolios. The data show that only about 13 percent of the farm assets are leveraged by debt because the long-term debt to asset ratio is about 9.2 percent and the short-term debt to asset ratio is 4 percent. On average, the tax liability to asset ratio is about 0.5 percent, while the average capital investment[13] to total asset ratio is 1.5 percent.

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[12] This is possibly because farms are randomly selected from a target population.
[13] This includes investment in vehicles, plant, machinery, buildings and farm improvement.

Table 1 Summary statistics of Western Australia farms 1995–2005 (in 1997/1998 prices)

Variable	Units	*N*	Mean	Std. Dev
Output (*Y*)	AUS$	2909	5019.79	3545.83
Capital (*K*)	AUS$	2909	25102.19	16305.45
Labour (*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
Return on assets (*ROA*)	Ratio	2909	−0.04	0.09

5. Empirical results

5.1. Stochastic frontier estimation

The estimation results for the stochastic production frontier are presented in Table 2. We estimated three models, a base model without an interactive time variable (SFA 1), a second model with an interactive time variable (SFA 2) and a final model with year dummies as intercept shifters (SFA3). The time variable is used to capture technological change while year dummies control for between-year weather variations. Based on the likelihood ratio test for model specification, SFA (1) and SFA (2) are rejected in favour of SFA (3) at the 1 percent level of significance. The hypothesis that the correct functional form is Cobb-Douglas is also rejected in favour of the translog specification. Therefore, we only discuss the results pertaining to SFA (3). Output production elasticities reported in Table 3 are used to provide economic interpretation of the results.

Except for labour, the sign on all other input elasticities evaluated at the sample mean are positive. This implies that, *ceteris paribus*, an increase in the use of each input would increase output. The average elasticity of output with respect to operation expenditure is relatively high (0.652) compared to that of capital (0.243) and land (0.142). Labour has the lowest elasticity (−0.0027) that is statistically different from zero. The low elasticity of labour is most likely a reflection of the capital-intensive nature of Broadacre farming. The sum of those elasticities for each farm indicate returns to scale; we find a majority of farms to operate under increasing returns to scale (65 percent) compared to constant (21 percent) and decreasing returns to scale (14 percent).

The technical inefficiency effect model provides valuable information about the impact of debt structure on the performance of individual farms. The null hypothesis that technical efficiency variables are statistically equal to zero was rejected[14] in favour of the alternative hypothesis that determinants of

[14] The likelihood ratio test for the null of no inefficiency, against the efficiency effects frontier, is rejected at 1 per cent significance level. Therefore, the efficiency effects frontier model is used.

Table 2 Stochastic production frontier models

	SFA (1)		SFA (2)		SFA (3)	
	Coeff.	SE	Coeff.	SE	Coeff.	SE
Intercept	0.4581	0.9820	0.2733	0.9877	−0.4901	0.9405
K	−0.4437	0.1889*	−0.2654	0.1956	−0.1015	0.1729
L	0.0300	0.0458	0.0262	0.0460	0.0041	0.0417
OEXP	1.7874	0.2311***	1.8208	0.2268***	1.6860	0.2123***
LD	−0.2959	0.2196	−0.4997	0.2165*	−0.3392	0.2037.
Time			−0.0320	0.0330		
K^2	0.1162	9.0244***	0.0905	0.0267***	0.0973	0.0214***
$K \times L$	0.0040	0.0063	0.0057	0.0066	0.0065	0.0057
$K \times OEXP$	−0.1526	0.0309***	−0.1797	0.0307***	−0.1865	0.0285***
$K \times LD$	0.0941	0.0284***	0.1282	0.0289***	0.1068	0.0265***
$K \times$ Time			0.0055	0.0051		
L^2	0.0008	0.0033	0.0003	0.0033	0.0009	0.0031
$L \times OEXP$	−0.0021	0.0080	−0.0034	0.0081	−0.0025	0.0076
$L \times LD$	−0.0071	0.0070	−0.0079	0.0071	−0.0072	0.0066
$L \times$ Time			0.0003	0.0011		
$OEXP^2$	0.2694	0.0348***	0.2606	0.0348***	0.2620	0.0315***
$OEXP \times LD$	−0.2318	0.0322***	−0.1919	0.0334***	−0.1604	0.0306***
$OEXP \times Time$			0.0017	0.0060		
LD^2	0.1813	0.0435***	0.1318	0.0442**	0.0922	0.0418*
$LD \times$ Time			−0.0145	0.0054**		
Time^2			0.0186	0.0016***		
Year-1996					−0.1471	0.0195***
Year-1998					−0.2663	0.0212***
Year-1999					−0.1672	0.0197***
Year-2000					−0.2792	0.0218***
Year-2001					0.0027	0.0246
Year-2002					−0.1031	0.0407*
Year-2003					0.0434	0.0316
Year-2004					−0.0531	0.0404
Year-2005					−0.0943	0.0518.
Technical inefficiency effect						
Time			0.0504	0.0053***	0.0333	0.0056***
LTDEBT	−0.0734	0.1623	−0.1601	0.1056	−0.1718	0.1235
STDEBT	−1.3123	0.4291**	−1.0704	0.2269***	−1.2675	0.2773***
TAX	−22.3272	3.7861***	−7.3846	1.5224***	−13.0652	2.3149***
OFINC	0.3996	0.0252***	0.2975	0.0206***	0.3309	0.0242***
INV	−4.6705	0.9273***	−2.6178	0.4251***	−3.0575	0.5298***
σ_{Sq}	0.1500	0.0090***	0.0933	0.0051***	0.0954	0.0073***
γ	0.7741	0.0238***	0.7532	9.0251***	0.7666	0.0249***
Log-likelihood	174		−84		126	

Notes: *$P < 0.05$; **$P < 0.01$; ***$P < 0.001$. Using the likelihood ratio test, SFA (3) is preferred over SFA (1) and SFA (2). The Cobb-Douglas specification is rejected in favour of the translog specification.

technical efficiency have a significant impact on the estimated model. The results in Table 2 (SFA 3) show that the long-term debt parameter is negative and statistically insignificant. Short-term debt and investment parameters are negative and statistically significant. This implies that an increase in any of these variables would increase efficiency (reduce inefficiency). We also find that off-farm income is positive and significant while tax liability is negative

Table 3 Production elasticities evaluated at the sample mean for SFA (3)

	CAP	LAB	OEXP	LAND	Return to scale
Mean	0.2431	−0.0027	0.6522	0.1424	1.0351
Standard error	0.0627	0.0039	0.1017	0.0626	

Note: Return to scale is the sum of production elasticities.

and significant. The linear time trend is positive and statistically significant, suggesting that average technical efficiency has decreased over time.

5.2. Technical efficiency scores

Table 4 is a summary of the estimates of average technical efficiency from the parametric and nonparametric models. Column 2 reports the efficiency scores for the stochastic frontier model SFA (3). Columns 3 to 5 are the DEA efficiency scores under VRS, CRS and NIRS (TEV, TEC and TEI), while column 6 shows the scale efficiency (SE) scores.

The estimated technical efficiency scores are comparable across the five models with overall average efficiency scores ranging from 65 to 80 percent. On average, technical efficiency scores from the SFA (3) model and TEV are 77 and 74 percent. Based on the DEA efficiency scores under VRS technology,[15] the percentage of farms on the frontier ranged from a low of 7 percent in 1999 and 2001 to a high of 27 percent in 2002.[16] Except for the SFA (3), all other models indicate that average technical efficiency was lowest in 2000. Average scale efficiency was 88 percent, suggesting that pure technical inefficiency is the main factor hindering farms from operating at an optimal scale.

Table 5 presents the input-oriented bias-corrected technical efficiency scores, under VRS, derived from the bootstrapping procedure with 2000 replications. Overall, the bias-corrected scores are less than the point estimates, a clear indication that the point estimates overstate efficiency. The average bias-corrected technical efficiency is 68 percent, and the confidence interval is wide, 63 to 73 percent, suggesting a high statistical variability of DEA efficiency estimates. The average estimated bias is about 5.88 percent. Overall, the technical efficiency analysis indicates that there are inefficiencies in Broadacre farm production.

The ratios of technical efficiency under CRS (TEC) to technical efficiency under VRS (TEV), and technical efficiency under CRS (TEC) to technical efficiency under NIRS (TEI) can be used to indicate whether the scale

[15] We chose VRS technology because it is the least restrictive compared to NIRS or CRS technologies.

[16] In 1999, 40 out of 496 farms (8 percent) were on the frontier compared to 2001 when 36 out of 498 farms (7 percent) were on the frontier. In 2002, 15 out of 56 farms (27 percent) were on the frontier.

Table 4 SFA and DEA technical efficiency scores, 1995–2005

Year	SFA (3)	TEV	TEC	TEI	SE
1995	0.854	0.8182	0.732	0.808	0.904
1996	0.848	0.8175	0.736	0.800	0.910
1998	0.826	0.7941	0.678	0.767	0.866
1999	0.796	0.7278	0.640	0.724	0.888
2000	0.764	0.6730	0.568	0.662	0.853
2001	0.745	0.6979	0.588	0.690	0.862
2002	0.749	0.7942	0.737	0.775	0.925
2003	0.716	0.6928	0.640	0.679	0.930
2004	0.708	0.7627	0.675	0.739	0.895
2005	0.727	0.8492	0.811	0.838	0.957
Average	0.773	0.735	0.646	0.723	0.888

Notes: SFA (3) are the average technical efficiency scores from the stochastic frontier model 3. 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.

inefficiency is due to small or large scale (i.e $SE1 = TEC/TEV$ and $SE2 = TEC/TEI$). Increasing returns to scale is inferred when $SE2 = 1$ given $SE1 < 1$, and decreasing returns to scale when $SE2 < 1$ given $SE1 < 1$. The analysis reveals that farms operated at a small scale 68 percent of the time, compared to large scale at 27 percent and optimal scale at 5 percent. This lends support to the results from the parametric analysis that, on average, farms exhibited increasing returns to scale.

5.3. Analysis of the determinant of efficiency and financial performance

The goal of the second stage of the nonparametric analysis is to investigate the dependency of the efficiency scores 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.[17] We also estimate two fixed-effects models with the bias-corrected efficiency score (BC-TEV) and return on assets (ROA) as dependent variables. The results are presented in Table 6. To check for robustness, the results from the technical inefficiency effect model of the stochastic frontier model (i.e SFA 3) are compared to those from the DEA stage-two regressions (TEV and BC-TEV) reported in Tables 2 and 6, respectively. We conclude that our results are robust as the sign of the factors that influence TE from both the DEA and SFA models are consistent.

Both fixed-effects and random-effects models were estimated using TEV and ROA as dependent variables, and the Haussman test was used to select the appropriate model. The test returned a $\chi2$ of 14.54 (P = 0.024) for the TEV model and $\chi2$ 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 was rejected and the fixed-effect models are preferred over the random-effects models. 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. Results are reported in Table 6.

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 3 and TEV models, but insignificant for the BC-TEV

Table 6 Results from return on assets and technical efficiency models

Variable	TEV	BC-TEV	SE	ROA
Time	−0.0048***	−0.0068***	0.0044***	−0.0022**
Long-term debt	0.0514	−0.0201	0.0047	−0.1039
Short-term debt	0.2055**	0.0093	0.3102***	−0.4793***
Tax liability	3.6143***	3.0263***	1.0117***	0.2581
Investment	0.6262***	0.3313*	0.3269***	−0.67169***
Off-farm income	−0.0790***	−0.0623***	−0.0551***	−0.0982***
Constant	0.7623***	0.7109***	0.8525***	0.0344***
N	2909	2909	2909	2909
R^2		0.1051		0.3558
Adjusted R^2		0.1032		0.3545
σ_u	0.1277***		0.0987***	
σ_e	0.1633***		0.0991***	

Notes: *P < 0.05; **P < 0.01; ***P < 0.001. 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.

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

model. The negative sign in the SFA 3 model (positive for the TEV model) suggests that an increase in short-term debt would increase technical efficiency (decrease technical inefficiency). Tax liability, investment and off-farm income are statistically significant across the three models and with consistent signs. Increases in either tax liability or investment would increase technical efficiency (reduce technical inefficiency), while increases in off-farm income would have the opposite effect. The time trend is significant in the SFA 3 model and the DEA stage-two models (TEV and BC-TEV). It indicates that, on average, technical efficiency has declined over the sample period.

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, on average, off-farm activities are negatively related to farm scale efficiency. On the other hand, tax liability has a positive correlation while short-term debt and investment drives have a positive effect on scale efficiency. The time trend variable suggests that average optimal scale of farms has been improving over time.

Except for long-term debt and tax liability, all the variables in the ROA model are statistically significant. The positive but insignificant coefficient of tax liability is consistent with *a priori* expectation that tax liability would increase with increase in profits and, therefore, ROA. We also find that increases in short-term debt, investment and off-farm income are negatively related to ROA. This could possibly be because short-term debt involves borrowing to meet the liquidity needs of a farm and results in lower net income; investment increases the capital base of a farm relative to net income, while diversion of farm family labour to off-farm activities may reduce managerial oversight leading to low returns. The positive and significant time trend suggests that average ROA had declined over the sample period, suggesting persistent low-income returns relative to assets held.

6. Concluding remarks

This paper provides one of the first analyses of the impact of debt structure on the financial performance and technical efficiency of Broadacre 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 variation in the DEA deterministic model.

We find evidence that Broadacre farms are not using the best available technology and are consequently operating below the optimal scale. The farms' short-term debt structure has a positive relationship with technical and scale efficiencies, but a negative relationship with ROA. Hence, technical efficiency can be improved by using short-term debt to purchase necessary farm inputs and maintain farm operations. Use of deferred income taxes to finance farm operations would also improve technical efficiency. However, allocation of family time and labour to off-farm activities would reduce technical efficiency. Short-term debt and investment have a negative effect on ROA, while long-term debt has an insignificant effect on farm efficiency and ROA. This may imply that long-term debt does not affect the day-to-day managerial operation activities.

Our results support the assertion by Zhengfei and Lansink (2006) that financial indicators may not fully account for management effort when studying the effect of debt on farms. In our case, the debt structure has a positive relationship with technical efficiency and a negative one with ROA. This relationship implies that lenders will provide short-term credit to farmers who are efficient and with high ROAs, presumably because of their low risk of default. This observation is consistent with the *free cash flow theory* which postulates that the benefits of short-term debt may motivate managers to be more efficient because of the higher interest rate the loans attract relative to long-term debt. Therefore, policy interventions that enable farmers to have access to short-term debt would improve technical efficiency in Broadacre farms of Western Australia. The implication of our results is that the recent (2013) release of concessional loans to farm businesses by the Australian government as a strategy to productivity enhancement and debt restructuring is a move in the right direction. The study points to the need for future research to further explore the relationship between deferred taxes and farm productivity and financial performance. It also points to the need for empirical studies that investigate the effects of increased off-farm employment and income on production efficiency and productivity.

There are several caveats to this analysis. First, we expect variation in weather conditions across regions and seasons and over time. Second, we also expect off-farm income to vary depending on endogenous and exogenous factors such as age of operator or type of off-farm activity. However, we were unable to control for those variations due to data limitations. Third, our sample has a high attrition rate. Conducting this type of analysis with a data sample that is more recent and balanced is an issue for future research too.

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