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Productivity and farm size in Australian agriculture: reinvestigating the returns to scale*

Yu Sheng, Shiji Zhao, Katarina Nossal and Dandan Zhang†

A positive relationship between farm size and farm productivity is often considered to be largely due to increasing returns to scale in farm production. However, using farm-level data for the Australian broadacre industry, we found that constant or mildly decreasing returns to scale is the more typical scenario. In this study, the marginal returns to various farm inputs are compared across farms with different sizes. We found that large farms achieved higher productivity by changing production technology rather than increasing scale alone. The results highlight the disparity between 'returns to scale' and 'returns to size' in the industry, suggesting that productivity improvement among smaller farms can be made through increasing their ability to access advanced technologies, rather than simply expanding their scale.

Key words: agricultural productivity, Australian broadacre agriculture, returns to scale/size, technological progress.

1. Introduction

Since the early 1980s, it has been observed that farm productivity has been increasing and also that the average operating size of farms in the Australian broadacre agricultural industry has also been increasing (Mullen 2007; Nossal and Sheng 2008; Gregg and Rolfe 2010). The relatively large farms in Australia have also demonstrated relatively high rates of return for investment and overall profits (Productivity Commission 2005; ABARES 2007; Nossal *et al.* 2009). A positive relationship has also been found to exist between farm operating size, productivity and other indicators of performance in the United States and European Union (Hallam 1991; Chavas 2001; Mundlak 2005; OECD 2012).

In examining the positive relationship between farm productivity and operating size, a typical explanation for the relatively strong performance of large farms is increasing returns to scale. In brief, the argument is that as

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† Yu Sheng (email: yu.sheng@daff.gov.au) is with the Department of Agriculture, Forestry and Fishery at the Australian Bureau of Agricultural and Resource Economics and Sciences, Canberra, Australia. Shiji Zhao is with the Australian Bureau of Agricultural and Resource Economics, Canberra, Australia. Katarina Nossal is with the International Trade Centre, Geneva, Switzerland. Dandan Zhang is with the National School of Development at Peking University, Beijing, China.

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farms expand their size, gross output increases proportionally more than the change in inputs (Lawrence and Williams 1990; Diewert and Fox 2010; O'Donnell 2010). Economists have therefore questioned the future of the small family farms in Australian agriculture and the ability of smaller farms to adapt to change (Productivity Commission 2005). Of particular interest is their ability to take advantage of emerging opportunities in international markets where large volumes are required and market competition is intense. As such, it is argued that the pace of productivity improvement in the agricultural industry may be hindered by the continued existence of significant numbers of small, yet tightly held family farms.

To justify the role of 'returns to scale' in contributing to the explanation of productivity differences between large and small farms in Australian broadacre industry, researchers and policymakers may need to know more about how large farms have achieved higher productivity than smaller farms. In other words, while the observed positive relationship between productivity and farm size is real, both theoretical and empirical evidence are still required to support the argument that this is because of increasing returns to scale – for example, larger farms are necessarily able to produce more output per unit of inputs solely because they are larger.

In this paper, we examine the theory underlying the relationship between farm productivity and operating size. This provides the context for empirically investigating the effect of returns to scale on productivity, using data from the Australian broadacre industry. According to our results, differences in the farm production technology (measured as input mix), in addition to increasing returns to scale, explains a significant part of productivity differences between large and small farms.[1] This finding suggests that productivity improvements among smaller farms can be achieved through increasing their ability to access advanced technologies, rather than simply expanding their operating scale.

The remainder of the paper is arranged as follows. Section 2 briefly describes Australian broadacre agriculture and its characteristics. Section 3 shows the theoretical relationship between farm productivity and its determinants including operating size, returns to scale and changes in production technology. Section 4 first presents a description of data and then specifies the empirical model used to estimate the contribution of returns to scale to farm productivity. Section 5 discusses our estimation results and findings with regard to farm size, production technology and productivity performance between large and small farms. Section 6 provides conclusions and policy implications.

2. Trends in broadacre agriculture

The Australian broadacre farm sector comprises cropping, mixed crop-livestock, sheep, beef and mixed livestock producers. The sector accounts for

[1] Larger farms tend to use relatively larger proportions of intermediate inputs to substitute labour and capital in production.

around 70 per cent of the output value of Australian agriculture (ABARES 2012). In 2011–2012, the approximately 54,000 broadacre farms that comprise this sector produced output to the gross value of A$36.4 billion. More than two-thirds of total output was exported.

Trends in the number of broadacre farms, their output value (based on farm cash receipts) and total land areas operated are shown in Figure 1. Although the number of broadacre farms in Australia halved between 1977–1978 and 2011–2012, the gross value of output (in real terms) remained relatively stable. Concurrently, the average land area operated per farm increased by 30 per cent and the average total capital value per farm increased 16 times, despite a decline in the total land area operated by broadacre farmers.

Broadacre farms became larger and more capital intensive enterprises on average over the three decades to 2011–2012, with the number of farms with an expected value of operations (EVAO) above A$5,00,000 increasing by 35 per cent, while the number with an output value less than A$1,00,000 fell by 60 per cent.

Farm productivity and size have been compared in a number of previous studies of broadacre agriculture, including Townsend *et al.* (1998), Chavas (2001) and Nossal and Sheng (2010). Larger broadacre farms tend to have significantly higher total factor productivity (TFP) than their smaller counterparts. In previous Australian Bureau of Agricultural and Resource Economics and Sciences (ABARES) studies, the smallest one third quantile of broadacre farmers were found to be least productive on average (Knopke *et al.* 1995; ABARES 2004; Nossal and Sheng 2010). Larger farms have also recorded higher rates of return for investment and profitability compared with smaller farms (Knopke *et al.* 2000; Hooper *et al.* 2002; Gleeson *et al.* 2003; Nossal *et al.* 2009). These findings suggest that increasing farm size may

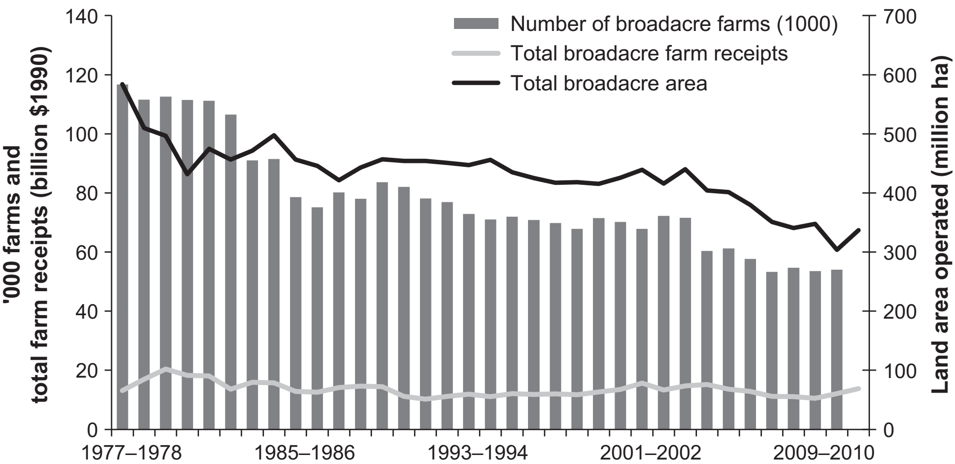

Figure 1 Number of broadacre farms, broadacre farm receipts and total broadacre land area operated (1977–1978 to 2010–2011). Source: ABARES AAGIS data.

be an important factor in explaining the pattern of productivity and profitability of farms in Australia's broadacre agriculture sector (Knopke *et al*. 2000).

Two explanations have typically been offered to explain the positive correlation between farm size and productivity. One is the presence of 'economies of scale' or increasing returns to scale (Knopke *et al*. 1995, 2000; Gregg and Rolfe 2010). The other is that emerging technologies have favoured farms of relatively large size, leading to greater scope for input substitution, and improved access to capital for financing investments in new management and farming practices (Hooper *et al*. 2002; Hughes *et al*. 2012). The following analysis aims to assess each of these explanations from both theoretical and empirical perspectives.

3. A theoretical framework: returns to scale versus returns to size

While the concepts of *returns to scale* and *returns to size* are often used interchangeably in practice, production theory distinguishes between the two under particular conditions. Based on Frisch's (1965) work on the relationship between the production technology and the U-shaped average cost curves, Hanoch (1975) proved that the two concepts are equivalent only if the input usage changes proportionally with size. Later, Chambers (1984) introduced specific production technologies (such as homothetic or ray-homogeneous technologies) to further explain the inter-relationship between the two concepts.

Theoretically, the relationship between returns to size and returns to scale can be summarised using two important theorems (McClelland *et al*. 1988; Boussemart *et al*. 2006; Diewert and Fox 2010; O'Donnell 2010). First, returns to size and returns to scale are equivalent if and only if the production technique is homothetic – a condition where an increase in size is not associated with the changes in the relative proportion of various inputs used in production.[2] Second, elasticity of size is the envelope of elasticity of scale, which implies that returns to size (global concept) is generally greater than returns to scale (local concept).

The literature cited above helps us to distinguish between returns to scale and returns to size. To illustrate how, assume that a farm can produce an output with various inputs using a given production technology;

$$Y = f(X) \tag{1}$$

where Y denotes total output and X denotes a vector of various inputs used in production (such as land, labour, capital and intermediate inputs), and $f(.)$ is

[2] When the output increase is due to a change in the relative proportions of the inputs used in production, one cannot claim it is a result of scale change. Instead, it is widely interpreted as the income effect obtained from input-saving technological progress (Mundlak 2005).

a generalised production function shaping the combination of inputs used to produce output. To establish the relationship between the output level (Y) and farm size (i.e. a proportional increase in all inputs), the generalised production function can be re-formulated as $f(kX) = G[k, X/|X|, f(X)]$, where $|X|$ is the Euclidian norm of the original input vector X, k is a scalar and $X/|X|$ is a ray from the origin in Euclidian N space.

Following McClelland *et al.* (1988), Diewert and Fox (2010) and O'Donnell (2010), it is assumed that production takes a ray-homothetic technology. This gives $G[k, X/|X|, f(X)] = k^{H(X/|X|)} \cdot f(X)$ and thus Equation (1) can be rearranged as:

$$Y = f(kX_0) = k^{H(X/|X|)} \cdot f(X_0) \tag{2}$$

where $H(X/|X|)$ is assumed to be a strictly positive and bounded function.[3]

Differentiating Equation (2) with respect to farm size (k) gives returns to size as $\partial \ln Y / \partial \ln k = H(X/|X|)$. Defining γ as the elasticity of scale (i.e., the proportional change in output resulting from a proportional change in all inputs) and $a \cdot h(X/|X| - 1)$ as the output increase due to the changing relative proportion of inputs used (Färe and Mitchell 1995), the returns to size can be decomposed into two components: returns to scale effect (captured by γ) and the input substitution effect (captured by $a \cdot h(X/|X| - 1)$). The second effect is a result of using different technology. Thus, the returns to farm size under the assumption of profit maximisation can be written as:

$$H(X/|X|) = \gamma + a \cdot h(X/|X| - 1) \tag{3}$$

Alternatively, under the assumption of cost minimisation, the returns to farm size can also be defined using duality theory as the proportional change in output associated with a proportional change in cost, as derived from $Y = TC$. Taking the first order condition leads to $\partial \ln Y / \partial \ln TC = AC/MC = \eta^{-1}$, where AC and MC are farm average and marginal costs, and η is the elasticity of costs (Chambers 1984; Chavas 2001; Mundlak 2005). Applying the duality theorem and under the assumptions of profit maximisation (and cost minimisation) and perfect competition in the output market (or zero profit), Equation (3) can be used to specify the relationship between returns to scale and returns to farm size:

$$\gamma = \eta^{-1} - a \cdot h(X/|X| - 1) \tag{4}$$

Increasing all inputs proportionally gives $h(X/|X| - 1) = 0$. In this case, returns to scale are equivalent to returns to size $\gamma = \eta^{-1}$. Since η^{-1} is always

[3] This assumption is reasonable since the marginal product value of one unit of input should always be equal to its marginal cost. In this paper, we assume that perfect competition holds for factor markets, and thus, marginal input costs are equal for all producers, independent of scale, and hence the marginal product of one unit of input should also be equal for all farms.

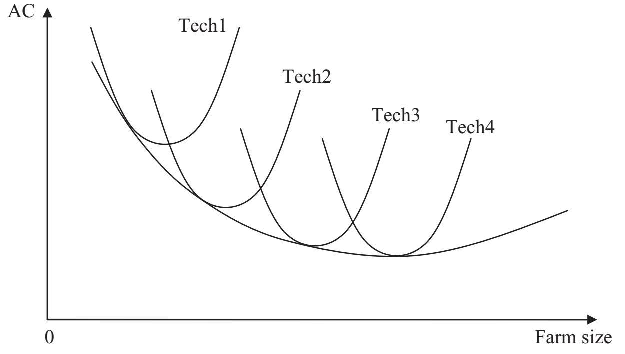

Figure 2 Relationship between farm average cost and operating size

greater than or equal to one in a competitive market (McClelland *et al.* 1988; Diewert and Fox 2010), it follows that increasing returns to scale must occur for production in the longer term.[4] However, if an increase in operating size is associated with some technological change that alters the relative input mix used in production, constant/decreasing returns to scale can coexist with increasing returns to size.

By way of illustration, the relationship between average cost and farm scale and size is shown in Figure 2. For a given technology characterised by a fixed input mix (e.g. Tech1, Tech2, . . .), average cost tends to decrease with scale up to a certain size, beyond which average cost begins to increase.[5] However, as farm size increases, it enables a switch to be made from one technology to another. For example, as farms become larger, farmers tend to able to afford to use more advanced technology in production (through increasing capital investment), which leads to a shift from Tech1 to Tech2. This shift is usually accompanied by some change in input mix (e.g., the capital–labour ratio). As a consequence, average cost can decrease further irrespective of whether increasing returns to scale exist or not. This implies that the benefits of increasing size can be a result of increasing returns to scale or technological progress enabled by increasing size or a combination of both.

The above analysis indicates that in the long run, agriculture may not necessarily experience increasing returns to scale. In fact, limitations in land availability and quality, labour availability, variable and sometimes particularly adverse seasonal conditions and missing markets for other inputs might act to limit the opportunities for increasing returns to scale in the industry. This suggests that the positive relationship between farm size and productivity is more likely to be the result of innovation and technology

[4] Reflecting McClelland *et al.* (1988), $\eta^{-1} = \mu(1 - S_\pi)$, where S_π is the average share of economic profits and μ is the corresponding mark-up of price above marginal cost. In a competitive market, S_π is small and μ is more than or equal to one, and thus $\eta^{-1} > 1$.

[5] Under increasing returns to scale, average cost falls as size increases; under decreasing returns to scale, average cost increase as size increases; and under constant returns to scale, average cost is not affected by operating size.

uptake by farmers as farm size increases (Chavas 2008). Other studies, including McClelland *et al.* (1988), Făre (1988), Basu and Fernald (1997) and Diewert and Fox (2010), have reached a similar conclusion.[6]

4. Data collection and estimation strategy

Drawing on the theoretical framework described above, this section details the farm-level data used to empirically test the relationships between productivity, farm scale and farm size. More specifically, the analysis involves a three-step procedure: (i) estimating the impact of farm size on productivity with a pre-assumed production functional form; (ii) identifying returns to scale when the production technology is restricted to be homogeneous; and (iii) testing for the existence of heterogeneous production technology for farms of different size.

4.1. Data collection and variable definition

The data set used in this study is from the Australian Agricultural and Grazing Industries Survey (AAGIS), which is carried out by the ABARES. The annual survey covers agricultural establishments across five broadacre farm types, including cropping specialists, mixed crop-livestock, sheep specialists, beef specialists and mixed sheep-beef for all Australian states and territories. After eliminating outliers and surveyed farms with missing variables, the sample contained 39,560 observations for the period between 1977–1978 and 2006–2007.

The three major variable types in the analysis were outputs, inputs and farm size category dummies. The dependent variable is output, while inputs and farm size dummies are the independent variables. To eliminate the impact of price changes across establishments, regions and over time, aggregate farm outputs were defined as a Fisher quantity index using prices of 13 output products as weights, while farm inputs were classed into four categories (land, labour, capital, and materials and services) and also aggregated using a Fisher quantity index of inputs estimated and weighted using the prices of 23 inputs. In addition, the Elteto-Koves-Szulc (Elteto and Koves 1964; Szulc 1964) formula was applied in the estimation process for each index to ensure transitivity and thus comparability of total output and various inputs across farms and over time.

To capture the impact of farm size on productivity, farms were categorised by their overall size of production. Specifically, each farm's size was defined

[6] In the context of agricultural production, McClelland *et al.* (1988) and subsequently Färe (1988) acknowledged that the returns to scale concept is too narrow for explaining the differences in performance between large and small sized farms. This discussion is elaborated on by Basu and Fernald (1997), who highlight that technological change and demand shocks can play a role in explaining the higher productivity experienced by larger farms over smaller ones.

Table 1 Broadacre farm output and input indexes by operating size and sectors: 1977–1978 to 2006–2007

	No. of observations	Output index	Land index	Labour index	Capital index	Intermediate inputs index
All broadacre	34,915	1.89 (2.31)	4.58 (16.82)	1.50 (1.21)	1.72 (2.42)	1.80 (2.15)
Small-size farms	10,475	0.38 (0.16)	0.73 (4.06)	0.74 (0.32)	0.53 (0.38)	0.50 (0.32)
Medium-size farms	13,965	1.22 (0.37)	2.62 (9.96)	1.28 (0.61)	1.23 (0.94)	1.26 (0.72)
Large-size farms	10,475	4.29 (2.97)	11.04 (27.06)	2.54 (1.61)	3.55 (3.63)	3.82 (2.90)

Note: Standard errors in parentheses.

according to how much dry sheep equivalents (DSE) it represented, and dummy variables were used to allocate farms to one of three size categories: small, medium and large. A DSE is the quantity of energy required to maintain a 50 kg wether at constant weight (Davies 2005). As such, DSE can be used to derive a measure of the overall physical 'size' of a farm, including some allowance for differences in land quality. Specifically, hectares of rangeland were converted to hectares of arable land by dividing total carrying capacity measured in DSE (where 1 cattle = 8 DSE) by 12 DSE/ha. For cropland, one hectare of cropping land for coarse grain production is equivalent to one unit of DSE (Millear *et al.* 2003).[7] When farms are ranked by size of output (in DSE terms), large farms were those forming the top 30 per cent of the sample in DSE per farm terms, small farms were those in the bottom 30 per cent and medium farms were the remainder. DSE (rather than the total input and output indices) is used as the measure for farm size mainly to avoid a potential multi-collinearity problem in regressions, which may otherwise be caused by the positive relationship between input use and farm size. To check the robustness of this approach, the total input and output Fisher quantity indices were also used to classify the samples into three farm size categories.[8]

Table 1 shows the average total output and various input indices. The table shows that as farm size increases, all input indices increase. Once sample weights are taken into account, medium farms are on average 1.1 times the size of small farms, while large farms are on average 5.1 times larger than small farms. The quantities of inputs used by bigger farms are found not all proportionally larger. In particular, large-sized farms tend to use more land and materials and services and have a higher capital to labour ratio relative to small farms. Over the study period, the average capital–labour ratio and materials–labour ratio for large farms were 1.2 and 1.6, which are 50 per cent and 100 per cent more than those for small farms (0.79 and 0.74) and 20

[7] Although the DSE was initially designed to measure the carrying capacity of grazing farms, it is widely used to measure the size of broadacre farms including their cropping activities.

[8] Results are available upon request.

per cent and 40 per cent more than those for medium farms (0.97 and 1.06). This is consistent across each of the broadacre farm types, indicating there are likely to be differences in the production technology used by large and small farms. All indices imply that the assumption of homothetic production technology across farms with different operating size might be invalid.

4.2. Empirical model specification

In order to examine the impact of size on farm productivity (output per unit of input), we first specify a production function for broadacre farms using the homothetic production technology locally. For simplicity, a Cobb-Douglas functional form is chosen for approximation, and two dummy variables for the medium-sized and large-sized farms are incorporated into the empirical specification, such that:

$$\begin{aligned}\ln Y_{it} = {} & \beta_0 + \beta_1 \ln Land_{it} + \beta_2 \ln Labour_{it} + \beta_3 \ln Capital_{it} + \beta_4 \ln Materials_{it} \\ & + \beta_5 DM_{it} + \beta_6 DL_{it} + \sum \theta_t D\_Year_t + \sum \vartheta_r D\_Region_r \\ & + \sum \kappa_i D\_Industry_i + \varepsilon_{it} \qquad (5)\end{aligned}$$

where Y_{it} represents farmer i's output at time t, and $\ln Land_{it}$, $\ln Labour_{it}$, $\ln Capital_{it}$ and $\ln Materials_{it}$ represent the log of land, labour, capital and materials and services. DM_{it} takes the value of one if farm i at time t is classified as the medium-sized farm and zero otherwise. Similarly, DL_{it} takes the value of one if farm i at time t is classified as the large-sized farm and zero otherwise.

It should be noted that the empirical specification contains three groups of dummy variables: $\sum \vartheta_r D\_Region_r$, $\sum \kappa_i D\_Industry_i$ and $\sum \theta_t D\_Year_t$. The dummy variables for industry $\left(\sum \kappa_i D\_Industry_i\right)$ and region $\left(\sum \vartheta_r D\_Region_r\right)$ are used to account for possible aggregation problems that may be associated with pooling farms that produce different products in different regions, while the dummy variables for year $\left(\sum \theta_t D\_Year_t\right)$ are used to account for time-specific factors such as climate conditions and the terms of trade.

Estimation of Equation (5) using the ordinary least squares (OLS) regression technique may be biased because of a potential endogeneity problem. Specifically, there are many unobserved, time-invariant, farm-specific characteristics (such as farmers' education levels, management skills and other omitted factors) that could improve farm performance while being positively correlated with farm size (Zhao *et al.* 2010). Without controlling for these factors, the regression estimates are likely to be overestimated or underestimated depending on their correlation with inputs. To deal with this problem, previous studies have suggested three possible regression techniques: first-differencing (FD), panel data with fixed effects (FE) and the generalised method of moments (GMM; Arellano and Bond 1991; Windmeijer 2005; Greene 2008). The FD and FE regression techniques are both criticised on the basis that they mainly reflect short-term effects and hence may not be suitable for the examination of benefits to farms from returns to scale, which usually occur over a long period of time (Basu 2008). Thus, we choose the GMM regression technique to address potential endogeneity problems and also use the FD and FE methods as robustness checks.

Equation (5) can be used for three purposes. The first is to examine the relationship between farm size and productivity, the second is to examine whether farms can benefit from increasing returns to scale (when imposing the conditions of $\beta_5 = 0$ and $\beta_6 = 0$), and the third is to examine the relative contribution of returns to scale to the observed productivity disparity between farms of different sizes. For the second purpose, a Chow test should be conducted to verify the hypothesis of $\beta_1 + \beta_2 + \beta_3 + \beta_4 > 1$ (Basu 2008). If the sum of estimated input elasticities (land, labour, capital and intermediate input) is greater than one, increasing returns to scale prevail.

Furthermore, we hope to establish whether or not the production technology is homothetic for farms of varying size. This is an important test because from Equation (4), if farms of different sizes do not use the homothetic production technology, increasing returns to scale will not be a necessary condition for larger farms to perform better than smaller ones. To perform this test, Equation (5) was revised by introducing the interaction of the two dummy variables (for medium and large-sized farms respectively) with input variables for land, labour, capital and intermediate inputs:

$$\begin{aligned}\ln Y_{it} = {} & \beta_0 + \beta_1 \ln Land_{it} + \beta_2 \ln Labour_{it} + \beta_3 \ln Capital_{it} + \beta_4 \ln Materials_{it} \\ & + \alpha_{11} DM_{it} + \alpha_{12} DM_{it}\_\ln Land_{it} + \alpha_{13} DM_{it}\_\ln Labour_{it} \\ & + \alpha_{14} DM_{it}\_\ln Capital_{it} + \alpha_{15} DM_{it}\_\ln Materials_{it} \\ & + \alpha_{21} DL_{it} + \alpha_{22} DL_{it}\_\ln Land_{it} + \alpha_{23} DL_{it}\_\ln Labour_{it} \\ & + \alpha_{24} DL_{it}\_\ln Capital_{it} + \alpha_{25} DL_{it}\_\ln Materials_{it} \\ & + \sum \theta_t D\_Year_t + \sum \vartheta_r D\_\mathrm{Region}_r + \sum \kappa_i D\_Industry_i + u_i + \varepsilon_{it}\end{aligned} \tag{6}$$

where $DM_{it}\_\ln Land_{it}$, $DL_{it}\_\ln Land_{it}$, $DM_{it}\_\ln Labour_{it}$, $DL_{it}\_\ln Labour_{it}$, $DM_{it}\_\ln Capital_{it}$, $DL_{it}\_\ln Capital_{it}$, $DM_{it}\_\ln Materials_{it}$ and $DL_{it}\_\ln Materials_{it}$ are interaction terms between DM_{it}, DL_{it} and land, labour, capital, and materials and services.

To see how Equation (6) works for the test, one can take the first differentiation of Equation (5) with respect to land, labour, capital, and materials and services, respectively. Under the assumption of perfect competition in the product and input markets, the condition $\beta_i / X_i = P_{X_i} / P_Y$ always holds, where β_i is the marginal output of input X_i (i represents land, labour, capital, and combined materials and services) and P_{X_i} / P_Y is the price of inputs relative to that of outputs. Since farms of different sizes face the same relative prices of inputs and outputs (P_{X_i} / P_Y), any difference in the marginal output of each farm input will reflect a difference in the mix of inputs used in production $X_i^L/X_i^S = \beta_i^L/\beta_i^S$ (Basu 2008). In other words, as farms become larger, only a disproportional change in the use of inputs in production will lead to a change in the marginal return to those inputs (or coefficients) in a perfectly competitive market. Thus, the null hypothesis is that if the production technology is homothetic, there would not be a significant difference in the estimated relative elasticities for each input (including land, labour, capital, and materials and services) between large and small farms. This is captured by identifying the significance of the interactions between the farm size dummies and input variables.

Finally, it could be argued that the Cobb-Douglas production function is too restrictive to reflect all other locally homothetic production technologies. In order to extend the empirical test to a more general framework, we also applied a trans-log production function to the data, with specific constraints imposed to ensure the homothetic production technology. A series of robustness checks were also carried out for each of the five farm types in the broadacre sector.

5. How does farm size affect productivity?

The estimated results for the broadacre sector as a whole and for individual industries are shown in Tables 2–5.

5.1. Farm productivity and returns to scale and to size

First, Table 2 illustrates the impact of farm size on broadacre farm productivity based on the results of Equation (5), assuming homogeneous production technology across farms of different sizes. After controlling for land, labour, capital, and materials and services, the estimated elasticities of farm output with respect to size category are positive and significant at the 1 per cent level. The magnitudes of elasticities estimated from the OLS regression show that medium and large farms have on average 32.3 per cent and 53.5 per cent higher output (when variations in input use are controlled for) than small farms. This result suggests that larger farms are more productive than smaller ones.

As mentioned in Section 4, the coefficients from the OLS regression may be over- or underestimated, because of endogeneity caused by unobserved farm-specific factors. To deal with this problem, the FD, FE and system-GMM regression techniques were used to re-examine the input-output relationships for broadacre farms. Compared with those from the OLS regression (Table 2), the estimated coefficients from the FD, FE and system-GMM regressions are smaller, indicating the existence of some endogeneity bias in the OLS regression results caused by the presence of unobserved farm-specific factors that contribute to farm productivity, which are also correlated with farm size. Nonetheless, the estimated elasticities of farm output with respect

Table 2 Estimation of the input–output relationships for all broadacre farms, 1977–1978 to 2006–2007

	OLS	FD	FE	System-GMM
Dependent variable: ln_*output*				
ln_*land*	0.036*** (0.000)	0.076*** (0.002)	0.033*** (0.005)	0.025*** (0.000)
ln_*labour*	0.124*** (0.001)	0.113*** (0.002)	0.179*** (0.016)	0.117*** (0.002)
ln_*capital*	0.360*** (0.001)	0.240*** (0.001)	0.235*** (0.009)	0.348*** (0.001)
ln_*materials*	0.385*** (0.002)	0.165*** (0.002)	0.195*** (0.022)	0.423*** (0.002)
Medium_Size_Dummy	0.323*** (0.001)	0.188*** (0.001)	0.206*** (0.014)	0.312*** (0.001)
Large_Size_Dummy	0.535*** (0.002)	0.445*** (0.003)	0.425*** (0.021)	0.513*** (0.002)
Constant	−0.315*** (0.017)	−0.194*** (0.023)	−0.217*** (0.026)	−0.279*** (0.024)
No. of observations	36,129	23,796	36,129	23,796
R^2 or adjusted R^2	0.812	0.262	0.826	0.8529
F-statistics/Wald test χ^2	15678.0	8229.3	122.6	2163.8
LM statistic (under-identification)	—	—	—	94000.0
Wald F statistic (weak identification)	—	—	—	9246.9

Note: *, ** and *** represent statistical significance at the 10%, 5% and 1% level, respectively. Dummy variables for industries, states and years have also been controlled, and they are jointly significant at the 1% level. FD, first-differencing; FE, fixed effects; GMM, generalised method of moments; OLS, ordinary least squares.

Table 3 Returns to scale for all broadacre farms, 1977–1978 to 2006–2007

	OLS	FD	FE	System-GMM
Dependent variable: ln_*output*				
ln_*land*	0.082*** (0.000)	0.092*** (0.002)	0.040*** (0.006)	0.064*** (0.000)
ln_*labour*	0.167*** (0.001)	0.121*** (0.002)	0.200*** (0.017)	0.157*** (0.002)
ln_*capital*	0.387*** (0.001)	0.232*** (0.001)	0.230*** (0.009)	0.383*** (0.002)
ln_*materials*	0.444*** (0.002)	0.171*** (0.002)	0.208*** (0.023)	0.490*** (0.002)
Constant	0.015*** (0.000)	−0.189*** (0.024)	0.005*** (0.000)	−0.373*** (0.003)
No. of observations	36,129	23,796	36,129	23,796
R^2 or adjusted R^2	0.7977	0.2419	0.81	0.8394
F-statistics	2610.0	98.7	114.1	1672.5
LM statistic (under-identification)	—	—	—	1482.3
F statistic (weak identification)	—	—	—	73.5
H0: Increasing return to scale	1.080	0.617	0.678	1.094
IRTS and CRTS (Wald test at 1% level)	Not rejected	Rejected	Rejected	Not rejected

Note: *, ** and *** represent statistical significance at the 10%, 5% and 1% level, respectively. Dummy variables for industries, states and years have also been controlled, and they are jointly significant at the 1% level. FD, first-differencing; FE, fixed effects; GMM, generalised method of moments; OLS, ordinary least squares.

Table 4 Production technology and farm size: all broadacre farms, between 1977–1978 to 2006–2007

	OLS	FD	FE	System-GMM
Dependent variable: ln_*output*				
ln_*land*	0.061*** (0.001)	0.059*** (0.002)	0.032*** (0.009)	0.052*** (0.001)
ln_*labour*	0.089*** (0.001)	0.115*** (0.002)	0.158*** (0.021)	0.056*** (0.002)
ln_*capital*	0.389*** (0.001)	0.256*** (0.001)	0.296*** (0.015)	0.388*** (0.002)
ln_*materials*	0.374*** (0.002)	0.147*** (0.002)	0.218*** (0.033)	0.382*** (0.003)
Medium_Size_Dummy	0.208*** (0.002)	0.240*** (0.003)	0.198*** (0.022)	0.229*** (0.003)
Large_Size_Dummy	0.425*** (0.003)	0.483*** (0.006)	0.460*** (0.032)	0.437*** (0.004)
Medium_Size_Dummy × ln_*land*	−0.052*** (0.001)	0.028*** (0.001)	0.001 (0.009)	−0.068*** (0.001)
Medium_Size_Dummy × ln_*labour*	0.102*** (0.003)	0.001 (0.003)	0.017 (0.029)	0.158*** (0.004)
Medium_Size_Dummy × ln_*capital*	−0.073*** (0.002)	−0.024*** (0.002)	−0.073*** (0.018)	−0.111*** (0.003)
Medium_Size_Dummy × ln_*materials*	−0.010** (0.004)	0.022*** (0.004)	−0.008 (0.037)	0.044*** (0.004)
Large_Size_Dummy × ln_*land*	−0.039*** (0.001)	0.035*** (0.003)	−0.002 (0.011)	−0.042*** (0.001)
Large_Size_Dummy × ln_*labour*	0.083*** (0.003)	−0.031*** (0.005)	0.043 (0.033)	0.111*** (0.004)
Large_Size_Dummy × ln_*capital*	−0.129*** (0.003)	−0.106*** (0.003)	−0.108*** (0.021)	−0.119*** (0.004)
Large_Size_Dummy × ln_*materials*	0.097*** (0.005)	0.118*** (0.009)	−0.051 (0.043)	0.114*** (0.005)
Constant	−0.195*** (0.002)	−0.221*** (0.002)	−0.193*** (0.031)	−0.347*** (0.004)
No. of observations	36,129	23,796	36,129	23,796
R^2 or adjusted R^2	0.8136	0.2643	0.8287	0.8541
F-statistics	2697.9	6769.6	108.23	7900.00
LM statistic (under-identification)	—	—	—	1084.973
F statistic (weak identification)	—	—	—	73.5
H0: no change in input mixture for median farms	Rejected	Rejected	Rejected	Rejected
Wald test	243.52	132.77	234.01	248.62
H0: no change in input mixture for large farms	Rejected	Rejected	Rejected	Rejected
Wald test	223.88	413.51	210.92	261.52

Note: *, ** and *** represent statistical significance at the 10%, 5% and 1% level, respectively. Dummy variables for industries, states and years have also been controlled, and they are jointly significant at the 1% level. FD, first-differencing; FE, fixed effects; GMM, generalised method of moments; OLS, ordinary least squares.

to size from the FD, FE and system-GMM regressions remain positive and significant at the 1 per cent level. This result confirms the finding that larger farms perform better than smaller ones in terms of productivity.

The second task was to test whether the higher productivity of large farms is caused by increasing returns to scale under the assumption of the use of the Cobb-Douglas production function. The null hypothesis is that there are increasing returns to scale if and only if the elasticities of land, labour, capital, and materials and services add up to more than one (when coefficients for the size dummies are constrained to be zero). The Chow test was conducted to test this hypothesis, using the OLS, FD, FE and system-GMM regression techniques. The Chow test results for the null hypothesis (the presence of increasing returns to scale) are mixed across different regressions (Table 3). Specifically, the estimation results obtained from the OLS and system-GMM regressions show that broadacre farms exhibit increasing returns to scale while those obtained from the FD and FE regressions show that broadacre farms do not exhibit increasing returns to scale.

Further analysis of the measured increasing returns to scale obtained from the OLS and system-GMM regressions – namely the sum of all input coefficients (Table 3) – shows that the magnitude of benefit from this effect is not large enough to explain the disparity in productivity between large and small farms. On average, farms that double their use of inputs will increase TFP by 8.0 per cent to 9.0 per cent. This, combined with the average difference in farm size among small, medium (1.1 times of small farms) and large farms (5.1 times of small farms), suggests that returns to scale can only raise the TFP of medium and large farms by 3.8–10.2 per cent and 17.3–45.8 per cent, which are much lower than what we have found in Table 2 (namely 18.8–32.3 per cent and 42.5–53.5 per cent). In other words, the existence of increasing returns to scale does not adequately explain the differences in productivity between large and small farms.

5.2. Homothetic versus non-homothetic production technology

If productivity differences among small, medium and large farms cannot be fully explained by increasing returns to scale, what is the cause of the remaining differences? Equation (4) shows that returns to size and returns to scale can diverge from each other if the production technology is

Table 5 Test for homothetic production technology with the trans-log function

	OLS	FD	FE	System-GMM
Dependent variable: ln_*output*				
H0: homothetic production technology	Rejected	Rejected	Rejected	Rejected
Wald test χ^2	78.54	62.10	61.30	115.02

Note: FD, first-differencing; FE, fixed effects; GMM, generalised method of moments; OLS, ordinary least squares.

non-homothetic. In other words, if the use of different production technologies allows large farms to use a different input mix from small farms (when faced with the same relative prices of various inputs), the difference in production technology could be an explanation for the productivity difference. Based on Equation (6), we test this hypothesis by introducing interaction terms between farm size dummies and the various inputs.

The estimated coefficients for the interaction terms between size category and the various inputs are jointly significant at the 1 per cent level (Table 4). This implies that the marginal outputs of (and thus the use of) various inputs on large and medium farms are different to those that apply on small farms. Compared with small farms, the marginal output of the land and capital inputs on medium and large farms are smaller, while the marginal outputs of labour and materials and services in medium and large farms are larger, suggesting that large and small farms have adopted different input mix and production technologies (or the production technology is non-homothetic given their different input mixes). In particular, large and medium farms tend to use more labour and materials and services but fewer land and capital inputs per unit of output. In other words, larger farms tend to substitute land and capital for materials and services. The above results are consistent with the estimation using the trans-log function, where the null hypothesis of farms using the homothetic production technology (from Kim 1992) is rejected at the 1 per cent level regardless of estimation techniques (Table 5).

A possible explanation for the findings in Table 4 is that as farms become larger, they can afford to invest in more advanced production technologies, which help to push their production frontier outwards. In this context, technological progress and farmers' financial capacity are likely to be two important factors determining the relationship between farm size and productivity, rather than increasing returns to scale alone.

5.3. Robustness check with different farm types

It is also possible that the above findings could partly be the result of an aggregation problem. In particular, as argued by Griliches (1957) and Basu and Fernald (1997), the use of different production techniques by different farm types (such as crops, beef or sheep) may lead to an over- or underestimation of marginal output with respect to inputs that are influenced by the aggregation method. Also, the various industries may be comprised of farms of different sizes that employ different production technologies. For example, sheep and beef specialists could be very different from cropping specialists in size and may use more labour in production. A regression that includes farms which are of different types (cropping or livestock) or sizes unrealistically assumes that they all use a homothetic production technology. To avoid this aggregation problem, the estimation process was repeated using data for each individual farm type using the three estimation techniques (FD, FE and system-GMM). For simplicity, only the estimation results from the system-GMM regressions are reported since system-GMM is the preferred estimation technique. The estimation results are shown in Tables 6–8, and three key findings are worth noting.

First, similar to the previous results, large farms in each industry are shown to have higher productivity than small farms. As shown in Table 6, the estimated elasticities of the size dummies for large farms are much larger than those of medium farms (and all are positive and significant at the 1 per cent level). This implies that there is a positive relationship between farm size and productivity for each farm type.

Second, although the estimated elasticities of various inputs differ across farm types, the sum of these elasticities is close to one for crop specialists and beef specialists. However, the crop-livestock mixed farms and sheep specialists exhibit significant increasing returns to scale at the 1 per cent level. After addressing the endogeneity problem through the system-GMM regressions, the sum of input elasticities (under the assumption of homogeneous production technology) is marginally above unity (around 1.06) for the crop specialists, the crop-livestock mixed farms and the beef specialists. The null hypotheses for increasing returns to scale among the crop specialists and the beef specialists are rejected at the 1 and 5 per cent levels. This suggests that evidence of increasing returns to scale is not strong among farms of particular types (namely crop specialists, crop-livestock mix, sheep specialist and beef specialists). Hence, increasing returns to scale cannot explain the disparity in productivity among farms of different sizes, although differences across industries are significant.

Third, there are significant differences in input mix among farms of different sizes in each industry. In particular, large and medium crop specialists are generally more intensive in the use of materials and services and less in the use of land and labour relative to smaller ones, while larger sheep specialists tend to be more intensive in the use of labour relative to the use of land and capital. This finding suggests that farms employ different technologies as they become larger. In other words, technology differences, rather than returns to scale, are more likely to be responsible for the gap in productivity between farms of different sizes.

In sum, Australian broadacre farms have been found to exhibit only mildly increasing returns to scale. This is true for estimation using the whole sample and when only considering farms of a particular type. However, larger farms are observed to display significantly higher productivity than their smaller counterparts. This suggests that adoption of different production technologies among farms of different size, rather than size itself, plays a more important role in explaining the productivity differences between large and small farms.

6. Concluding remarks

This paper examines the relationship between the productivity and operating size of Australian broadacre farms. While the benefits of increasing farm size

Table 6 Estimation of the input–output relationship by broadacre farm type: 1977–1978 to 2006–2007

	Crop specialists	Crop-livestock mix	Sheep specialists	Beef specialists
Dependent variable: ln_*output*				
ln_*land*	0.028*** (0.001)	0.036*** (0.001)	0.016*** (0.001)	0.004*** (0.001)
ln_*labour*	0.208*** (0.007)	0.129*** (0.003)	0.161*** (0.003)	0.082*** (0.002)
ln_*capital*	0.188*** (0.004)	0.195*** (0.002)	0.294*** (0.002)	0.497*** (0.003)
ln_*materials*	0.426*** (0.009)	0.461*** (0.002)	0.484*** (0.003)	0.315*** (0.003)
Medium_Size_Dummy	0.372*** (0.005)	0.322*** (0.003)	0.392*** (0.003)	0.401*** (0.004)
Large_Size_Dummy	0.585*** (0.009)	0.611*** (0.005)	0.527*** (0.007)	0.585*** (0.007)
Constant	−0.575*** (0.009)	−0.548*** (0.006)	−0.490*** (0.007)	−0.421*** (0.007)
No. of observations	4217	5565	4470	6320
R^2 or adjusted R^2	0.787	0.851	0.891	0.871
F-statistics/Wald Test	21401.9	42418.0	39259.4	31029.8
LM statistic (under-identification)	3649.8	61000.0	38000.0	53000.0
Wald *F* statistic (weak identification)	495.5	3057.8	893.1	9150.7

Note: *, ** and *** represent statistical significance at the 10%, 5% and 1% level, respectively. Dummy variables for states and years have also been controlled, and they are jointly significant at the 1% level.

Table 7 Returns to scale by broadacre farm type: 1977–1978 to 2006–2007

	Crop specialists	Crop-livestock mix	Sheep specialists	Beef specialists
Dependent variable: ln_*output*				
ln_*land*	0.112*** (0.002)	0.080*** (0.001)	0.038*** (0.001)	0.065*** (0.001)
ln_*labour*	0.234*** (0.007)	0.210*** (0.003)	0.212*** (0.003)	0.088*** (0.002)
ln_*capital*	0.226*** (0.005)	0.237*** (0.002)	0.338*** (0.003)	0.533*** (0.003)
ln_*materials*	0.484*** (0.009)	0.536*** (0.002)	0.583*** (0.003)	0.373*** (0.003)
Constant	−0.146*** (0.010)	−0.188*** (0.005)	−0.246*** (0.007)	−0.109*** (0.006)
No. of observations	4217	5565	4470	6320
R^2 or adjusted R^2	0.768	0.837	0.875	0.860
F-statistics	17664.3	36021.8	35167.0	25220.9
Kleibergen-Paap rk LM statistic (under-identification test)	3724.3	60000.0	39000.0	52000.0
Kleibergen-Paap rk Wald *F* statistic (weak identification test)	772.9	3736.2	1681.3	11000.0
H0: increasing returns to scale	1.057	1.063	1.171	1.060
IRTS and CRTS (Wald test at 1% level)	7.1	69.2	263.7	4.7

Note: *, ** and *** represent statistical significance at the 10%, 5% and 1% level, respectively. Dummy variables for states and years have also been controlled, and they are jointly significant at the 1% level.

Table 8 Production technologies and farm size by broadacre farm types: 1977–1978 to 2006–2007

	Crop specialists	Crop-livestock mix	Sheep specialists	Beef specialists
Dependent variable: ln_output				
ln_land	0.080*** (0.005)	0.076*** (0.002)	0.032*** (0.001)	0.072*** (0.001)
ln_labour	0.218*** (0.011)	0.047*** (0.005)	0.071*** (0.003)	0.088*** (0.003)
ln_capital	0.185*** (0.009)	0.169*** (0.004)	0.315*** (0.003)	0.531*** (0.003)
ln_materials	0.337*** (0.014)	0.441*** (0.004)	0.549*** (0.004)	0.250*** (0.003)
Medium_Size_Dummy	0.204*** (0.015)	0.260*** (0.006)	0.136*** (0.006)	0.166*** (0.006)
Large_Size_Dummy	0.314*** (0.014)	0.422*** (0.008)	0.462*** (0.019)	0.505*** (0.008)
Medium_Size_Dummy × ln_land	−0.087*** (0.006)	−0.065*** (0.002)	−0.049*** (0.002)	−0.154*** (0.003)
Medium_Size_Dummy × ln_labour	−0.022 (0.016)	0.123*** (0.007)	0.386*** (0.008)	−0.037*** (0.008)
Medium_Size_Dummy × ln_capital	−0.007 (0.011)	0.078*** (0.005)	−0.142*** (0.006)	−0.104*** (0.007)
Medium_Size_Dummy × ln_materials	0.163*** (0.016)	0.049*** (0.006)	−0.241*** (0.008)	0.147*** (0.008)
Large_Size_Dummy × ln_land	−0.058*** (0.005)	−0.087*** (0.002)	−0.052*** (0.003)	−0.099*** (0.003)
Large_Size_Dummy × ln_labour	−0.114*** (0.014)	0.294*** (0.011)	0.252*** (0.021)	−0.125*** (0.013)
Large_Size_Dummy × ln_capital	0.041*** (0.010)	0.064*** (0.008)	−0.176*** (0.012)	−0.132*** (0.011)
Large_Size_Dummy × ln_materials	0.276*** (0.015)	−0.021** (0.010)	−0.125*** (0.014)	0.243*** (0.011)
Constant	−0.493*** (0.015)	−0.513*** (0.007)	−0.375*** (0.008)	−0.307*** (0.007)
No. of observations	4217	5565	4470	6320
R^2 or adjusted R^2	0.789	0.852	0.893	0.873
F-statistics	20686.1	38516.7	37096.3	29860.6
Kleibergen-Paap rk LM statistic (under-identification test)	10000.0	30000.0	8491.0	5993.9
Kleibergen-Paap rk Wald F statistic (weak identification test)	113.0	1285.2	60.8	160.2
H0: no change in input mixture for median farms	Rejected	Rejected	Rejected	Rejected
Wald test for homothetic technology	19.5	1075.2	74.8	290.4
H0: no change in input mixture for large farms	Rejected	Rejected	Rejected	Rejected
Wald test for homothetic technology	222.2	981.9	62.8	189.7

Note: *, ** and *** represent statistical significance at the 10%, 5% and 1% level, respectively. Dummy variables for states and years have also been controlled, and they are jointly significant at the 1% level.

have often been attributed to increasing returns to scale, the results from this analysis suggest that this might not be the case. Australian broadacre farms typically exhibit only mildly increasing returns to scale, suggesting that there is a more complex relationship between farm size and productivity. Although larger farms tend to perform better in terms of productivity, it has been found that these productivity differences are more likely to be caused by differences in production technology rather than returns to scale. The results demonstrate the importance in distinguishing between 'returns to scale' and 'returns to size'.

Our findings suggest that smaller farms have limited capability to improve productivity by increasing their size, unless they are able to adopt different technologies. However, adopting advanced technologies involves more than just purchasing and learning how to operate equipment suitable for a larger operating size. For example, farmers need to acquire the knowledge and skills to deal with the more complex management, financial, technical and operational matters that are associated with the operation of large farms. This is not necessarily a straightforward process, and like any other kinds of transformation in the rural economy, its success depends on many conditions, including the availability and accessibility of financial, human, social, and natural capital (Ellis 2000).

Our findings are also relevant when considering the ongoing structural adjustment that is occurring in the broadacre agriculture sector. As circumstances change, it is important for farms to develop the capabilities and resources required to cope with climate change and other challenges. Specifically, regardless of size, farmers' ability to adopt suitable production technology is essential to maintain productivity performance and to be resilient in the face of challenges. In this context, governments can play a role by promoting innovation adoption – for example, through building capacity, sharing information, supporting training and facilitating R&D.

References

ABARES (2004). *Australian Beef Industry Productivity*, Australian Beef 04.2, Canberra, November.

ABARES (2012). *Australian Commodity Statistics*, ABARES, December 2012, Canberra.

Arellano, M. and Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations, *Review of Economic Studies* 58, 277–297.

Basu, S. (2008). Returns to scale measurement, in Durlauf, S.N. and Blume, L.E. (eds), *The New Palgrave Dictionary of Economics*, 2nd edn. The Palgrave Macmillan, New York.

Basu, S. and Fernald, J.G. (1997). Returns to scale in U.S. production: estimates and implications, *Journal of Political Economy* 105, 249–283.

Boussemart, J.P., Briecy, W., Peypoch, N. and Tavera, C. (2006). Characterizing strictly increasing and decreasing returns to scale in multi-output production technologies, *Management Science* 34, 1507–1511.

Chambers, R. (1984). *Some Conceptual Issues in Measuring Economies of Size, Economics of Size Studies*. Center for Agricultural and Rural Development, Iowa State University, Ames, IA.

Chavas, J.P. (2001). Structural change in agricultural production: economics, technology and policy, in Gardner, B. and Rausser, G. (eds), *Handbook in Agricultural Economics*, Vol. 1. Elsevier Science, Amsterdam, pp. 263–285.

Chavas, J.P. (2008). On the economics of agricultural production, *Australian Journal of Agricultural and Resource Economics* 52, 365–380.

Davies, L. (2005). Using DSEs and carrying capacities to compare beef enterprises, NSW Department of Primary Industries. Available from URL: www.agric.nsw.gov.au/reader/beefbudinfo/dse-carrying-capacity.htm [accessed 10 Mar 2012].

Diewert, W.E. and Fox, K. (2010). Malmquist and Tornqvist productivity indexes: returns to scale and technical progress with imperfect competition, *Journal of Econometrics* 101, 73–95.

Ellis, F. (2000). *Rural Livelihoods and Diversity in Developing Countries*. Oxford University Press, Oxford, UK.

Elteto, O. and Koves, P. (1964). [On an index number computation problem in international comparison], *Statisztikai Szemle* 42, 507–518 (in Hungarian).

Färe, R. and Mitchell, T. (1995). Multiple outputs and 'homotheticity', *Southern Economic Journal* 60, 287–296.

Fǎre, R. (1988). *Fundamentals of Production Theories*. Springer-Verlag, Berllin.

Frisch, R. (1965). *Theory of Production*. Rand-McNally, Chicago, IL.

Gleeson, T., McDonald, D., Hooper, S. and Martin, P. (2003). *Australian Beef Industry* 2003. Canberra, ABARE Research Report 03.3.

Greene, W. (2008). *Econometric Analysis*, 7th edn. New York University, Prentice Hall, Upper Saddle River, New Jersey.

Gregg, G. and Rolfe, J. (2010). Identifying sources and trends for productivity growth in a sample of Queensland broadacre beef enterprises, *Animal Production Science* 51, 443–453.

Griliches, Z. (1957). Hybrid Corn: An exploration in the economics of technological change, *Econometrica* 25, 501–522.

Hallam, A. (1991). Economies of size and scale in agriculture: an interpretive review of empirical measurement, *Review of Agricultural Economics* 13, 155–172.

Hanoch, G. (1975). The elasticity of scale and the shape of average costs, *American Economic Review* 65, 492–497.

Hooper, S., Martin, P., Love, G. and Fisher, B. (2002). Farm size and productivity: where are the trends taking us? *Australian Commodities* 9, 495–500.

Hughes, N., Lawson, K., Davidson, A., Jackson, T. and Sheng, Y. (2012). Productivity: where are the trends taking us?, *Australian Commodities* 19, 495–500.

Kim, H.Y. (1992). The translog production function and variable returns to scale, *The Review of Economics and Statistics* 74, 546–552.

Knopke, P., Strappazzon, L. and Mullen, J. (1995). Productivity growth: total factor productivity on Australian broadacre farms, *Australian Commodities* 2, 486–497.

Knopke, P., O'Donnell, V. and Shepherd, A. (2000). *Productivity Growth in the Australian Grains Industry*. ABARE, Canberra.

Lawrence, G. and Williams, C. (1990). Productivity growth: total factor productivity on Australian broadacre farms, in Cullen, T., Dunn, P. and Lawrence, G. (eds), *Rural Health and Welfare in Australia*. Centre for Rural Welfare Research, Charles Stuart University, Wagga Wagga, pp. 38–59.

McClelland, J.W., Wetzstein, M.E. and Musser, W.N. (1988). Returns to scale and size in agricultural economics, *Western Journal of Agricultural Economics* 11, 129–133.

Millear, G., Conway, A. and Mills, T. (2003). *Calculating a Gross Margin for Sheep, Goat and Cattle Enterprises*. Brisbane, Queensland Government: Department of Primary Industries and Fisheries. Retrieved 2006-10-18.

Mullen, J.D. (2007). Productivity growth and the returns from public investment in R&D in Australian broadacre agriculture, *Australian Journal of Agricultural and Resource Economics* 51, 359–384.

Mundlak, Y. (2005). Economic growth: lessons from two centuries of American agriculture, *Journal of Economic Literature* 43, 989–1024.
Nossal, K. and Sheng, Y. (2008). Productivity in the beef cattle and slaughter lamb industries. ABARES Research Report for Australian Meat and Livestock Association, Canberra, ABARE Report No. 08.13.
Nossal, K. and Sheng, Y. (2010). Productivity growth: trends, drivers and opportunities for broadacre and dairy industries, *Australian Commodities* 17, 216–230.
Nossal, K., Zhao, S., Sheng, Y. and Gunasekera, D. (2009). Productivity movements in Australian agriculture, *Australian Commodities* 16, 206–216.
O'Donnell, C.J. (2010). Measuring and decomposing agricultural productivity and profitability change, *Australian Journal of Agricultural and Resource Economics* 54, 527–560.
OECD (2012). Cross country analysis of farm performance. Working Party on Agricultural and Markets, TAD/CA/AMP/WP(2012)20, Paris.
Productivity Commission (2005). Trends in Australian agriculture. Canberra, Productivity Commission Research Paper, Commonwealth of Australia.
Short, C., Chester, C., Berry, P. and Elliston, L. (2007). Australian food industry: performance and competitiveness, *Australian Commodities* 14, 221–226.
Szulc, B. (1964). Index numbers of multilateral regional comparisons, *Przeglad Statysticzny* 3, 239–254 (in Polish).
Townsend, R.F., Kirsten, J. and Vink, N. (1998). Farm size, productivity and returns to scale in agriculture revisited: a case study of wine producers in South Africa, *Agricultural Economics* 19, 175–180.
Windmeijer, F. (2005). A finite sample correction for the variance of linear efficient two-step GMM estimators, *Journal of Econometrics* 126, 25–51.
Zhao, S., Sheng, Y. and Kee, H.J. (2010) Exploring determinants of the total factor productivity in Australia's broadacre grain farms, ABARES Working Paper presented to the Australian Conference of Economists 2010.