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# Input Substitution, Productivity Performance and Farm Size

Yu Sheng, Alistair Davidson, Keith Fuglie and Dandan Zhang<sup>†</sup>

This paper develops a theoretical model to examine the relationship between the input elasticity of (technical) substitution and both farm total factor productivity and size. In the presence of ongoing technical change and its factor bias, the ‘income effect’ arising from farms’ cost minimising behaviour enables them to increase productivity by saving inputs or, through the dual equivalent, enlarging farm size. As such, farms with higher elasticities of substitution tend to grow larger and become more productive, which provides a new mechanism through which farm heterogeneity in productivity growth can be examined. Empirical evidence from Australian broadacre agriculture supports this theory and points to important policy implications.

**Key words:** elasticity of technical substitution, income effect, total factor productivity.

## 1. Introduction

Industry-level productivity growth arises from the combined productivity improvement of firms within that industry. But firm-level productivity performance, especially in a natural resource-dependent sector such as agriculture, is typically very heterogeneous, and many studies have found that productivity differences are correlated with farm characteristics (Bravo-Ureta *et al.* 2007). Leading firms experience above-average productivity growth, while the poorest performers may exit the industry due to their declining competitiveness and profitability. However, the specific mechanisms by which these characteristics influence growth in productivity and size are not well understood.

One factor influencing firm-level productivity growth is the ease at which it can adjust its input mix to meet new economic conditions and exploit new technological opportunities. In Australian agriculture, capital costs have been gradually declining relative to labour costs, and technological and efficiency changes may be biased in a labour-saving direction. These forces would seem to favour firms that are more able (or willing) to substitute capital (including land) for labour. Under these conditions, we would expect to

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observe a link between the elasticity of technical substitution (ETS) between capital and labour of a firm and its growth in total factor productivity (TFP) and size.

However, most studies of the dynamic determinants of agricultural productivity growth have focused on industry-level TFP (see the recent set of studies in Fuglie *et al.* 2012; for example) or on the empirical relationship between farm size and productivity, assuming that this simply reflects economies of scale or heterogeneous access to input and output markets (Boserup 1965; Binswanger *et al.* 1993; Binswanger and Deininger 1997 and Chavas 2008). If in fact farms differ in their ETS between capital and labour and ETS influences growth in TFP and size, such findings would provide a new perspective on sources of (and constraints to) productivity growth in agriculture. Understanding why ETS differs among farms would likely have important implications for farm policies.

In this paper, we test the hypothesis that there is substantial heterogeneity among Australian farms in their ETS between capital and labour, and that this can explain a significant part of the dynamics of farm growth in TFP and size. Following Klump and de La Grandville (2000), we first develop a theoretical framework of the linkages between ETS, productivity and farm size. An important mechanism through which ETS influences growth is the ‘income effect’ arising from capital–labour substitution. We then empirically test our main hypotheses using panel observations of 256 Australian broadacre agricultural farms between 1978 and 2007. Specifically, the empirical process involves two steps: the first step is to estimate the ETS between capital and labour for each farm in the sample, and the second step is to use regression analysis to examine how ETS and other factors influence firm-level growth in TFP and size. The results show significant and positive influences of ETS on both factors, even after controlling for regional effects, output composition effects, education and experience of the farm operators, and other characteristics of the farms. Finally, we also discuss how human capital of farmers, their aversion to risk, and other factors may account for differences in ETS among farms and what this may imply for farm and rural policies.

The paper proceeds as follows. Section 2 develops a theoretical framework that relates the ETS to farm TFP and size, following Klump and de La Grandville (2000). Section 3 derives the empirical specification and describes the data used. In particular, it details the methodologies used for estimating ETS and farm TFP. Sections 4 and 5 describe the panel estimation techniques and their results. Section 6 provides some discussion and conclusions.

## **2. Theoretical framework: elasticity of substitution, farm productivity and size**

Farm production is a complex process involving multiple market and natural resource inputs, and often highly variable operating conditions. In this section, we simplify this process by using a constant elasticity of substitution (CES) production function with two inputs to derive the

relationships between ETS and both farm TFP and size (Klump and de La Grandville 2000). The results can be easily extended to a multi-input case.

Assuming a representative farm using only two inputs, labour and capital, the (CES) production function is given as:

$$Y = A[aK^\psi + (1-a)L^\psi]^{1/\psi} \quad (1)$$

where  $0 < a < 1$  and  $\psi = \frac{\sigma}{\sigma-1}$ .  $Y$  measures output,  $L$  is the quantity of labour inputs, and  $K$  is the quantity of capital inputs.  $A$  is productivity, or Hicks neutral technical change, and  $a$  measures the distribution of production costs between capital and labour.  $\psi$  determines the (constant) elasticity substitution ( $\sigma$ ).

Defining output per capita and the capital–labour ratio as  $y = Y/L$  and  $k = K/L$  respectively, we can normalise the CES function as  $y = A[ak^\psi + (1-a)]^{1/\psi}$  with the assumption of constant returns to scale (Arrow *et al.* 1961).

At some arbitrarily chosen baseline values for the capital–labour ratio (that is, capital intensity)  $\bar{k}$ , the initial value of output per capita is  $\bar{y} = A[a\bar{k}^\psi + (1-a)]^{1/\psi}$ . Also, we assume the marginal rate of technical substitution (or the relative price between inputs) is equal across farms, defined as  $\bar{\omega} = \bar{r}/\bar{w} = [f(\bar{k}) - \bar{k}f'(\bar{k})]/f'(\bar{k})$  and determined by market competition and thus independent of  $\sigma$ . Thus, technology parameters  $a$  and  $A$  can be derived (given  $\bar{k}$ ,  $\bar{y}$  and  $\bar{\omega}$ ) as a function of the elasticity of substitution  $\sigma$  (de La Grandville 1989).

$$a(\sigma; \bar{k}, \bar{\omega}) = \frac{\bar{k}^{1-\psi}}{\bar{k}^{1-\psi} + \bar{\omega}} \quad (2)$$

$$A(\sigma; \bar{k}, \bar{\omega}, \bar{y}) = \bar{y} \cdot \left( \frac{\bar{k}^{1-\psi} + \bar{\omega}}{\bar{k}^{1-\psi} + \bar{\omega}} \right)^{1/\psi} \quad (3)$$

Substituting Equations (2) and (3) into (1), the normalised CES production function of the representative farm is

$$y = f_\sigma(k) = A(\sigma) \{a(\sigma)k^\psi + [1 - a(\sigma)]\}^{1/\psi} \quad (4)$$

Defining the representative farm as a profit maximiser and its profit share as

$$\pi = kf'_\sigma(k)/f_\sigma(k) \quad (5)$$

we can substitute Equations (2)–(4) into Equation (5) to derive the profit share in general form as

$$\pi(\sigma; \bar{k}, k) = \frac{k^\psi \bar{k}^{1-\psi}}{k^\psi \bar{k}^{1-\psi} + \bar{\omega}} \quad (6)$$

which depends on  $\sigma$  and  $k$  (for  $k \neq \bar{k}$ ), whereas the profit share at the initial point is

$$\bar{\pi} = \frac{\bar{k}}{\bar{k} + \bar{\omega}} \quad (7)$$

which is independent of both  $\sigma$  and  $k$  (since both  $\bar{k}$  and  $\bar{\omega}$  are independent of  $\sigma$ ). This helps to separate farm final equilibrium from its initial condition, thereby allowing the ETS to be exogenously determined.

Using Equations (2), (3), (6) and (7), we can recast the normalised CES production function (Eqn 4) as

$$y = \frac{\bar{y}}{\bar{k}} \cdot \left( \frac{\bar{\pi}}{\pi} \right)^{1/\psi} \cdot k \quad (8)$$

which can be used to derive the TFP of the representative farm (Eqn 3) as

$$A = \frac{\bar{y}}{\bar{k}} \cdot \left( \frac{\bar{\pi}}{a} \right)^{1/\psi} \quad (9)$$

**Proposition 1:** If two farms described by CES technologies differ only by their input elasticity of substitution and share initially a common capital–labour ratio, labour usage and marginal investment propensity, the farm with a higher input elasticity of substitution will tend to have a higher level of total factor productivity. (See Appendix I for proof.)

Proposition 1 suggests that, starting from the same initial condition (where all farms share the same production technology, capital–labour ratio and labour use), farms with a higher ETS realise higher productivity than those with a lower ETS. This follows from profit maximising/cost minimising behaviour, which spurs farms to adjust their input mix in response to input-biased technology progress. More specifically, as continuous capital accumulation and technology progress reduce the relative price of capital to labour in a competitive market, farms substituting capital for labour may obtain a productivity gain due to ‘income effects’ (de La Grandville 1989). As de La Grandville (1989) argued, it is these ‘income effects’ that drive labour productivity, thus providing an additional source of per capita income

growth independent of pure technology progress. Further, farms that are more flexible in adjusting their input mix have higher ETS and thus larger income effects over the long run. In equilibrium, this may allow them to produce the same output with less input or allow them to produce more output with the same input. As such, we would expect the production possibility frontier for farms with a higher ETS to be beyond that for farms with a lower ETS.

As a corollary to Proposition 1, when using total output (or total input) as a measure of operational scale, we can prove this also increases with ETS. Thus, farm size and TFP are correlated and increase with the ETS. This provides an alternative explanation for the positive correlation between farm TFP and size to that which is commonly assumed to apply – namely increasing returns to scale.

**Proposition 2:** If two farms described by CES technologies differ only by their input elasticity of substitution, that is, they initially share a common capital–labour ratio, labour usage and marginal investment propensity, the farm with higher input elasticity of substitution will tend to be larger in terms of their operation scale (that is, farm size). (See Appendix II for proof.)

Propositions 1 and 2 are illustrated across linked diagrams in Figure 1. The upper diagram represents firms' cost minimising decision (here, the choice of input mix between capital and labour), while the lower diagram represents the input–output relationship.

Assume two farms with differing ETS (i.e.  $\sigma_1 < \sigma_2$ ). This implies that farm 2 ( $F_2$ ) has a lower curvature in its unit cost curve than farm 1 ( $F_1$ ), as shown in the upper diagram. Starting with the same initial condition ( $K_0, L_0$ ), farms 1 and 2 have the same productivity and size (measured by output–input ratio and total output) since their unit cost curves are tangential to the budget constraint ( $\bar{K}\bar{L}$  at the same point). If technological progress relaxes the budget constraint, say, from ( $\bar{K}\bar{L}$ ) to ( $\bar{K}'\bar{L}'$ ), both farms can afford to operate using more inputs (in effect, at a larger size) due to the income effect. However, since the two farms have different ETS, the income effects are different. The farm with higher ETS tends to use more (cheaper) capital to substitute for (more expensive) labour, thereby realising a higher income effect. As shown in the upper diagram, holding the same unit cost curve, the distance between  $\bar{K}_2'\bar{L}'$  and  $\bar{K}'\bar{L}'$  is larger than that between  $\bar{K}_1'\bar{L}'$  and  $\bar{K}'\bar{L}'$ . Transferring those effects to the input–output space (lower diagram), the output–input ratio (or TFP) in the new equilibrium and the total output (or operational scale) of farm 2 (with higher ETS) exceed those of farm 1 (with lower ETS). This suggests that farms with higher ETS will, in the long run, increase in size and TFP compared with those of lower ETS even though they all started with the same initial condition and faced the same technology progress and change in relative input prices.

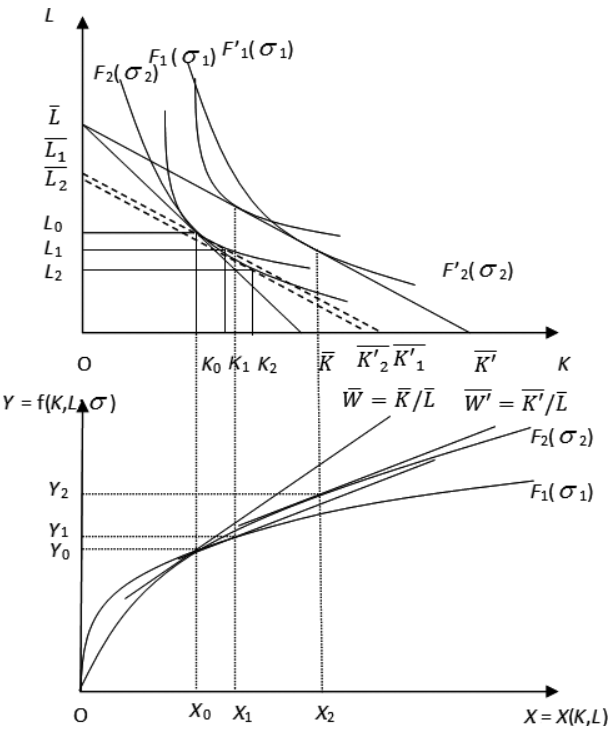


Figure 1 Elasticity of substitution and farm size and productivity.

3. Empirical strategy, variable definition and data source

Broadacre agriculture, also termed non-irrigated agriculture, is an important component of Australian agricultural industry. In 2014, the industry produced around A \$29 billion output value accounting for around 70 per cent of total agricultural output, accommodated 5300 farms operating in a competitive market and hosted 27,000 workers (ABARES 2014). Since 1978, TFP of broadacre farms has grown at the rate of 1.1 per cent a year and average farm size increased by more than two times. Underlying the growth of farm TFP and size, the declined input use (−0.85 per cent a year) has played an important role, which on average accounted for more than 80 per cent of farm TFP growth. Moreover, the declined input use has been accompanied with significant changes in input mix, since more and more farms attempted to use more capital and intermediate inputs to replace labour in production. This phenomenon could not be well explained only by using the existing theory (i.e. changes in output mix efficiency) and thus provided us with a good opportunity to test our theory.

As mentioned in previous section, propositions 1 and 2 present two hypotheses for testing the causal relationship between the ETS and farm TFP and size.



**Hypothesis 1:** Farms with higher ETS tend to have higher TFP.

**Hypothesis 2:** Farms with higher ETS tend to be of larger size.

### 3.1 Empirical model specification

Empirical specifications for testing hypotheses 1 and 2 can be written as

$$\ln\_TFP_i = \alpha + \beta \ln\_ETS_i + \gamma X_i + \varepsilon_i \quad (10)$$

$$\ln\_SIZE_i = \alpha' + \beta' \ln\_ETS_i + \gamma' X_i + u_i \quad (11)$$

where  $\ln\_TFP_i$  and  $\ln\_SIZE_i$  denote logarithm of farm  $i$ 's TFP and size.  $\ln\_ETS_i$  is the logarithm of elasticity of substitution between capital and labour specific to each farm.  $X_i$  are control variables covering farms' initial condition in terms of productivity and size, climate and social environments that they are operating in, commodity-specific production technique (i.e. capital–labour ratio and output mixture), farmers' education levels and various farm-specific effects.  $\alpha$ ,  $\alpha'$ ,  $\beta$ ,  $\beta'$ ,  $\gamma$  and  $\gamma'$  comprise the coefficient matrix. In estimating Equations (10) and (11), a cross-sectional regression has been applied to farm-level observations and we expect positive and significant  $\gamma$  (and  $\gamma'$ ) if the model projections hold true.<sup>1</sup> Moreover, a weak condition for that outcome would exist where the null hypothesis for vector  $\beta$  (and  $\beta'$ ), being jointly insignificant or negative, can be rejected at the 1 per cent level.

However, before we can estimate  $\beta$  and  $\beta'$  appropriately using Equations (10) and (11), we need to address two econometric issues.

The first is the potential endogeneity problem. In practice, there are many farm-specific factors that could affect ETS, TFP and size. These may include, for example, climate condition and soil quality, farmers' age, experience and education level, and commodity-specific production technique and so on. Inadequately controlling for these factors may lead to biased estimates. To account for the impact of these factors, we added a large number of controlled variables and dummy variables for sectors and regions. In addition, we have also included the initial condition of each farm in total factor productivity level and farm size and a year dummy for the farm to be first observed to avoid other sources of endogeneity and reverse causality problems that could related to time.

Second, while TFP and size can be estimated at the farm level for each year, ETS can only be estimated at the farm level only once for the whole sample period. This is because that we need to use variation in input usage of

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<sup>1</sup> Since elasticities of substitution are stable over time as assumed in the theoretical model, we can use the cross-sectional regression for empirical test.



each farm over time corresponding to different relative input prices to retrieve farmers' investment behaviour and thus estimate ETS. As Moulton (1990 p. 334) argued: 'When one tends to use the aggregate market or public policy variables to explain the economic behaviour of micro units, it is possible that the standard errors of estimated coefficients of those aggregate variables from OLS might be underestimated, which would lead to the overstated significance of coefficients'. In our case, a constant ETS at the farm level may violate the assumption of independently and identically distributed residuals, thereby biasing the estimated errors downwards. We deal with this by taking the average of TFP and size for each farm, and align those average TFP and size with the estimated ETS in a cross-sectional regression.

To proceed with empirical estimation, we designate the ETS of farms as the key independent variable, and farm TFP and size as dependent variables.

### 3.2 Estimation of elasticity of substitution

In the literature, ETS has typically been estimated via either of two approaches: the Allen-Uzawa (AUES) approach (Allen and Hicks 1934; Uzawa 1962) or the Morishima–Blackorby–Russell (MES) approach (Morishima 1967; Blackorby and Russell 1981, 1989). Although neither is constrained by the form of the production function, the MES measure is widely considered to be superior to the AUES measure, which suffers from several shortcomings. As Blackorby and Russell (1989) pointed out, the AUES measure cannot provide information about income distribution among factor inputs, nor can it be interpreted as the relative change of an input ratio to a price ratio since it does not allow for optimal adjustment of all inputs to a change in a price ratio. Thus, 'only if the two [input] variables were separable from all other variables would the AUES provide information about factor shares' (Blackorby and Russell 1989, p. 1).

However, using the MES measure to directly approximate the ETS may introduce another problem. This is because the CES production function assumed in our theoretical model holds the property that the substitutability of each pair of inputs is reversible. In other words, the input elasticity of substitution between A and B should equal that between B and A. In contrast, the less restrictive trans-log production function used to estimate the MES does not require this property. To overcome this, the duality constraint was usually imposed on the input distance function method to restrict the estimation process (Kim 2000). In doing so, some previous studies (Kmenta 1967; Zarembka 1970; Duffy and Papageorgiou 2000) further proposed to use the second-order Taylor expansion to approximate the CES production function and apply a linear regression to the data on output–labour and capital–labour ratios for the MES measure of ETS. However, this method is also criticised for generating large bias and mean square errors since the approximated linear function is a truncated series of second order and will leave omitted variables in the regression estimation process (Mallick 2007).

Given the limitations mentioned above, this paper adopts the nonlinear least square (NLS) technique, following Mallick (2007), to estimate a normalised CES production function such as

$$\frac{Y_t}{Y_0} = A_t \left[ \alpha \left( \frac{K_t}{K_0} \right)^{\frac{\sigma-1}{\sigma}} + (1-\alpha) \left( \frac{L_t}{L_0} \right)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{1-\sigma}} \quad (12)$$

where output (defined as value-added in real term), capital and labour variables for each farm are normalised by dividing their initial values, respectively. In addition, we assume that there is a Hicks neutral technology term ( $A_t$ ) and it takes the exponential form in growth such that  $A_t = A_0 e^{\lambda t}$  where  $A_0$  is the initial level of production technology and  $\lambda$  is its growth rate.

Taking logarithm on both sides of Equation (12), we have

$$\ln \bar{Y}_t = \ln A_0 + \lambda t + \rho \ln [\alpha \bar{K}_t^{\frac{1}{\rho}} + (1-\alpha) \bar{L}_t^{\frac{1}{\rho}}] \quad (13)$$

where  $\rho = \frac{\sigma}{1-\sigma}$ ,  $\bar{Y}_t = \frac{Y_t}{Y_0}$ ,  $\bar{K}_t = \frac{K_t}{K_0}$  and  $\bar{L}_t = \frac{L_t}{L_0}$ . Using the NLS regression technique, we estimate  $\rho$  and calculate  $\sigma = \frac{\rho}{\rho+1}$  and its standard error by using the ‘delta method’ (Mallick 2007).

### 3.3 Estimation of total factor productivity and farm size

In contrast to estimating ETS, estimating farm TFP is relatively straightforward. This is because we can use an index approach to approximate a flexible form production function, consistent with our assumed CES production function (Diewert 1992). Specifically, we choose the Fisher indexing approach to aggregate multiple inputs and outputs using their respective market prices as weights (Christensen 1975; Diewert 1992; Coelli *et al.* 1998). Consistent with the ETS measure, we adopt the value-added-based model for farm TFP estimates, where outputs are defined as gross output minus intermediate inputs and inputs are defined to include only capital (including land) and labour. Input and output index transitivity was imposed using the EKS formula.

Total factor productivity (TFP) is defined as the ratio of an output quantity index to an input quantity index:

$$TFP_{it} = \frac{Q_{it}^{FO}}{Q_{it}^{FI}} \quad (14)$$

where  $O$  is value-added outputs and  $I$  is capital and labour inputs for farm  $i$  in year  $t$ .  $Q_{it}^{FO}$  and  $Q_{it}^{FI}$  are Fisher ideal indexes such that  $Q_{it}^{FO} = \sqrt{Q_{it}^{LO} Q_{it}^{PO}}$  and  $Q_{it}^{FI} = \sqrt{Q_{it}^{LI} Q_{it}^{PI}}$ , or the geometric means of the Laspeyres and Paasche indexes:

$$Q_{it}^{Lj} = \frac{\sum_{k=1}^N p_{ki0}^j q_{kit}^j}{\sum_{k=1}^N p_{ki0}^j q_{ki0}^j} \quad \text{and} \quad Q_{it}^{Pj} = \frac{\sum_{k=1}^N p_{kit}^j q_{kit}^j}{\sum_{k=1}^N p_{kit}^j q_{ki0}^j} \quad \text{where } j = \{O, I\}. \quad (15)$$

For robustness check, a regression-based farm TFP was also estimated by using the Wooldridge GMM nonparametric regression-based method (Wooldridge 2009) and used in place of the Fisher index measure.

In addition, farm size is measured using the total input quantity index with the adjustment for transitivity. For a robustness check, the dry sheep equivalent (DSE) measure (an indicator for the carrying capacity) is also used for farm size.

Data used to estimate ETS, farm TFP and size are available from the Australian Agriculture and Grazing Industry Survey (AAGIS). ABARES, a division of the Australian Department of Agriculture and Water Resources, has surveyed farms annually since the late 1970s, to gather input, output and related information in five broadacre sectors (cropping specialists, mixed cropping–livestock, sheep specialists, beef specialists and mixed beef–sheep) across seven states (New South Wales, Victoria, Queensland, South Australia, Western Australia, Tasmania, North Territory and Australian Capital Territory). Since the survey uses a rotation sampling strategy, the original data sets used in this study form an unbalanced panel with the sample sizes ranging from 1375 in the financial year ended June 1978 to 1454 in 2007. As time series data are required to estimate ETS for each farm, we restrict our sample to those farms that have been observed at least for 10 consecutive years. In addition, the top 5 per cent and the bottom 5 per cent of sample in terms of farm TFP and size are also excluded to reduce the effects of outliers in the exercise. The final sample used in this paper contains 3, 525 observations which cover 256 farms between 1978 and 2007.<sup>2</sup> Appendix III contains definitions and detailed information on the input and output data.

#### 4. Empirical results: how ETS affects farm TFP and size

How does the ETS affect farm TFP and size? Although the model derivation has provided a theoretical mechanism through which the ‘income effect’ could arise from farms increasing their use of cheaper inputs, empirical evidence would provide greater assurance.

##### 4.1 Correlation between ETS and farm TFP/size

Table 1 presents descriptive statistics of the major variables used for the empirical analysis: average farm TFP and size, estimated ETS between

<sup>2</sup> Although we sacrificed the number of observations, the remaining sample still provided a good representation of continuing broadacre farms. Between 1978 and 2007, the gross output value of our sample has accounted for around 33 per cent of population after taking into account of sample weights.

capital and labour, and selected control variables. As mentioned earlier, data constraints render it necessary to measure a fixed ETS between capital and labour for each farm that is observed for at least 10 consecutive years.

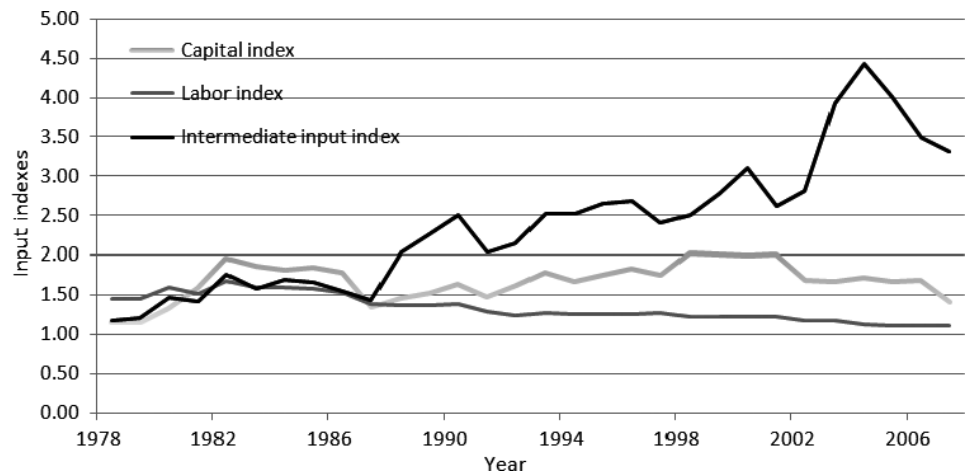
As discussed above, the relationship between ETS and farm TFP and size results from farms' use of cheaper inputs over time. Due to the declining price of capital inputs relative to labour, farms have increasingly relied more on capital inputs than labour (Figure 2). This observation is consistent with previous literature describing capital and labour use in the economy as a whole (Arrow *et al.* 1961; Barro and Sala-i-Martin 1995). We also observe concurrent increases in farm TFP and size (Figure 3). This suggests that changing input mix might be correlated with farm TFP and size, where the ETS may play a role.

In preparation for the empirical analysis, we first inspected the correlation between farm TFP and ETS (Figure 4) and between farm size and ETS (Figure 5). In both instances, an initial investigation that involved pooling all periods seemingly resulted in expected relationships: the estimated ETS between capital and labour was positively correlated with average farm TFP and size. This inspection, however, could not be used for conclusions since it may suffer from two data issues. First, the estimated ETS have varied considerably between industries and across regions. Consequently, failure to account for the cross-industry and cross-region variation of ETS may obscure the true correlation with farm TFP and size. Second, there are significant correlations between farm TFP and other factors such as climate conditions and difference in farm initial productivity levels and size (Table 2). Again, it is necessary to account for this correlation before establishing the true impact of ETS between capital and labour on farm TFP and size.

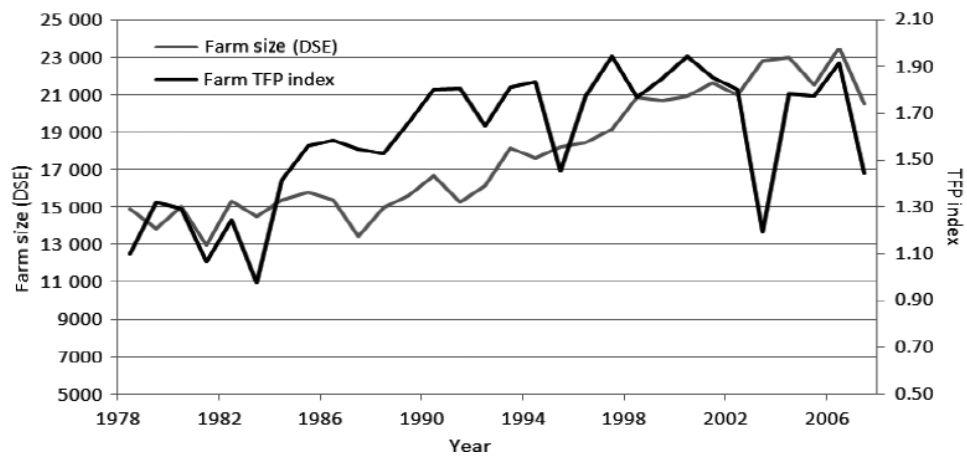
**Table 1** Descriptive statistics on major variables: 1978–2006

	Mean	Std. Dev.	Min	Max
Average farm TFP	1.36	0.65	0.19	3.23
Average farm size	2.61	3.69	0.08	31.16
Elasticity of Substitution	1.35	2.38	0.02	26.61
Initial farm tfp level	0.73	0.45	0.01	1.46
Initial farm size level	1.87	2.89	0.01	17.83
Pasture growth index	29.89	10.35	6.57	59.21
Education level of farmers	3.85	1.94	1.00	9.36
Age of farmers	45.60	12.66	23.32	79.08
Logarithm of terms of trade	0.04	0.02	0.01	0.10
Output mixture (share of crop in total output value)	0.16	0.21	0.00	0.87
K-L ratio	1.10	1.52	0.08	16.05

Note The elasticity of substitution refers to the elasticity of substitution between capital and labour, and farm size is measured by using the total input quantity index. The number of observations is 256.



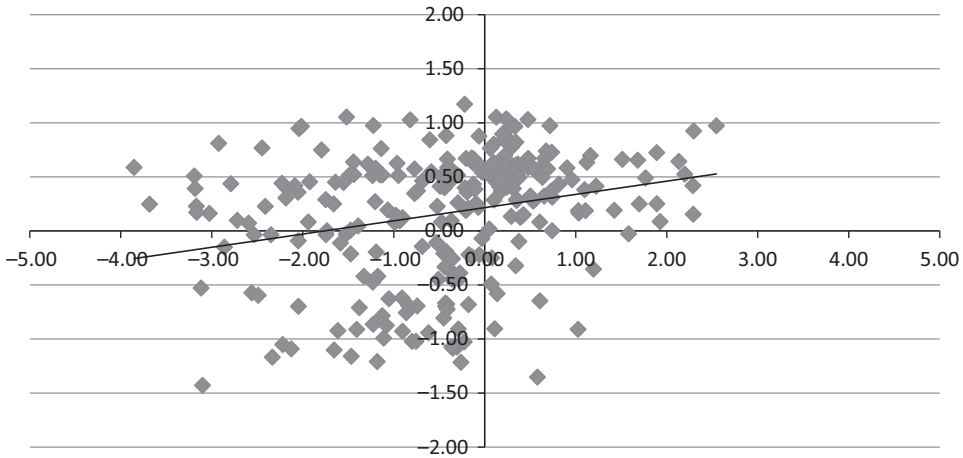
**Figure 2** Changes in average farm usage of capital, labour and intermediate inputs. Note: Both ETS and farm TFP are in logarithm and the top and bottom 5 per cent outliers are excluded.



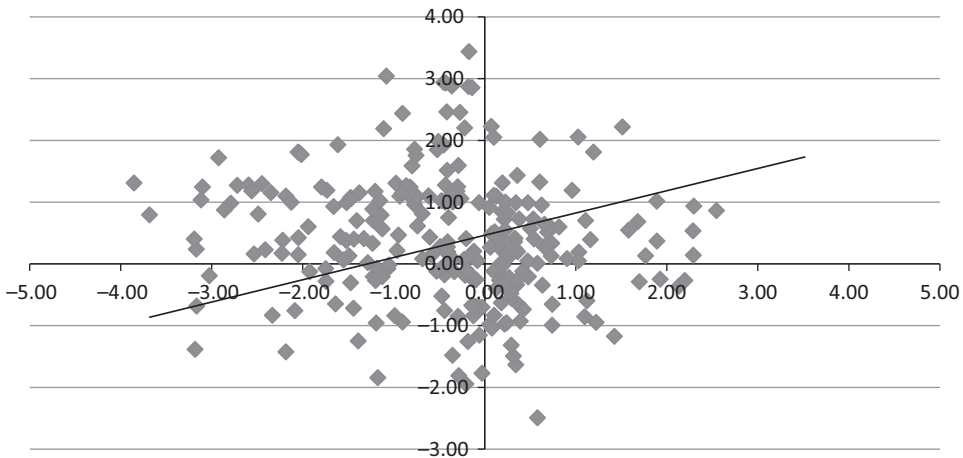
**Figure 3** Average farm TFP and size between 1978 and 2007.

**4.2 The relationship between ETS and farm TFP**

Table 3 presents the results obtained from regression of the ETS between capital and labour on farm TFP in Australian broadacre agriculture. To deal with a potential endogeneity problem (i.e. correlation between ETS and residuals), we performed this regression using cross-sectional data with control variables for a large number of productivity drivers and dummy variables to account for productivity differences between industries and regions. The regression results indicate that the ETS between capital and labour has positively influenced farm TFP (Columns 1–4 in Table 3). In the



**Figure 4** Plot of farm TFP and ETS, by cell for all years. Note: Both ETS and farm TFP are in logarithm and some outliers are excluded.



**Figure 5** Plot of farm size and ETS, by cell for all years.

estimation using the Fisher TFP estimates as the dependent variable, a one per cent increase in the ETS between capital and labour is likely to increase farm TFP by 1.1 per cent when dummy variables for industry and region are included, and by 1.4 per cent when these variables are not included (Table 3). The influence of the ETS between capital and labour is positive and significant at the 1 per cent level. Moreover, the null hypothesis that the ETS between capital and labour is less than or equal to zero is rejected at 1 per cent level (F statistics are 10.38 and 9.56). The magnitude and significance of these results are generally consistent with those obtained from the regression using the Wooldridge GMM TFP measure as the dependent variable.

Table 2 Correlation between farm TFP and other factors

	Logarithm of average farm TFP	Elasticity of Substitution	Initial farm tfp level	Pasture growth index	Education level of farmers	Age of farmers	Logarithm of terms of trade	Output mixture (crop in total)	Capital- labour ratio
Logarithm of average farm TFP	1.00								
Elasticity of Substitution	0.14	1.00							
Initial farm tfp level	0.83	0.06	1.00						
Pasture growth index	0.46	-0.08	0.41	1.00					
Education level of farmers	0.37	0.01	0.30	0.39	1.00				
Age of farmers	0.19	-0.03	0.15	0.27	0.01	1.00			
Logarithm of terms of trade	0.05	0.05	0.00	0.17	0.20	0.01	1.00		
Output mixture (crop in total)	0.54	0.04	0.53	0.17	0.16	0.25	-0.07	1.00	
Capital-labour ratio	0.72	0.15	0.56	0.40	0.36	0.09	0.26	0.33	1.00



Table 3 Relationship between ETS and TFP

	Fisher TFP index		Wooldridge GMM TFP estimates	
	(1)	(2)	(3)	(4)
Dependent variable: logarithm of farm-level TFP				
Elasticity of substitution	0.014*** (0.004)	0.011*** (0.003)	0.007*** (0.002)	0.007*** (0.002)
Initial TFP condition	0.220*** (0.020)	0.219*** (0.019)	0.146*** (0.019)	0.151*** (0.019)
Pasture growth index	0.004*** (0.002)	0.007*** (0.002)	0.002*** (0.001)	0.002* (0.001)
Education level of farmers	0.022** (0.010)	0.021** (0.009)	-0.003 (0.004)	-0.002 (0.004)
Age of farmers	0.003* (0.002)	0.002 (0.002)	-0.001 (0.001)	-0.001 (0.001)
Terms of trade	-1.536 (1.002)	-1.031 (0.976)	-1.474*** (0.409)	-1.502*** (0.435)
Output mixture share (crop in total)	0.360*** (0.096)	0.369*** (0.135)	-0.033 (0.036)	0.146** (0.060)
Logarithm K-L ratio	0.180*** (0.023)	0.109*** (0.034)	0.072*** (0.014)	0.082*** (0.018)
Constant	-0.349*** (0.112)	-0.344*** (0.126)	0.316*** (0.043)	0.235*** (0.053)
Number of observations	256	256	256	256
Adjusted $R^2$	0.807	0.822	0.575	0.614

Note Numbers in parenthesis are standard errors. \*, \*\* and \*\*\* represent 10 per cent, 5 per cent and 1 per cent significance levels, respectively. Dummy variables for industries and regions are included in columns (2) and (4).

The results also show that several of the control variables also have a positive, significant effect on farm TFP. These variables include the pasture growth index (which represents the combined effect of climate conditions and soil quality), farms' initial TFP level, the logarithm of the capital–labour ratio and the proportion of cropping products in total output (Table 3). These results are generally consistent with expectations, since farm TFP will tend to be higher when climate conditions and soil quality are better, and when the farm's initial production conditions and embodied technology (reflected in the average capital–labour ratio) are more favourable. The finding that the proportion of cropping products in total output also increases farm TFP is consistent with an observed reallocation of resources towards crop products, and the effects this has had on within-farm efficiency improvement or improvement in output mix efficiency (O'Donnell *et al.* 2010; O'Donnell 2012; Tozer and Villano 2013; Sheng *et al.* 2015). Other control variables such as farmer age and education level are also positively correlated to farm TFP, but significance levels are much lower, at 5 to 10 per cent or less.

Finally, our estimation shows that differences between industries and regions affect farm TFP, but that accounting for these disparities does not change the relationship between farm TFP and the ETS. Specifically, regardless of whether the Fisher index or Wooldridge GMM TFP estimates are used as the dependent variable, the coefficients estimated for the industry and region dummy variables are significant, but including them in the regression does not change the sign or significance of the relationship between the ETS and farm TFP (Table 3).

### 4.3 The relationship between farm size and ETS

Table 4 presents results obtained from regression of the ETS between capital and labour on farm size. As shown, the ETS has a positive impact on the size of Australian broadacre farms. After accounting for other determinants of farm size and differences in farm size between industries and regions, the coefficients estimated for the ETS variable are positive and significant at the 1 per cent level. Using two different measures of farm size as the dependent variable produces coefficients of similar magnitude (Table 4). In addition, the null hypothesis that the coefficients of ETS are jointly less than or equal to zero is rejected at the 1 per cent level (F statistics ranged from 10.92 to 15.81).

In sum, the empirical analysis provides evidence that positive relationships exist between the ETS between labour and capital and farm TFP and size, after accounting for the role of other drivers. This finding supports the hypotheses derived from the theoretical model. In the presence of ongoing input-biased technological progress and changes in relative input prices, farms adjust their input mix by choosing cheaper inputs over more expensive ones. Cost minimising/profit maximising behaviour gives rise to the usual substitution effects plus additional income effects.

**Table 4** Relationship between elasticity of substitution and farm scale (measured with total input usage and DSE measure)

	Total farm input		Dry sheep equivalent	
	(1)	(2)	(3)	(4)
Dependent variable: logarithm of farm size				
Elasticity of substitution	0.029*** (0.007)	0.028*** (0.009)	0.010*** (0.001)	0.017*** (0.001)
Initial size condition	0.279*** (0.026)	0.279*** (0.026)	0.012*** (0.004)	0.013*** (0.004)
Pasture growth index	0.001 (0.004)	-0.000 (0.004)	0.006 (0.005)	0.001 (0.006)
Education level of farmers	-0.028* (0.016)	-0.022 (0.015)	-0.088*** (0.027)	-0.077*** (0.027)
Age of farmers	-0.004* (0.002)	-0.004* (0.002)	-0.007* (0.004)	-0.007* (0.004)
Terms of trade	-9.485*** (1.734)	-9.927*** (1.823)	-15.908*** (2.440)	-16.886*** (2.586)
Output mixture share (crop in total)	0.158 (0.129)	0.394 (0.241)	-0.057 (0.192)	0.174 (0.371)
Logarithm of K-L ratio	0.256*** (0.073)	0.226*** (0.073)	0.783*** (0.071)	0.650*** (0.098)
Constant	0.937*** (0.172)	0.835*** (0.212)	10.629*** (0.247)	10.431*** (0.298)
Number of observations	256	256	256	256
Adjusted $R^2$	0.818	0.820	0.720	0.732

Note: Numbers in parenthesis are standard errors. \*, \*\* and \*\*\* represent 10 per cent, 5 per cent and 1 per cent significance levels, respectively. Dummy variables for industries and regions are included in columns (2) and (4).

If there is no change in output mix, the income effect contributes to increasing farm TFP and size insofar as farms either produce the same (more) output with less (same) inputs, or increase operational scale – an option made possible by the increased budget. For some, the latter will involve expanding land area and increasing investment, which may generate further benefits from increasing returns to scale. A direct implication is that TFP and size generally move in the same direction across farms, with both dependent on continuous input substitution.

The finding that the ETS between capital and labour has positive effects on farm TFP and size provides new insights into the presence and nature of farm heterogeneity. Specifically, irrespective of their initial conditions, farms differing only in their ETS can coexist in the long run with varying TFP and size, as is commonly observed. Furthermore, since farms with greater flexibility to adjust their input mix are more likely to realise higher productivity and, in some cases, expand their farm size, the ETS between capital and labour may serve as a useful indicator of adaptive capacity, insofar as farms are willing and able to adapt to various pressures by adjusting their input mix.

## **5. Discussion: factors determining farm elasticities of substitution**

Given that ETS between capital and labour plays an important role in affecting farm TFP and size, it is useful to ask what are the likely determinants of ETS on individual farms? Answers to this question would explain differences in productivity between farms and provide useful insights for policymakers seeking to enhance farmers' capacity and willingness to innovate. In this section, we discuss some possible determinants of ETS relating to farm operator characteristics, although the literature in this field is relatively embryonic (Klump and de La Grandville 2000).

Theoretically, the ETS governs the curvature of farms' isoquants and determines how expenditure on inputs changes with changes in relative prices. One interpretation is that ETS is a measure of risk aversion, or farms' capacity and willingness to adopt alternative input mixes, including new management practices and technologies. In this sense, farm operator characteristics (such as their age, education level and financial status) are likely to be important determinants of ETS (Nossal and Lim 2011; OECD 2011). These variables have previously been identified as important drivers of productivity (Mundlak 2005; Prokopy *et al.* 2008), but the mechanism by which they do so has not been clarified. This paper proposes a mechanism by which these drivers can affect productivity.

First, farm operators' attitude towards risks, usually determined by their age (as a proxy for experience) and education, is likely to positively affect ETS. According to human capital theory (Becker 1993), farmers with higher education levels are usually more willing to try new production processes and thus they may have relatively higher ETS. So does farmers' experience. As

such, these factors tend to play a positive role in affecting substitutability between capital and labour, thereby increasing farm TFP and size in the long run.

Second, farm financial status may also affect ETS. Adopting new production process typically involves substantial investments, with attendant risks. Farmers with a sound financial status are better placed to manage these. In particular, farmers that face lower borrowing costs (e.g. because of a lower farm debt–equity ratio) or otherwise face a less strict budget constraint are better placed to absorb the risks associated with adjusting their input mix.

In addition, it is to be noted that ETS could also be influenced by the physical characteristics of the farm, such as the topology of the land or the degree of fragmentation of land holdings, all of which may limit possibilities for mechanisation or the substitution of capital for labour.

Understanding the drivers of ETS is just as important as those for productivity per se, because the two are dynamically and interactively determined. However, in contrast to many productivity drivers, which are exogenous to the farm (such as government and industry funded RD&E and economy-wide macroeconomic settings), those closely linked to ETS can be relevant to farmers' choice, such as education and training. Further research to identify the determinants of ETS would assist policymakers, who have an interest in reforming policies as a means of promoting productivity growth.

## 6. Conclusion

This paper explores the relationship between the input elasticity of substitution, farm productivity and size. Assuming CES technology, a theoretical model is developed and tested using farm survey data from Australian broadacre agriculture. The results show that farmers responding to changing technologies and prices through input substitution consequently obtain 'income effects', with the control of output mix. As such, there is a positive relationship between ETS and farm productivity and between ETS and farm size, even if other aspects of farms (such as their initial endowments, operating environments and other productivity drivers) are held constant. This provides a new explanation for observed heterogeneity in farm productivity and size – namely variation in ETS between farms.

As the ETS reflects the extent to which farmers are willing and able to optimise their input mix, it can be viewed as a lower-bound measure of overall farm adaptive capacity – the ability to adapt to changes in the operating environment (including technological progress and movements in relative prices). The extent to which behavioural attitudes towards risk, human capital of farmers, or their access to farm services and financial markets may influence their ETS has implications for farm policies designed to promote productivity and income growth in the farm sector. Further research directed at identifying the key determinants of ETS would assist

policymakers seeking to promote productivity improvements through this channel.

## References

- ABARES (2014). *Agricultural Commodity Statistics* 2014, ABARES, December 2014, Canberra.
- Allen, R.G.D. and Hicks, J.R. (1934). A reconsideration of the theory of value, Pt. II, *Economica* 1, 196–219.
- Arrow, K.J., Chenery, H.B., Bagicha, M. and Solow, R.M. (1961). Capital-labour substitution and economic efficiency, *The Review of Economics and Statistics* 43, 225–250.
- Barro, R.J. and Sala-i-Martin, X. (1995). *Economic Growth*. McGraw-Hill, New York.
- Becker, G.S. (1993). *Human Capital: A Theoretical and Empirical Analysis, with Special Reference to Education*, 3rd edn. University of Chicago Press, Chicago.
- Binswanger, H.P. and Deininger, K. (1997). Explaining agricultural and agrarian policies in developing countries, *Journal of Agricultural Economics* 75, 1242–1248.
- Binswanger, H.P., Deininger, K. and Feder, G. (1993). Agricultural land relations in the developing world, *American Journal of Agricultural Economics* 75, 1242–1248.
- Blackorby, C. and Russell, R.R. (1981). The Morishima elasticity of substitution: symmetry, constancy, separability, and relationship to the Hicks and Allen elasticities, *Review of Economic Studies* 43, 147–158.
- Blackorby, C. and Russell, R.R. (1989). Will the real elasticity of substitution please stand up? (A comparison of the Allen/Uzawa and Morishima elasticities), *The American Economic Review* 79, 882–888.
- Boserup, A. (1965). *The Conditions of Agricultural Growth: the Economics of Agrarian Change under Population Pressure*. Aldine Publishing Company, Chicago.
- Bravo-Ureta, B., Solis, D., Lopez, V.M., Maripani, J., Thiam, A. and Rivas, T. (2007). Technical efficiency in farming: a meta-regression analysis, *Journal of Productivity Analysis* 27, 57–72.
- Chavas, J.P. (2008). One the economics of agricultural production, *Agricultural and Resource Economics* 52, 365–380.
- Christensen, L. (1975). Concepts and measurement of agricultural productivity, *American Journal of Agricultural Economics* 57, 910–915.
- Coelli, T., Prasada-Rao, D.S. and Battese, G.E. (1998). *An Introduction to Efficiency and Productivity Analysis*. Kluwer Academic Publishers, London.
- Diewert, W. (1992). Fisher ideal output, input and productivity indexes revisited, *Journal of Productivity Analysis* 3, 211–248.
- Duffy, J. and Papageorgiou, C.E. (2000). A cross country empirical investigations of the aggregate production function specification, *Journal of Economic Growth* 5, 87–120.
- Fuglie, K., Wang, S.L. and Ball, V.E. (eds) (2012). *Productivity Growth in Agriculture: An International Perspective*. CAB International, Wallingford, UK.
- Kim, H.Y. (2000). The Antonelli versus Hicks elasticity of complementary and inverse input demand systems, *Australian Economic Papers* 39, 245–261.
- Klump, R. and de La Grandville, O. (2000). Economic growth and the elasticity of substitution: two theorems and some suggestions, *The American Economic Review* 90, 282–291.
- Kmenta, J. (1967). On estimation of the CES production function, *International Economic Review* 8, 180–189.
- de La Grandville, O. (1989). In quest of the Slutsky diamond, *American Economic Review* 79, 468–481.
- Mallick, D. (2007). The role of the elasticity of substitution in economic growth: a cross-country test of the de la Grandville hypothesis, the conference paper presented to the 76th Southern Economic Association Meeting and the American Economic Association Meeting.

- Morishima, M. (1967). A few suggestions on the theory of elasticity (in Japanese), *Keizai Hyoron (Economic Review)* 16, 78–83.
- Moulton, B.R. (1990). An Illustration of a pitfall in estimating the effects of aggregate variables on micro unit, *The Review of Economics and Statistics* 72, 334–338.
- Mundlak, Y. (2005). Economic growth: lessons from two centuries of American agriculture, *Journal of Economic Literature* XLIII, 989–1024.
- Nossal, K. and Lim, K. (2011). Innovation and productivity in the Australian grains industry, ABARES research report 11.6, Canberra, July.
- O'Donnell, C.J. (2012). Nonparametric estimates of the components of productivity and profitability change in U.S. agriculture, *American Journal of Agricultural Economics* 94, 873–890.
- O'Donnell, C.J., Chambers, R.G. and Quiggin, J. (2010). Efficiency analysis in the presence of uncertainty, *Journal of Productivity Analysis* 33, 1–17.
- OECD (2011). *Fostering Productivity and Competitiveness in Agriculture*. OECD Publishing, Paris, France. <http://dx.doi.org/10.1787/9789264166820-en>.
- Prokopy, L.S., Floress, K., Klotthor-Weinkauff, D. and Baumgart-Getz, A. (2008). Determinants of agricultural best management practice adoption: Evidence from the literature, *Journal of Soil and Water Conservation* 63, 300–311.
- Sheng, Y., Jackson, T and Gooday, P. (2015). Resource reallocation and its contribution to productivity growth in Australian broadacre, *Australian Journal of Agricultural and Resource Economics*, forthcoming.
- Tozer, P. and Villano, R. (2013). Decomposing productivity and efficiency among Western Australian grain growers, *Journal of Agricultural and Resource Economics* 38, 312–326.
- Uzawa, H. (1962). Production functions with constant elasticities of substitution, *Review of Economic Studies* 29, 291–299.
- Wooldridge, J.M. (2009). On estimating firm-level production functions using proxy variables to control for unobservables, *Economic Letters* 104, 112–114.
- Zarembka, P. (1970). On the empirical relevance of the CES production function, *Review of Economics and Statistics* 52, 47–53.

### Supporting Information

Additional Supporting Information may be found in the online version of this article:

**Appendix A:** Proof of Proposition 1

**Appendix B:** Proof of Proposition 2

**Appendix C:** Definition of Labour, Capital and Intermediate Inputs and other control variables