Elasticity of Substitution and Farm Heterogeneity in TFP and Size: A Theoretical Framework and Empirical Application to Australian Broadacre Farms

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[Abstract]

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 minimizing 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, Total Factor Productivity, Income Effect

[JEL Code]

Q12, D92

I. Introduction

Globally, policy makers continue to seek avenues to promote farm-level productivity, since it determines 'long-term welfare and income' in rural areas (Krugman 2000). In support, researchers have identified various mechanisms through which changes in productivity occur. Apart from various exogenous effects (such as changing climatic, macroeconomic or policy conditions), productivity drivers can generally be classified as either new technologies, or more efficient ways to combine inputs. However, while there is a growing body of literature discussing their individual effects on productivity, the dynamic interaction between the two is less well understood (Boserup, 1965, Binswanger et al., 1993, Binswanger and Deininger, 1997, Chavas, 2008).

It is widely believed that changes to the mix of farm inputs at least partly reflect ongoing technology progress and its bias. At an industry level, the trend towards substituting land and labour for capital and intermediate inputs has occurred concurrently with ongoing productivity growth. For example, in most developed countries, farms now rely more heavily on capital service inputs, rather than land and labour, particularly among larger sized farms (OECD 2012). However, industry-level data masks significant variation. We also observe that individual farms choose different input mixes and exhibit different productivity performance over time. In a competitive market, this would happen even if they started with the same initial conditions (such as production technology and input usage). Specifically, those that have adjusted more quickly to changes in technology and prices appear more likely to become larger and more productive in the long run.

The general starting point for considering farmers' behaviour and their choice of input mix is profit maximisation. Assuming perfect competition, its dual of cost minimisation explains choice of cheaper inputs over more expensive ones, particularly from a comparative static perspective. However, it does little to explain how farmers' decisions to change input combinations leads to growth in productivity and farm size, nor why these outcomes vary across farms over time.

Following Klump and de La Grandville (2000), this paper develops a theoretical framework that describes the link between farmers' profit maximising/cost minimising behaviour, choice of input mix and total factor productivity (TFP). In sum, it provides a new mechanism to explain the presence of heterogeneity in farm productivity and size.

The logic proceeds as follows. Over time, the relative prices of farm inputs change due, in part, to input-biased technological progress. In response, farmers' profit maximizing/cost minimizing behaviour leads them toward lower-cost input combinations. This practice gives rise to substitution and income effects which, in the latter case, contributes to productivity growth from input saving.

While some farmers may choose to produce the same output using less input, others may increase inputs and produce even more—in some instances, through expanding farm size to further exploit the benefits from increasing returns to scale. As such, we propose that farms that have greater flexibility over input choices are more likely to realise higher productivity.

To test the validity of the theoretical proposition, the paper draws on Australian broadacre farm survey data for empirical evidence. Using unbalanced panel data from the late-1970s onwards, we demonstrate that farm size and TFP have been increasing with the elasticity of (technical) substitution (ETS) between capital, labor and intermediate inputs (that is, materials and services). Finally, a series of drivers of the ETS are discussed.

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.

II. 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 Grandville, 2000). The results can be easily extended to a multi-input case.

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

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

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

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-labor 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 $\bar{\varpi} = \bar{r}/\bar{w} = [f(\bar{k}) - \bar{k}f'(\bar{k})]/f'(\bar{k})$ and determined by market competition and thus independent of σ . Thus, technology parameters a and A can be derived (given $\bar{k}$, $\bar{y}$ and $\bar{\varpi}$) as a function of the elasticity of substitution σ (de La Grandville 1989).

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

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

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

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

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

$$\pi = kf'_{\sigma}(k)/f_{\sigma}(k), \tag{5}$$

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

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

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

$$\bar{\pi} = \frac{\bar{k}}{\bar{k} + \bar{\varpi}} \tag{7}$$

which is independent of both σ and k (since both $\bar{k}$ and $\bar{\varpi}$ are independent of σ). 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 normalized CES production function (equation (4)) as

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

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

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

Proposition 1: If two farms described by CES technologies differ only by their input elasticity of substitution, and share initially a common capital-labor ratio, labor 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 A for proof.)

Proposition 1 suggests that, starting from the same initial condition (where all farms share the same production technology, capital-labor ratio and labor use), farms with a higher ETS realise higher productivity than those with a lower ETS. This follows from profit maximizing/cost minimizing 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 labor in a competitive market, farms substituting capital for labor 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 labor 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.

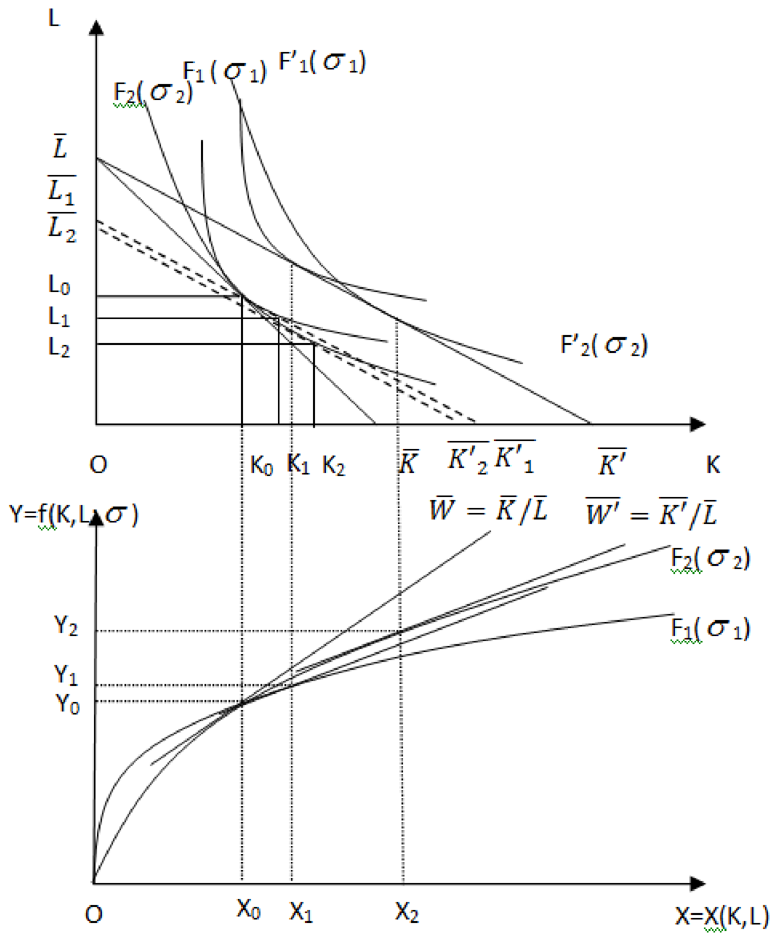
As a corollary to Proposition 1, when using total output (or total input) as a measure of operational scale, we can prove this also increases with ETS. Thus, farm size and TFP are correlated and increase with the ETS. This provides an alternative explanation for the positive correlation between farm 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-labor ratio, labor 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 B for proof.)

Propositions 1 and 2 are illustrated across linked diagrams in Figure 1. The upper diagram represents firms' cost minimizing 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 ($\overline{K}\overline{L}$) at the same point. If technological progress relaxes the budget constraint, say, from ($\overline{K}\overline{L}$) to ($\overline{K'}\overline{L}$), 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) labor, thereby realising a higher income effect. As shown in the upper diagram, holding the same unit-cost curve, the distance between $\overline{K'_2}\overline{L}$ and $\overline{K'}\overline{L}$ is larger than that between $\overline{K'_1}\overline{L}$ and $\overline{K'}\overline{L}$. 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



III. Empirical Strategy, Variable Definition and Data Source

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.

Empirical Model Specification

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

$$TFP_{it} = \alpha + \beta ETS_{it} + \gamma X_{it} + \varepsilon_{it} \quad (10)$$

$$SIZE_{it} = \alpha' + \beta' ETS_{it} + \gamma' X_{it} + u_{it} \quad (11)$$

where TFP_{it} and $SIZE_{it}$ denote farm i's TFP and size at time t. ETS_{it} is the elasticity of substitution specific to each farm. Since we wish to include three inputs (capital, labor and intermediate inputs), we treat ETS_{it} as a vector containing three elements: ETS_{it}^{KL} for the substitutability between capital and labor; ETS_{it}^{KM} for capital and intermediate inputs; and ETS_{it}^{LM} for labor and intermediate inputs. X_{it} are control variables covering technology change (i.e. year dummy) and various farm specific effects. α, α', β, β', γ and γ' comprise the coefficient matrix. In estimating equations (9) and (10), we expect positive and significant β (and β') if the model projections hold true. Moreover, a weak condition for that outcome would exist where the null hypothesis for vector β (and β'), being jointly insignificant or negative, can be rejected at the 1 percent level.

However, before we can estimate β and β' appropriately using equations (9) and (10), we need to address two econometric issues.

First are potential endogeneity problems. In practice, there are many time-invariant and time-variant farm-specific factors that could affect ETS, TFP and size. These may include, for example, farmers' age, experience and education level. Inadequately controlling for these factors may lead to biased estimates. To account for the impact of time-variant farm-specific factors, we added dummy variables corresponding to each year. To account for the impact of time-invariant farm-specific factors, we adopted a dynamic fixed effects panel data regression. In addition, we have also applied first-differencing and general method of moment (GMM) regression techniques to avoid other sources of endogeneity and reverse causality problems.

Second, while TFP and size can be estimated at the farm level, ETS can only be estimated at a cell level due to the restricted sample size over time.[1] A cell is defined over industry sector, region and time period. As Moulton (1990 p. 334) argued: 'When one tends to use the aggregate market or public policy variables to explain the economic behavior 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, estimating ETS at the cell-level may violate the assumption of independently and identically distributed residuals, thereby biasing the estimated errors downwards. We deal with this by using a cluster-robust method to correct for any intra-cell correlation in standard errors between farms belonging to the same cell.

[1] The data used in this exercise are an unbalanced panel, that is, most farms have a limited number of observations over time. This makes it impossible for the input elasticities to be estimated at the farm level. To deal with this problem, we assume farms that belong to the same cell share input elasticities of substitution.

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

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 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 elasticiticity 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 hold this property. To overcome this, we have applied the duality constraint to the MES measure of ETS using the input distance function method. In doing so, the MES measure becomes the Hicks-neutral elasticity of substitution—the HES (Kim 2000).

This study adopts the HES approach to estimate the ETS by using the cost share function. We approach estimation by measuring the maximum amount by which inputs can be feasibility reduced while still producing given outputs. Specifically, assuming that the trans-log input distance function for farm u producing a single (aggregate) output y_t^u using $m \in (1, \dots, M)$ types of inputs x_t^{um} in period t, is given by

$$\begin{aligned}\max D_t^u &= \alpha_0 + \alpha_y^u \ln y_t^u + \sum_{m=1}^{M} \alpha^u \ln x_t^{um} + \alpha_\tau^u \tau_t + \frac{1}{2}\beta_{yy}^u \ln(y_t^u)^2 \\ &+ \sum_{m=1}^{M} \beta_y^u \ln x_t^{um} \ln y_t^u + \frac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{M} \beta_{mn} \ln x_t^{um} \ln x_t^{un} + \beta_x^u \ln y_t^u \tau_t + \sum_{m=1}^{M} \beta_x^u \ln x_t^{um} \tau_t + \varepsilon_t^u\end{aligned} \quad (12)$$

where τ is a linear time trend and α's and β's are coefficients to be estimated and used later for the HES calculation. Moreover, it is assumed that the input distance function is homogenous of degree one, increasing and concave with respect to the inputs and decreasing with respect to the output. This assumption ensures the estimated ETS is constant and symmetric between inputs (Kim 2000).

Equation (12) is not directly estimable since it involves maximisation. Instead, we can estimate the same coefficients from its dual form—using the cost share functions. Applying Shephard's Lemma (where the derivatives of input distances with respect to individual input m is given by $p_{tm} = D_t^u / x_{tm}^u$) and imposing the normalisation condition that $D_t^u = 1$ (Coelli and Rao 2005), we can derive the corresponding cost share function[2]:

$$S_t^m = \alpha^m + \beta_y^m \ln y_t^u + \sum_{n=1}^{M} \beta_n^m \ln x_t^u + \beta_\tau^m \tau + \varepsilon_t^m \;\; \forall m, n = L, K, M \tag{13}$$

where S_t^m is the cost share of input m for farm u at time t and ε_t^u is the random error term. Equation (13) can be estimated by the simultaneous equation technique (Zellner 1962). The estimated coefficients represent the marginal input use in response to changes in the relative prices of capital, labor and intermediate inputs. The coefficients are assumed symmetric to restrict the trans-log production function for consistency.

Finally, ETS can be derived as:

$$ETS_{m,n} = [\frac{1}{\alpha^m} + \frac{1}{\alpha^n}]/[\frac{\alpha^m - \beta_m^m}{(\alpha^m)^2} + 2 * \frac{\beta_n^m}{\alpha^m \alpha^n} + \frac{\alpha^n - \beta_n^n}{(\alpha^n)^2}] \;\; \forall m, n = L, K, M \tag{14}$$

As for the estimation of Equation (13) (to calculate the ETS in Equation (14)), the data were pooled cross-sectionally, which does not support time-series analysis. For measurement purposes, we assumed farms within a cell (defined by sector, region and time period) shared the same ETS.

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

[2] For simplicity, we omit discussing duality between the input distance function, the cost functions and the corresponding derivation. Interested readers can refer to Kim (2000) for more detail.

(Christensen 1975, Diewert 1992, Coelli et al. 1998). 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:

$$TFP_{it} = \frac{Q_{it}^{FO}}{Q_{it}^{FI}} \tag{15}$$

where *O* are outputs and *I* 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:

$$Q_{it}^{Lj} = \frac{\sum_{k=1}^{N} p_{ki0}^{j} q_{kit}^{j}}{\sum_{k=1}^{N} p_{ki0}^{j} q_{ki0}^{j}} \text{ and } Q_{it}^{Pj} = \frac{\sum_{k=1}^{N} p_{kit}^{j} q_{kit}^{j}}{\sum_{k=1}^{N} p_{kit}^{j} q_{ki0}^{j}} \text{ where } j = \{O, I\} \tag{16}$$

In addition, farm size is measured using Dry Sheep Equivalents (DSEs).[3]

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 Government Department of Agriculture, Fisheries and Forestry, 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 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. To estimate the ETS, the sample period was split into three sub-periods: 1978 to 1988, 1989 to 1999 and 1999 to 2007. Appendix C contains definitions and detailed information on the input and output data used in this study.

[3] Using DSE as the measure of farm size was done to account for land quality differences in terms of approximate livestock dry matter demand or potential supply, relative to one dry sheep.The results from using other measures of farm size are available from the authors on request.

IV. 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.

Correlation between ETS and Farm TFP/Size

Table 1 presents descriptive statistics of the major variables used for the empirical analysis: farm inputs, outputs, TFP, size and estimated ETS. As mentioned earlier, data constraints render it necessary to measure ETS at the cell level. As such, the number of observations for the three elasticities of substitution (ETS_KL, ETS_KM and ETS_LM) is far less than the number of farms.

Table 1 Descriptive Statistics on major variables: 1978 to 2007

	Num. of Obs.	Mean	Std. Dev.	Min.	Max.
Output Index	36129	2.31	6.74	0.00	417.86
Labour Index	36129	1.63	1.99	0.00	57.29
Capital Index	36129	1.67	4.29	0.01	88.81
Intermediate Inputs Index	36129	2.48	10.24	0.00	609.95
Farm TFP	36129	1.62	0.97	0.00	11.52
Farm Size (DSE)	36129	18085	38044	0	937800
ETS_KL	90	0.13	0.12	-0.80	0.31
ETS_LM	90	1.79	0.38	-0.30	2.58
ETS_KM	90	1.41	0.50	-0.60	2.46

Notes: ETS_KL is the elasticity of substitution between Capital and Labour; ETS_LM between Labor and Intermediate Inputs; ETS_KM between Capital and Intermediate Inputs. DSE is dry sheep equivalent.

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 and intermediate inputs relative to labor, farms have increasingly relied more on capital and intermediate inputs than labor (Figure 1). This observation is consistent with previous literature describing capital and labor 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 2). This suggests that changing input mix might be correlated with farm TFP and size, where the ETS may play a role.

Figure 1 Changes in Average Farm Usage of Capital, Labor and Intermediate Inputs

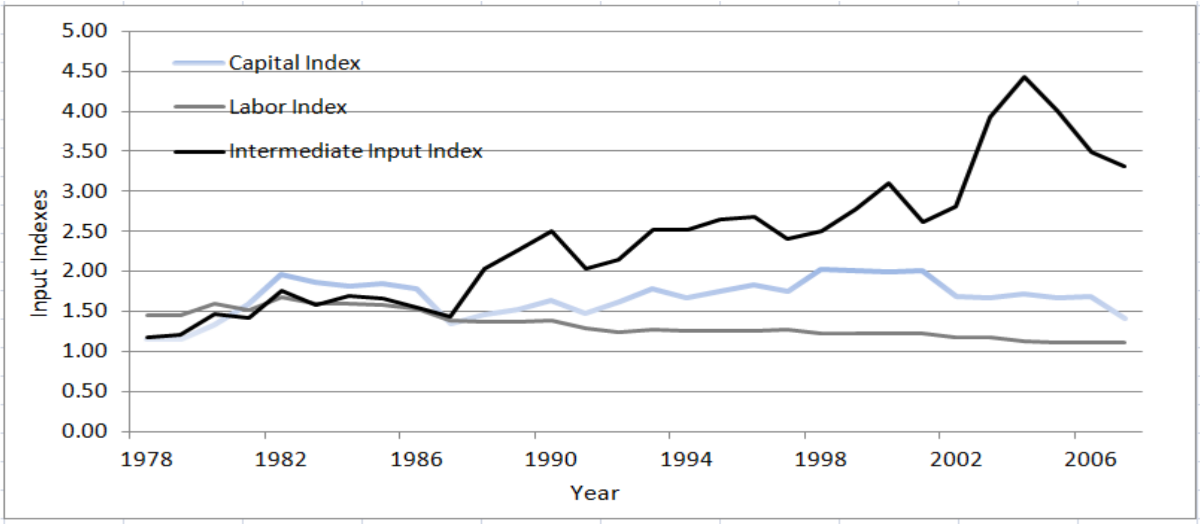
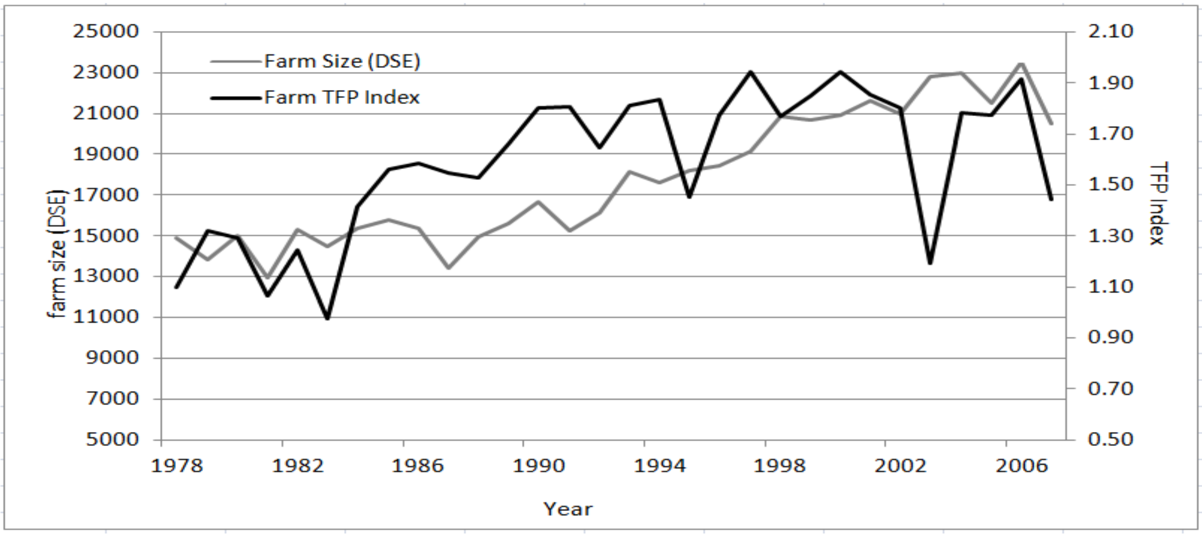
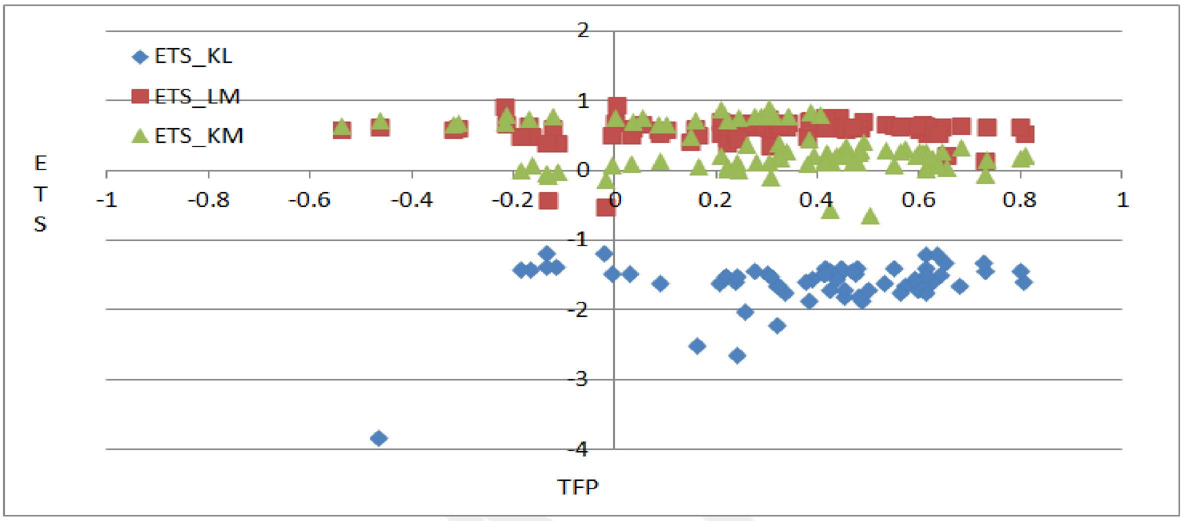


Figure 2 Average Farm TFP and Size between 1978 and 2007



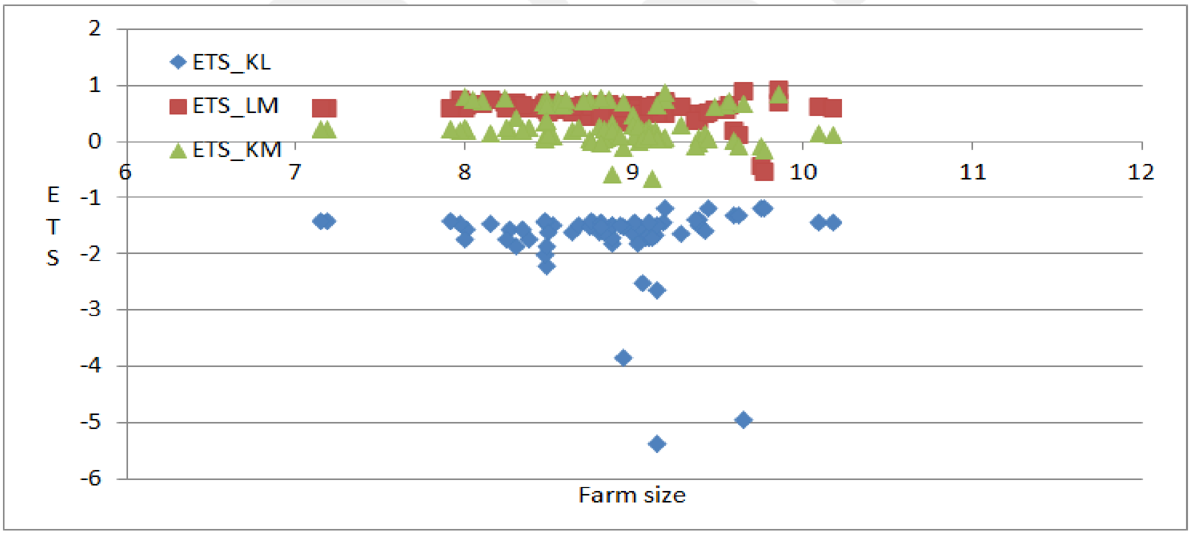
In preparation for the empirical analysis, we first inspected the correlation between farm TFP and ETS (Figure 3) and between farm size and ETS (Figure 4). In both instances, an initial investigation that involved pooling all periods seemingly resulted in unexpected relationships: the estimated ETS between capital and labour was positively correlated with farm TFP and size, but not for labor and intermediate inputs, nor for capital and intermediate inputs. This inspection, however, suffers from two data issues. First, the estimated ETS have varied considerably over time. Consequently, failure to account for the time specific variation of ETS may obscure the true correlation with farm TFP and size. Second, there are significant correlations between the estimated ETS (Table 2). Again, it is necessary to account for this correlation before establishing the true impact of a specific ETS on farm TFP and size.

Figure 3 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 4 Plot of farm size and ETS, by cell for all years



Note: both ETS and farm TFP are in logarithm and some outliers are excluded.

Table 2 Correlation matrix between ETS_KL, ETS_LM and ETS_KM

	ETS_KL	ETS_LM	ETS_KM
ETS_KL	1.00	-	-
ETS_LM	-0.36	1.00	-
ETS_KM	-0.71	0.34	1.00

Notes: Labels as per table 1

The Relationship between ETS and Farm TFP

Table 3 presents the results obtained from regressing three ETS variables with farm TFP in Australian broadacre agriculture. To deal with a potential endogeneity problem (i.e. correlation between ETS and residuals), we performed this estimation using the first-differencing GMM regression technique (with the system-GMM estimates as a robustness check). The regression results indicate that all ETS have positively influenced farm TFP (Columns 1 and 2 in Table 3). In the first-differencing GMM estimation, a unit increase in ETS_KL, ETS_KM and ETS_LM is likely to increase farm TFP by 0.322 per cent, 0.005 per cent and 0.045 per cent respectively (Table 1). The influences of ETS_KL and ETS_LM on farm TFP are positive and significant at 1 per cent level. Moreover, the null hypothesis that all three ETS coefficients are jointly less than or equal to zero is rejected at 1 per cent level (F-statistic is 191). The magnitude and significance of the results are generally consistent with those obtained from the system-GMM estimation.

In addition, we modified the regression to account for potential cluster effects. As discussed above, using the cell-level ETS to explain farm TFP may underestimate the variance of estimated coefficients, thereby implying an overly strong correlation (Columns 3 and 4 in Table 3). Consistent with the unadjusted regression results, the impact of ETS on farm TFP is positive for each pair of inputs: capital and labor (0.287), capital and materials (0.027) and labor and materials (0.054), at the 10 per cent significance level. Again, substitution between capital and labor plays the most important role—a unit increase in ETS_KL increases farm TFP by 0.287 per cent on average, all other things being equal. These results, consistent with the system-GMM estimates, further confirm the positive relationship between ETS and farm TFP.

Table 3 Relationship between ETS and TFP

	Panel Data Regression		***Regression with Cluster Effects***	
	1st differencing GMM	***System GMM***	***1st-differencing GMM***	***System GMM***
Dependent Variable: lnTFP				
ETS_KL	0.322**	0.657***	0.287**	1.070*
	(0.156)	(0.082)	(0.075)	(0.368)
ETS_KM	0.005	0.145***	0.027*	0.317
	(0.044)	(0.023)	(0.011)	(0.144)
ETS_LM	0.045***	0.131***	0.054**	0.269***
	(0.016)	(0.011)	(0.014)	(0.042)
Year Dummy	Yes	Yes	Yes	Yes

	(Significant)	(Significant)	(Significant)	(Significant)
Constant	-0.011	-0.513***	0.060**	-1.145**
	(0.074)	(0.045)	(0.017)	(0.409)
F-statistics	157.4	231.8	190.6	245.7
Number of Obs.	22862	34950	22862	34950
H_0: $\beta \leq 0$	191.0	231.2	178.6	208.7

Notes: Numbers in parenthesis are standard errors. *, ** and *** represent 10 per cent, 5 per cent and 1 per cent of significance respectively.

The Relationship between Operation Size and ETS

Table 4 presents the results obtained from regressing the three ETS (including ETS_KL, ETS_KM and ETS_LM) to farm size for Australian broadacre agriculture. Likewise, we can claim a positive impact of ETS on farm size. After accounting for potential endogeneity problems and cluster effects, the estimated coefficients of ETS are positive. The two methods (first-differencing and system GMM) produce coefficients of similar rank: ETS_KL (0.260, 0.651), ETS_KM (0.007, 0.343) and ETS_LM (0.048, 0.468) respectively. In particular, ETS_KL and ETS_LM are significant at the 1 per cent level. In addition, the null hypothesis that all three coefficients are jointly less than or equal to zero is rejected at the 1 per cent level (F-statistics is 278.6)

Table 4 Relationship between Elasticity of Substitution and Farm Scale (Measured with DSE)

	Panel Data Regression		***Regression with Cluster Effects***	
	1st differencing GMM	***System GMM***	***System GMM***	***1st-differencing GMM***
Dependent Variable: lnDSE				
MES_KL	0.476***	0.372***	0.260***	0.651*
	(0.107)	-0.064	(0.037)	(0.333)
MES_KM	0.017	0.023	0.007	0.343
	(0.027)	(0.016)	(0.018)	(0.045)
MES_LM	0.029*	0.022**	0.048***	0.468*
	(0.015)	(0.011)	(0.010)	(0.193)
Year Dummy	Yes	Yes	Yes	Yes
	(Significant)	(Significant)	(Significant)	(Significant)
Constant	8.755***	8.800***	-0.022	10.359***

	(0.055)	(0.038)	(0.035)	(1.283)
F-statistics	35.8	57.9	70.2	68.9
Number of Obs.	22853	34940	22853	34940
H_0: $\boldsymbol{\beta}' \leq \mathbf{0}$	278.6	351.2	179.3	247.9

Notes: Numbers in parenthesis are standard errors. *, ** and *** represent 10 per cent, 5 per cent and 1 per cent of significance respectively.

In sum, the empirical analysis provides evidence of positive relationships between the ETS and farm TFP and size. This supports the hypotheses proceeding from the theoretical model. In the presence of ongoing input-biased technological progress which, in part, contributes to changes in relative input prices, farms adjust their input mix by choosing cheaper inputs over more expensive ones. Cost minimizing/profit maximizing behaviour gives rise to the usual substitution effects plus additional income effects.

The income effect contributes to increasing farm TFP and size insofar as farms either produce the same (more) output with less (same) inputs, or enlarge operational scale—an option made possible by the increased budget. For some, the latter will typically involve expanding land area and increasing investment, which could generate further benefits from increasing returns to scale. A direct implication is that, across individual farms, TFP and size generally move in the same direction, with both depending on continuous input substitution.

In addition, the two propositions stated earlier also provide new insights about the presence and nature of farm heterogeneity. Irrespective of their initial conditions, farms differing only by their ETS can coexist in the long run with varying TFP and size, as commonly observed. In practice, farms with greater flexibility to adjust their input mix are more likely to realise higher productivity and, in some cases, expand their farm size. As such, the ETS 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.

V. Discussion: Factors Determining Farm Elasticities of Substitution

Having found that ETS 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 policy makers 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' iso-cost curves and determines how expenditure on inputs changes with relative prices. It can be generally interpreted as 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' 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 labor, 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 with a low debt-equity ratio are better placed to absorb the risks associated with adjusting their input mix.

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 policy makers, who have an interest in reforming policies as a means of promoting productivity growth.

VI. 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’. 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) 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). Further research directed at identifying the key determinants of ETS would assist policy makers seeking to promote productivity improvements through this channel.

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