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Input usage, output mix and industry deregulation: an analysis of the Australian dairy manufacturing industry*

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In this paper we estimate a Translog output distance function for a balanced panel of state level data for the Australian dairy processing sector. We estimate a fixed effects specification employing Bayesian methods, with and without the imposition of monotonicity and curvature restrictions. Our results indicate that Tasmania and Victoria are the most technically efficient states with New South Wales being the least efficient. The imposition of theoretical restrictions marginally affects the results especially with respect to estimates of technical change and industry deregulation. Importantly, our bias estimates show changes in both input use and output mix that result from deregulation. Specifically, we find that deregulation has positively biased the production of butter, cheese and powders.

Key words: Bayesian, deregulation, output distance function.

1. Introduction

The dairy industry in Australia is currently a major growth industry in terms of value of production, employment and export earnings. With an estimated gross value of production of nearly $A3 billion a year, the dairy industry ranks third behind wheat and beef in terms of output value at the farm gate. It is also an important value adding industry, with four fifths of its production being used to manufacture dairy products, mainly butter, cheese and milk products. Australia is the third largest exporter behind the European Union and New Zealand and its share of the world dairy product trade has risen to 15 per cent (ABARE 2001).

All parts of the Australian dairy industry supply chain have experienced a prolonged period of structural change as a result of various waves of deregulation. The need for structural change was initially recognised by government and the industry in the early 1980s. The processing/manufacturing sector was the first to start deregulating. Up until 1986 the Australian dairy

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processing sector was heavily regulated by the Australian federal government, but in 1986 price-pooling arrangements on major dairy manufacturing products stopped (ADC 1997). This change in policy gave manufacturers the incentive to monitor market developments and adjust their mix of output. The significance of the changes introduced in 1986 can be understood in terms of the sharp decline in industry support, initially for manufacturers and subsequently for dairy farmers. The Productivity Commission's annual Trade and Assistance Review outline the large declines in dairy industry assistance since 1986.

From 1986 further changes in industry regulation forced dairy manufacturers to base production decisions on international price changes. For example, under the Kerin and Crean Plans (1986–1995) a tax was levied on all raw milk production with the levy revenue used to raise the price of exported manufactured milk products above world market levels. This tax and associated industry payments were removed in 1995 by the introduction of the Domestic Market Support scheme. Finally, all Australian States removed regulations on dairy farmers in July 2000 (Edwards 2003; Kompas and Che 2004).

In this paper we employ an output distance function to examine the impact of deregulation on the dairy processing sector using a balanced panel of state level data. There already exists a large literature that has examined issues of regulation and deregulation of the Australian dairy industry from a milk production (i.e. the farm) perspective, for example, Knopke (1988), Kompas and Che (2004), Fraser and Graham (2005), Watson (2005) and Balcombe *et al*. (2006). In contrast, our research adds to a small literature on the impact of regulatory change for the processing sector of the dairy industry. Specifically, our research adds to that of Doucouliagos and Hone (2000a,b). They examined the impact of deregulation on the processing industry identifying a marked increase in restructuring and investment at the factory level. In these papers a restricted cost function and stochastic frontier production function have been used with output measured as real financial turnover. Our analysis extends these papers in three main ways.

First, we model explicitly the multi-output nature of this industry. To our knowledge, the multi-output nature of this industry has yet to be explored. To undertake our analysis we employ an output distance function. An output distance function can be used to describe the technology of a multi-input and multi-output production process, and hence can be used to measure the maximum proportional expansion of a vector of outputs, given an existing vector of inputs (Coelli *et al*. 1998). Our paper adds to a relatively small number of papers that have estimated distance functions to examine industry specific issues. Examples to date include, Grosskopf *et al*. (1995), Coelli and Perelman (1999, 2000), Paul *et al*. (2000), Atkinson *et al*. (2003), Paul and Nehring (2005) and O'Donnell and Coelli (2005). Our research contributes to this literature by estimating a fixed effects output distance function like Coelli and Perelman (1999, 2000). Unlike Coelli and Perelman we estimate our model using Bayesian methods. Our results allow us to examine relative technical efficiency within the Australian dairy processing industry. The fixed effects approach previously has been used to examine technical efficiency for the Australian wool industry (Fraser and Horrace 2003). We follow Kim and Schmidt (2000) and construct credible intervals for our point estimates of technical efficiency. Although the construction of credible (confidence) intervals in the efficiency literature has become relatively straightforward since Horrace and Schmidt (1996), few papers report these measures.

Second, we examine how our results are impacted by the imposition of economic theory. We achieve this by employing Bayesian methods in a manner similar to O'Donnell and Coelli (2005). The attraction of employing Bayesian methods is that we are able to impose various theoretical requirements on our data such that we can be certain that our various elasticity estimates conform to theory (e.g. montonicity and curvature). We also examine how sensitive our data are to the imposition of theoretical requirements in terms of the elasticity estimates derived.

Third, and most importantly, by employing the methodology introduced by Paul *et al*. (2000) we examine how deregulation has impacted on the mix of inputs used and output produced by the Australian dairy processing industry. Paul *et al*. (2000) used an output distance function to examine how the mix of inputs and outputs changed through time as a result of deregulation of New Zealand agriculture. Specifically, we focus on the change in input and output mix in the dairy processing industry in response to regulatory change. The way in which an industry responds to deregulation is important. In the case of the Australian dairy processing industry we would expect to see a significant response with regard to input use and output mix, because of changing farm level policy initiatives, the domestic demand for dairy products, and because Australia is a major dairy exporter and as such needs to react to global changes in consumption. Our understanding of the impacts of deregulation is helped by the use of a significantly longer data set compared to earlier research on this topic. Doucouliagos and Hone (2000a,b) used data relating to the 1969–1996 period. Our data set is significantly longer, covering the period 1961–2001. By employing a longer and improved data set this allows us to better examine and understand the impacts of the deregulation.

Overall our analysis reveals that there are potentially significant differences between Australian States in their relative technical efficiency. We find that Tasmania and Victoria are the most efficient and New South Wales the least. But, the fixed effect specification is subject to a number of criticisms (i.e. Greene 2002) that require us to treat these results with caution. In addition, we only consider six states in our analysis and this is a relatively small number compared to other applications.[1] More importantly we observe significant changes in input and output mix as a result of industry deregu-

[1] For example, Coelli and Perelman (1999) had a sample of 17 national railways over six years, Kim and Schmidt (2000) employed data on Texas utilities with 10 firms over 18 years and Atkinson *et al*. (2003) had 12 firms over 25 years.

lation. The pattern of results we obtain are in keeping with the views expressed by existing industry researchers in that regulation biased production in favour of milk as opposed to the more export orientated output. Methodologically, we find that imposing various theoretical restrictions does not impact on our results to the same extent as O'Donnell and Coelli (2005) found with their data. The theoretically correct specification does yield certain parameter estimates that are in keeping with previous research on the industry.

2. Theory and estimation

2.1 Methodology

In this paper we explore the impact of deregulation by estimating an output distance function. We take this approach because the output distance function can be used to describe the technology of a multi-input and multi-output production process. Also it can measure the maximum proportional expansion of the vector of outputs, given an existing vector of inputs (Coelli *et al*. 1998). In keeping with normal practice the output distance function is denoted as $D_0(x, y, r)$. The following properties follow immediately from the definition of the distance function; non-decreasing with respect to the elements of the input vector x; is linearly homogenous with respect to the elements of an output vector y; and r is a vector of exogenous variables.[2] A formal definition of the output distance function is as follows:

$$D_0(x, y, r) = \min\{\theta: (y/\theta) \in P(x, r)\} \quad (1)$$

where $P(x, r)$ is the output set for the given technology.

There are several issues to consider when estimating the output distance function. First, there is the issue of functional form. In keeping with the literature, we employ a Translog because it is a general and flexible representation of the underlying multi-input, multi-output technology. In particular and following Paul *et al*. (2000) and Paul and Nehring (2005) the Translog functional form provides cross-terms that provide important insights regarding input and output substitution possibilities. Second, we estimate the distance function using Bayesian methods, following Kim and Schmidt (2000) and O'Donnell and Coelli (2005). As previously noted, the Bayesian approach allows us to consider how the imposition of theoretical requirements on the data impacts on estimates of key elasticities.

Our Translog output distance function has M outputs ($m = 1 \ldots M$), K inputs ($k = 1 \ldots K$), an exogenous variable, r, describing industry regulation, T is time a proxy for technical change and I states ($i = 1, 2, 3, 4, 5, 6$) and is represented by Equation (2), for the ith state:

[2] For a full theoretical discussion of the output distance function see Shepard (1970) and Fare and Primont (1995).

$$\ln D_{0i} = \alpha_{0i} + \sum_{m=1}^{M}\alpha_m \ln y_{mi} + \frac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{M}\alpha_{mn}\ln y_{mi}\ln y_{ni}$$
$$+ \sum_{k=1}^{K}\beta_k \ln x_{ki} + \frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K}\beta_{kl}\ln x_{ki}\ln x_{li} + \sum_{k=1}^{K}\sum_{m=1}^{M}\gamma_{km}\ln x_{ki}\ln y_{mi} \tag{2}$$
$$+ \sum_{m=1}^{M}\tau_m \ln y_{mi} r_i + \sum_{k=1}^{K}\psi_k \ln x_{ki} r_i + \eta r_i + \delta T_i + \frac{1}{2}\delta T_i^2$$

where ln denotes natural log and D_0 is the output distance function, y output, x inputs, r is a vector of exogenous variables (i.e. deregulation) and T is a time trend used to capture technical change.

Following O'Donnell and Coelli (2005) it is necessary to impose a number of constraints on the output distance function in order to ensure that homogeneity of degree one in outputs, as well as symmetry, are satisfied. To impose homogeneity, we select one output as the normalising variable. The restrictions required for homogeneity of degree one in outputs are:

$$\sum_{m=1}^{M}\alpha_m = 1; \tag{3}$$
$$\sum_{n=1}^{M}\alpha_{mn} = 0; \quad \text{and} \tag{4}$$
$$\sum_{m=1}^{M}\gamma_{km} = 0\,. \tag{5}$$

For symmetry we require:

$$\alpha_{nm} = \alpha_{mn} \quad \text{and} \quad \beta_{kl} = \beta_{lk}. \tag{6}$$

Equation (7) shows the normalised output distance function.

$$\ln(D_{1i}/y_{li}) = \alpha_{0i} + \sum_{m=2}^{M}\alpha_m \ln y^*_{mi} + \frac{1}{2}\sum_{m=2}^{M}\sum_{n=1}^{M}\alpha_{mn}\ln y^*_{mi}\ln y^*_{ni}$$
$$+ \sum_{k=1}^{K}\beta_k \ln x_{ki} + \frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K}\beta_{kl}\ln x_{ki}\ln x_{li} + \sum_{k=1}^{K}\sum_{m=2}^{M}\gamma_{km}\ln x_{ki}\ln y^*_{mi} \tag{7}$$
$$+ \sum_{m=2}^{M}\tau_m \ln y^*_m r + \sum_{k=1}^{K}\psi_k \ln x_{ki} r_i + \eta r_i + \delta T_i + \frac{1}{2}\delta T_i^2$$

where $y^*_m = y_m/y_1$ and thus $y^*_1 = 1$.

At this point it is necessary that we mention and deal with the issue of endogeneity and distance function estimation. The choice of one normalising output which in turn becomes the dependent variable (i.e. y_{1i} in Equation (7)) in the econometric specification can be considered somewhat *ad hoc*. Which output we choose to use is arbitrary and as such any of the outputs could be considered as endogenous. As explained by Kumbhakar and Lovell (2000, p. 95) this implies that maybe some regressors are not exogenous and as such introduce simultaneous equation bias. However, various authors, in particular Coelli (2000) have argued that the endogeneity issue is less important than we might imagine. Coelli proves that under typically accepted behavioural assumptions (e.g. expected profit maximising or revenue maximising) Ordinary Least Squares yields consistent output distance function estimates for a Translog functional form. Thus, like other authors, such as Cuesta and Zofio (2005) we assume that Coelli's results apply to our econometric approach and that we need not be concerned with the endogeneity issue.[3]

2.2 Estimation

We estimate Equation (7) as a fixed effects specification employing Bayesian methods. Our output distance function is estimated using Bayesian methods, following Kim and Schmidt (2000) and Chib and Greenberg (1995a). Given that there are relatively few Bayesian applications in the literature to date, we briefly detail the estimation procedure.

The estimation approach uses the Markov Chain Monte Carlo (MCMC) method of Gibbs sampling with a Metropolis-Hastings (M-H) step (Casella and George 1992; Chib and Greenberg 1995b; O'Donnell and Coelli 2005). The Gibbs sampler allows us to approximate the marginal posterior distribution of a parameter of interest by generating a sample drawn from the marginal posterior distribution. The sample is derived by making random draws from the full conditional distributions of all parameters in a model. Employing Gibbs sampling, it is relatively straightforward to estimate the parameters β, the regression vector, and Ω, the covariance matrix of the errors. This is achieved by making successive sequential draws from the posterior conditional distributions of β given Ω, and Ω given β. The collection of these draws can then be used to map the unconditional posterior distributions.

Formally, we employ what Chib and Greenberg (1995a) refer to as their hierarchical Seemingly Unrelated Regression (SUR) model. The model we estimate is:

$$y_t = X_t\beta + \varepsilon_t \quad \text{where} \quad \varepsilon_t \sim N_p\,(0, \Omega) \tag{8}$$

The Gibbs sampler for this model is described in full in Chib and Greenberg (1995a). Equation (8) assumes a non-informative Normal prior on β and a Wishart prior for Ω^{-1} such that $\Omega^{-1} \sim W_p(v_0, R_0)$ where both hyper parameters are assumed known but non-informative. For β and Ω these are natural conjugate

[3] Atkinson and Dorfman (2005) introduce an interesting but highly technical econometric procedure to introduce instruments to address the endogeneity issue inherent in distance function estimation.

priors, providing there are no additional restrictions on the parameter space. If additional restrictions are placed on the parameter space, the priors are, by definition, informative. However, the posteriors can be sampled using the Normal and Wishart distributions, in conjunction with additional rejection steps within the sampler.

With non-informative priors, it follows that the posterior density of the parameter vector $\psi = (\beta, \Omega)$ is given by $\Pi(\psi \mid Y_n) \propto f(Y_n \mid \beta, \Omega)\Pi(\psi)$ where the likelihood is proportional to:

$$f(Y_n \mid \beta, \Omega) \propto |\Omega|^{-n/2} \exp\left[-\frac{1}{2}\sum_{t=1}^{n}(y_t - X_t\beta)'\Omega^{-1}(y_t - X_t\beta)\right] \tag{9}$$

where $Y_n = (y_1, \ldots, y_n)$ is the sample data and $\Pi(\psi)$ is constructed from the prior distribution on the parameters.

The only modification we need to make to the Gibbs sampler is to include a rejection step because we require that our data satisfy monotonicity and curvature at sample means. This is easily done by including an indicator function along with the conditional distribution of β as in O'Donnell and Coelli (2005). Thus, the Gibbs sampler to generate the $j + 1$ draw is computed by simulating $\Omega^{-1(j+1)}$ from $f_W(\Omega^{-1} \mid Y_n, \beta^{(j)})$ and $\beta^{(j+1)}$ from $f_N(\beta \mid Y_n, \Omega^{-1(j+1)}, \beta^{(j)}) \times I(\beta \in R)$ where I is the indicator function and R is the set of permissible parameter values when monotonicity and curvature are satisfied. If the number of rejections is very large (e.g. the Gibbs sampler repeatedly delivers values that do not conform to the restrictions), the rejection step within the Gibbs sampler may lead to impractically long estimation times. In these circumstances the M-H algorithm is employed for the β parameters. This algorithm has been detailed in a number of papers (e.g. Chib and Greenberg 1995b), and therefore is not outlined here.

In undertaking our Bayesian estimation we conducted 100 000 burn-in iterations, sampling each 100th iteration. We then undertook 1 000 000 iterations in the main phase again sampling each 100th iteration (leaving 10 000 sample observations). To assess the convergence of our results we compared results from the first and second 5000 iterations. For all parameters, our results are equivalent to three decimal places. In addition we performed a modified t-test which accounted for dependency in the sample sequence. This test failed to reject no-difference in the means of the first and second half of the sample for nearly all 51 parameters, at a 5 per cent level of significance for both models. All estimation was undertaken in *GAUSS*.

3. Technical efficiency, elasticities and bias measures

3.1 Technical efficiency estimates

In keeping with a number of applications in the efficiency frontier literature we can capture efficiency as part of our estimation of the fixed effects model.

Specifically, we follow Coelli and Perelman (1999, 2000), Kim and Schmidt (2000) and Fraser and Horrace (2003). First, we estimate the output distance function including a fixed effect for each of the dairy processing states in Australia. We can do this because we can re-express the dependent variable in Equation (7) as $\ln(D_{0i}) - \ln(y_{1i})$. This in turn allows us to transfer the unobservable term, $\ln(D_{0i})$, to the right hand side and it can be interpreted as a random error term. Second, we can adjust and then transform the fixed effect estimates to yield measures of technical efficiency. We do this by arranging in rank order the α_i (i.e. $\alpha_{[1]} \leq \alpha_{[2]} \leq \ldots \leq \alpha_{[N]}$ where $[N]$ is the index of the state with the largest α_i $(i = 1, \ldots, N)$ in the population. We then define u_i which represents technical inefficiency such that $u_i = \alpha - \alpha_i$ and it follows that $u_{[N]} \leq u_{[N-1]} \leq \ldots \leq u_{[1]}$. Clearly, $\alpha_{[N]} = \alpha - u_{[N]}$ and state $[N]$ has the largest α_i (smallest u_i) for $i = 1, 2, 3, 4, 5, 6$. Thus, the measure of relative efficiency (r_i) is estimated from Equation (7) as follows:

$$\hat{\alpha} = \max_{i=1,\ldots,6} \hat{\alpha}_i,\ \hat{u}_i = \hat{\alpha} - \hat{\alpha}_i \text{ and } \hat{r}_i = \exp(-\hat{u}_i),\ i = 1, 2, 3, 4, 5, 6.$$

In addition to providing point estimates of technical efficiency, we follow Kim and Schmidt (2000) and construct credible intervals. As they note, the posterior distribution of the inefficiency estimate can be revealed by Monte Carlo draws from the posterior distribution of $\alpha_1, \alpha_2, \ldots, \alpha_n$. Credible intervals can be constructed from the percentiles of the resulting density. We adopt a slightly different approach, in that the posterior draws of the state dummies are used to map the posterior densities and construct credible intervals for the state efficiency measures directly. This should yield more accurate results than the Kim and Schmidt approach, since there is no guarantee that the posteriors should be approximately normal or t-distributed should the curvature and monotonicity restrictions be heavily binding.

Finally, it is important to note that the fixed effect method of estimating relative inefficiency is subject to a number of limitations. First, as noted by Kim and Schmidt (2000) the 'max' operator induces an upward bias which generally results in efficiency estimates being underestimated (p. 96). As we will see when we present our results, the relative size of the efficiency estimates reported in this paper are significantly less than those reported previously by Doucouliagos and Hone (2000b).[4] Second, probably of greater significance, Greene (2002) explains that the measure of inefficiency revealed using this approach may well be detecting other unmeasured sources of heterogeneity. As a result we treat our measures of technical efficiency with caution. However, as the main purpose of the paper is to examine changes in input use and output mix as a result of deregulation we are prepared to accept this limitation of the results.

[4] However, since Doucouliagos and Hone (2000b) abstract from the multi-output nature of this industry, their efficiency rankings may be upwardly biased.

3.2 Elasticities and bias measures

The main purpose for estimating the output distance function in this paper is because we wish to measure a number of elasticities and bias measures that are of interest for an industry that has undergone profound regulatory change. For example, the output distance function can estimate the relationship between inputs and outputs (i.e. production function), the relationship between inputs (i.e. isoquants) and the relationship between outputs (i.e. production possibilities). In particular, we can observe important results about the underlying input and output substitutability by examining cross-products, as they may be interpreted as bias measures (Paul *et al*. 2000). When we consider the output side, things are complicated by the fact that we have to normalise data prior to estimation. As a result all measures are expressed as ratios relative to the output used to normalise the data. In this context we can recover measures that provide insights into production possibilities, production substitutability and output composition effects.

In terms of output elasticities we can measure returns to an input, or the elasticity of total output with respect to inputs, that is, ($\varepsilon_{y,k} = \partial \ln y / \partial \ln x_k$). This elasticity measure reveals if an input is contributing positively to output or if its use is such that the production process is experiencing 'congestion' in that additional input use adds nothing to, or even reduces output. Similarly, we can consider input substitutability that reveals insights about the shape of isoquants. This measure is provided by parameter estimates of cross-products for inputs.

Another important measure is the elasticity of total output with respect to other output. The output parameter estimates from Equation (7) are the elasticities of total output with respect to particular types of output ($\varepsilon_{y,m} = \partial \ln y / \partial \ln y_m$) when the data are at sample means. This estimate measures the contribution of output m to overall output, in the same way we measure the contribution of inputs to overall output. We can also consider cross-terms from Equation (7) with respect to y_m which if positive imply a greater contribution of output y_m in total output from increases in the associated variable.

In terms of bias measures, Paul *et al*. (2000) show how to examine if an increase in the use of one input in production is biased, where its impact on the marginal productivity of other inputs depends on whether the inputs are complements or substitutes. This measure is derived by recovering $\partial^2 y / \partial x_k \partial x_l$. If the measure is negative then the inputs are technically competitive, if zero then the inputs are independent, and if positive they are technically complementary. These measures are calculated by multiplying the parameter estimate on an input–input term by the average of the natural logarithm of one of the inputs and are denoted by Paul *et al*. (p. 330) as C_{kl}. For example, $C_{\text{labour, capital}}$ is estimated by multiplying the coefficient on the labour–capital joint term by the average value of the natural logarithm of capital.

Similarly, we can measure output substitutability bias. This bias measures the contribution of output m to total output resulting from an increase in output n. Thus, it measures if production is output-using or output-displacing with respect to a specified output. We calculate the bias, denoted as C_{mn}, as $\alpha_{mn} \times \ln y_n^*$, where * indicates a normalised output variable. Finally, we can measure regulatory bias (C_{kr}) for inputs and similarly for outputs, that is, C_{mr}. This is an important measure in the analysis we present as it empirically captures many of the facets of industry response to deregulation. As with the other parameters and functions of parameters in the model, we map the posterior distributions of these functions, and report the mean bias measures, along with their standard deviations.

4. Data

Our data comprises a balanced panel for the six main dairy producing states in Australia, that is, New South Wales, Victoria, South Australia, Queensland, Western Australia and Tasmania. Our state level data are an aggregation of individual plants of firms operating within each state. It was necessary to use the state-level data as firm/plant data are not available.[5] As a result we view our state-level data as being consistent with the assumption of a representative firm. The state-level data captures the regional nature of milk production and processing. While firm level data would be preferable, the use of aggregate level data is common. For example, Doucouliagos and Hone (2000b) also used state-level data in their analysis of the same industry. Several papers have used data aggregated at the national level to compare performance across nations. For example, Adkins *et al*. (2002) use stochastic frontier analysis to explore the impact of economic freedom on technical efficiency in 73 countries. Similar analysis has been undertaken by Lall *et al*. (2002) and Klein and Luu (2003). Our view is that the firms operating in a state like Victoria are broadly similar in their use of technology and the market conditions under which they operate. Hence, the use of data aggregated at the state level should lead to no real loss of information. State-level data are a reasonable approximation to the underlying firm level data.

The data covers the period 1961–2001 and are drawn from various published and unpublished sources (i.e. ABS, ABARE). A full discussion of the construction of the database, as well as all the sources, is available from the authors on request. Our data comprises four outputs; butter, cheese, milk powders and liquid milk. On the input side are labour, milk, capital (plant plus buildings) and energy.[6] Labour is measured as the number of workers employed by the industry. The milk input is measured as the volume of

[5] There is no firm level data for this industry. The ABS does not release the information relating to the individual firms from which they compile the state level data. There is only limited firm level data available from annual reports, and reliable data is available only for the leading firms. The use of such data raises issues of sample selection, and would be less representative of the industry than the state-level data used here.

[6] That is, milk is both an input and an output. Milk produced in each state is taken to be the milk input and milk sales are taken to be the liquid milk output.

whole-milk produced by each state.[7] Capital stock was calculated using the Perpetual Inventory Method, following the procedure outlined in the Bureau of Industry Economics (1985) regarding asset lives. Energy usage is the total petajoules (from unpublished ABARE data). All four output series are measured in terms of volumes, rather than values.

There is no index on deregulation in this industry. Hence, to this basic data set we added a dummy variable to capture the impact of deregulation on the industry, a common approach in the literature (e.g. Paul *et al*. 2000). The dummy variable is assumed to be 1 up until 1985 and 0 thereafter. A similar approach was adopted by Doucouliagos and Hone (2000a) in their variable cost function analysis, although they used a single output measure aggregated for Australia and they used Australia-wide data (i.e. they did not use state-level data).[8] The study that comes closer to ours is Doucouliagos and Hone (2000b). They estimated a stochastic production frontier using state-level data, within a single output rather than our multi-output framework. However, the effects of deregulation in that study were explored only by comparing the results in the pre to the post-deregulation periods, without a formal deregulation variable introduced into the econometric specification.

The binary (deregulation) variable captures differences in the broader operational environment. While there are different phases within this period, the post-1986 era was the period of deregulation. We wish to explore whether there are differences in the parameters between the pre- and post-deregulation periods. While the single binary variable does not inform on individual aspects of deregulation, it offers sufficient information on the overall process compared to the pre-deregulation period.[9] Paul *et al*. (2000) used a similar binary variable to capture regulatory impact on the efficiency of New Zealand farms, even though the reforms were over several years.[10] Our model also includes interactions between the regulation dummy and all inputs and outputs. Finally, we also include a time trend and a time trend squared as a proxy for technical change in our econometric estimation.

Summary statistics for each state for the entire data period are presented in Table 1.

The statistics in Table 1 reveal the relative size of Victoria in terms of manufactured milk output (i.e. butter, cheese and powders). For example, Victoria produced almost 10 times more butter on average than the next biggest producer, NSW. The only market in which there is parity in terms of quantity

[7] Over the period studied, there was limited interstate trade in wholemilk (Doucouliagos and Hone 2000b).

[8] They found that using the effective rates of industry assistance produced essentially the same results as the binary variable.

[9] It is also the case that the inclusion of multiple dummy variables (e.g. Kerin and Crean Plans, Domestic Market Support Scheme and post-2000 deregulation) to describe the deregulation process would increase the number of parameters to be estimated by 21 because of the way in which we interact our regulatory measure with all the regressors.

[10] Paul *et al*. (2000) found that adjusting the timing of the binary variable made no real difference to their results.

Table 1 Descriptive statistics (1961–2001)

State	Outputs				Inputs			
	Butter (Tonnes)	Cheese (Tonnes)	Powders (Tonnes)	Milk (ML)	Labour (Workers)	Milk (ML)	Capital ($)	Energy (PJ)
New South Wales								
Mean	12 216	12 037	8 742	669	5 212	1 121	285	21
Standard Deviation	13 220	6 741	3 495	133	1 635	223	112	4
Minimum	829	4 122	1 378	502	3 275	840	142	12
Maximum	39 185	29 639	16 155	971	7 564	1 567	643	29
Victoria								
Mean	106 373	88 708	172 717	450	8 236	3 991	670	18
Standard Deviation	22 288	62 460	105 258	35	629	1 059	269	4
Minimum	65 599	19 977	39 289	352	6 630	2 713	336	9
Maximum	147 593	246 765	455 254	528	9 128	6 870	1 527	23
Queensland								
Mean	12 851	13 216	5 032	361	2 220	751	167	9
Standard Deviation	11 328	5 655	2 449	83	113	174	69	3
Minimum	2 795	7 222	460	238	1 996	506	80	4
Maximum	36 456	32 694	9 634	534	2 519	1 114	371	15
South Australia								
Mean	3 461	21 764	1 514	157	1 376	419	97	2
Standard Deviation	2 467	6 712	1 159	18	569	70	32	1
Minimum	296	12 609	25	122	681	306	51	1
Maximum	7 702	40 593	4 275	199	2 266	646	199	4
Western Australia								
Mean	3 659	3 356	2 117	147	1 091	288	72	3
Standard Deviation	2 364	1 765	953	25	239	106	21	1
Minimum	799	1 206	723	112	553	209	39	1
Maximum	8 189	7 306	4 151	193	1 352	714	137	6
Tasmania								
Mean	9 149	13 949	7 185	49	760	407	51	2
Standard Deviation	3 461	8 990	3 984	5	76	83	13	1
Minimum	3 882	348	2 488	37	624	289	29	1
Maximum	15 274	33 462	19 774	61	888	609	74	3

Note: ML, megalitre; PJ, petajoule.

Table 2 Percentage share by state of total inputs and outputs

Year	Region	Output (%)				Input (%)			
		Butter	Cheese	Powders	Milk	Labour	Milk	Capital	Energy
1961	NSW	19	12	25	44	22	24	21	42
2001	NSW	2	6	1	33	20	13	22	36
1961	QLD	17	15	7	23	15	16	12	14
2001	QLD	4	9	1	20	13	7	12	19
1961	SA	4	27	2	7	6	7	8	4
2001	SA	1	9	1	10	5	4	7	5
1961	TAS	6	1	4	2	4	5	4	4
2001	TAS	4	9	2	3	4	6	3	4
1961	VIC	50	43	61	17	50	45	50	33
2001	VIC	88	66	94	24	53	64	52	29
1961	WA	4	3	1	7	3	4	6	3
2001	WA	1	2	1	10	4	7	5	8

produced is milk. We can further illustrate the relative difference in size as well as the changing composition of input use and output mix by looking at the percentages by state for inputs and outputs in 1961 and 2001. These statistics are presented in Table 2.

The figures in Table 2 amplify those in Table 1. In addition, they show the changing balance of output over the sample period. It is particularly striking to see just how important Victoria has become in terms of total Australian output of manufactured milk products. We can also see that Tasmania has increased its share of cheese production. Given that these figures are not adjusted for quality it is likely that this is an underestimate of market share by value. We can also see on the input side how the derived demand for milk has declined in particular states and increased in others almost certainly as a result of industry restructuring as a result of deregulation.

5. Results

Our results are composed of two parts. First, we present the output distance function estimates and the measures of technical efficiency. Second we examine the various elasticity and bias measures described. All results are presented in terms of the mean and standard deviations of the posterior distributions as generated by the MCMC samplers.[11]

5.1 Output distance function estimates

For the estimated Translog output distance function represented by Equation (7) we present results with monotonicity and curvature imposed (restricted

[11] When interpreting our results it needs to be borne in mind that our dependent variable is negative and so the reader needs to interpret parameter estimates accordingly.

model) and not imposed (unrestricted model). To facilitate interpretation of the parameter estimates we have mean corrected our data. This means that the output and inputs parameter estimates are the elasticities of total output with respect to particular types of output and inputs. Our results are presented in Table 3.

The first thing to note about the results presented in Table 3 is that all input and output elasticities are correctly signed according to theory. For the elasticities of total output with respect to particular types of output, all estimates are positively signed which is interpreted as meaning that total output increases as the production of that individual output increases. The results for the restricted specification also show that the imposition of monotonicity and curvature at the point of sample means does have an impact on the elasticity estimates. This can be seen on the output side with respect to the estimates for powders and liquid milk. On the input side we see that the imposition of the theoretical restrictions has led to a slightly more uniform contribution of all inputs to output, compared to the unconstrained model that indicated a larger contribution from the raw milk input.

Next we can observe important results about the underlying input and output substitutability by examining cross-products, as they may be interpreted as bias measures. A positive cross-term with respect to y_m implies a greater contribution of output y_m in total output from increases in the associated variable. So, for example, for the unrestricted model there is a negative cross-term on Cheese × Powders (α_{23}) and Cheese × Liquid milk (α_{24}) that suggests that processors with higher cheese output will in turn reduce their production of liquid milk relative to butter. The signs are the same for the restricted specification albeit somewhat smaller.

Turning to the input cross-terms (β_{kl}), if they are negative (positive) an increase (decrease) in one, raises (reduces) the (proportional) marginal product or implicit share of the other suggesting complementarity (substitutability). From Table 3 we can see that Labour × Capital, Labour × Energy, Milk × Capital, Milk × Energy and Capital × Energy are positive, and the rest are negative. In this case, labour is complementary with milk and capital but a substitute with energy.

Turning to the regulatory cross-terms we find several interesting results which are consistent across specifications. For outputs we have positive estimates on cheese and powders, implying a preference not to produce these outputs relative to butter and liquid milk under regulation. These results support typical opinions expressed about the Australian dairy processing industry and the impact of regulation on output mix. That is, the industry in several states (e.g. NSW and Queensland) has decreased the production of butter in response deregulation and increased the production of cheese for export demand as a result of the removal of various production quotas and liquid milk marketing requirements.

On the input side milk has a negative sign while labour, capital and energy are positive. The negative sign on milk indicates a decrease in its productive

Table 3 Output distance function results

Variables		Unrestricted Parameters	Unrestricted Standard Deviation	Restricted Parameters	Restricted Standard Deviation
NSW (Fixed Effect)	α_{01}	–9.350	0.038	–9.445	0.043
VIC (Fixed Effect)	α_{02}	–8.831	0.043	–8.794	0.047
QLD (Fixed Effect)	α_{03}	–9.216	0.018	–9.274	0.018
SA (Fixed Effect)	α_{04}	–9.137	0.023	–9.114	0.026
WA (Fixed Effect)	α_{05}	–9.338	0.035	–9.337	0.028
TAS (Fixed Effect)	α_{06}	–8.353	0.037	–8.259	0.039
Cheese	α_2	0.003	0.013	0.001	0.001
Powders	α_3	0.049	0.010	0.001	0.001
Liquid Milk	α_4	0.925	0.022	0.994	0.004
Labour	β_1	–0.123	0.024	–0.154	0.019
Milk	β_2	–0.378	0.042	–0.238	0.031
Capital	β_3	–0.160	0.028	–0.198	0.038
Energy	β_4	–0.207	0.026	–0.194	0.031
Cheese × Cheese	α_{22}	0.049	0.009	0.012	0.006
Cheese × Powders	α_{23}	–0.036	0.005	–0.004	0.003
Cheese × Liquid Milk	α_{24}	–0.022	0.008	–0.008	0.005
Cheese × Labour	γ_{21}	0.044	0.011	0.072	0.011
Cheese × Milk	γ_{22}	0.020	0.014	–0.029	0.015
Cheese × Capital	γ_{23}	–0.138	0.019	–0.113	0.018
Cheese × Energy	γ_{24}	0.080	0.014	0.061	0.011
Powders × Powders	α_{33}	–0.006	0.004	0.000	0.002
Powders × Liquid Milk	α_{34}	0.034	0.006	0.003	0.002
Powders × Labour	γ_{31}	0.034	0.014	–0.016	0.011
Powders × Milk	γ_{32}	0.003	0.016	0.020	0.013
Powders × Capital	γ_{33}	0.063	0.016	0.044	0.016
Powders × Energy	γ_{34}	–0.087	0.014	–0.034	0.012
Liquid Milk × Liquid Milk	α_{44}	0.012	0.013	0.009	0.006
Liquid Milk × Labour	γ_{41}	–0.073	0.014	–0.058	0.014
Liquid milk × Milk	γ_{42}	–0.079	0.022	–0.064	0.021
Liquid milk × Capital	γ_{43}	0.144	0.019	0.122	0.019
Liquid milk × Energy	γ_{44}	–0.010	0.020	–0.007	0.015
Labour × Labour	β_{11}	0.072	0.048	–0.134	0.026
Labour × Milk	β_{12}	–0.222	0.052	–0.018	0.022
Labour × Capital	β_{13}	0.023	0.052	0.049	0.032
Labour × Energy	β_{14}	0.098	0.034	0.124	0.032
Milk × Milk	β_{22}	–0.219	0.082	–0.432	0.066
Milk × Capital	β_{23}	0.501	0.048	0.480	0.045
Milk × Energy	β_{24}	0.042	0.047	0.021	0.045
Capital × Capital	β_{33}	–0.641	0.053	–0.608	0.054
Capital × Energy	β_{34}	0.150	0.042	0.129	0.041
Energy × Energy	β_{44}	–0.233	0.049	–0.270	0.052
Regulation × Cheese	τ_2	0.105	0.013	0.046	0.013
Regulation × Powders	τ_3	0.030	0.010	0.072	0.010
Regulation × Liquid Milk	τ_4	–0.131	0.014	–0.143	0.016
Regulation × Labour	ψ_1	0.058	0.037	0.199	0.035
Regulation × Milk	ψ_2	–0.474	0.052	–0.689	0.047
Regulation × Capital	ψ_3	0.252	0.043	0.288	0.051
Regulation × Energy	ψ_4	0.147	0.030	0.112	0.029
Time	δ	–0.001	0.002	0.005	0.002
Time × Time	δ^2	0.001	0.000	0.001	0.000
Regulation	η	–0.030	0.030	0.061	0.049

Table 4 Technical efficiency estimates: mean, standard deviation and 95% credible intervals

	Unrestricted	Restricted
NSW	0.37 (0.025) [0.335, 0.419]	0.31 (0.0213) [0.272, 0.341]
VIC	0.62 (0.042) [0.564, 0.697]	0.58 (0.0453) [0.517, 0.664]
QLD	0.42 (0.021) [0.387, 0.460]	0.37 (0.0173) [0.355, 0.392]
SA	0.46 (0.016) [0.428, 0.482]	0.43 (0.0153) [0.401, 0.451]
WA	0.37 (0.019) [0.343, 0.406]	0.34 (0.0124) [0.320, 0.361]
TAS	1 (0.000) [1, 1]	1 (0.000) [1,1]

Note: Standard deviation in round parentheses. 95% credible intervals in square brackets.

contribution as a result of deregulation, whereas for labour, capital and energy the positive sign implies an increase in their productive contribution. These results again confirm industry comment with respect to the relative contribution of various inputs.

Finally, from Table 3 we examine the time trend and the regulatory dummy. In this case there is contradictory evidence from the restricted and unrestricted specifications. For unrestricted specification we find evidence of technical regress and a negative impact as a result of regulation. The point estimates for the time trend and regulation need to be treated with caution because the associated standard errors indicates they are zero. In contrast the restricted results indicate a more plausible scenario of technical progress, albeit 0.7 per cent per annum and a positive estimate for regulation implying a positive impact as a result of deregulation. This level of technical progress is somewhat lower than previous estimates. For example, Doucouliagos and Hone (2000b) report technical progress of 2.6 per cent per annum.

Overall, an initial inspection of the results indicates that there is reasonably little to choose between the two model specifications. However, the restricted model does yield economically more meaningful estimates for technical progress and the impact of deregulation. It is also the case that there are some sign reversals and changes in the magnitude on some of the second order coefficients. Examples include, Cheese × Milk, Powder × Labour, and Labour × Labour.

Turning to Table 4 we now examine the level of technical efficiency. The results in Table 4 reveal an interesting picture of technical efficiency although the reader should be cognisant of the potential problems with these results identified by Greene (2002). We find that Tasmania is the most technically efficient state, followed by Victoria. This is in reasonable agreement with Doucouliagos and Hone (2000b) who identified Victoria as being the most efficient state. We have also identified NSW as being the most technically inefficient state. Our 95 per cent credible intervals are reasonably narrow indicating that Tasmania and Victoria are different from each other. In the case of NSW there is a degree of overlap of the credible intervals with WA and Queensland.

Table 5 Bias estimates–restricted model specification

Outputs	Butter	Cheese	Powders	Liquid Milk	Regulation
$C_{m,\text{ Butter}}$	0.0042	–0.00011	–0.0002	0.0176	0.1151
	(0.0042)	(0.0014)	(0.0005)	(0.0159)	(0.0277)
$C_{m,\text{ Cheese}}$	–0.0002	0.00541	0.0013	0.0284	0.0457
	(0.0032)	(0.0028)	(0.0009)	(0.0178)	(0.0129)
$C_{m,\text{ Powders}}$	0.0008	–0.00183	–3.6E-05	–0.0116	0.0717
	(0.0016)	(0.0012)	(0.0006)	(0.0080)	(0.0096)
$C_{m,\text{Liquid Milk}}$	–0.0042	–0.00347	–0.0010	–0.0344	–0.1428
	(0.0044)	(0.0022)	(0.0007)	(0.0213)	(0.0155)
Inputs	**Labour**	**Milk**	**Capital**	**Energy**	**Regulation**
$C_{k\text{Labour}}$	–1.0279	–0.1169	0.2434	0.2228	0.1985
	(0.1969)	(0.1421)	(0.1570)	(0.0577)	(0.0351)
$C_{k,\text{Milk}}$	–0.1361	–2.8437	2.3812	0.0376	–0.6886
	(0.1654)	(0.4334)	(0.2223)	(0.0803)	(0.0472)
$C_{k,\text{Capital}}$	0.3758	3.1588	–3.016	0.2327	0.2884
	(0.2423)	(0.2949)	(0.2703)	(0.0743)	(0.0510)
$C_{k,\text{Energy}}$	0.9482	0.1377	0.6417	–0.4862	0.1118
	(0.2456)	(0.2938)	(0.2048)	(0.0936)	(0.0294)

Note: Standard deviations in parentheses.

5.2 Bias estimates

We now examine the various bias estimates described in Section 3.2. These bias estimates provide additional insights into the substitutability between pairs of inputs and pairs of outputs. Given the results reported in the previous section we will only present results for the restricted model. Our bias estimates are evaluated at sample means and are presented in Table 5.

On the output side, because of the need to normalise the output distance function, all bias estimates (C_{mY}) are expressed as ratios relative to butter. The first thing to note is that like Paul *et al*. (2000), there are no large estimates indicating significant output using/displacing effects between outputs. The most important and significant results are for the bias estimates involving regulation. With regard to regulation we find that only liquid milk is positively biased. That is, all other outputs have been positively biased by the deregulation process. These results are as we would expect given the descriptive statistics presented in Table 2 and the views typically expressed in the Australian dairy processing sector with respect to the impact of deregulation.

The input substitutability measure, C_{kl}, indicates whether inputs are technically complementary, independent or competitive. For the results presented in Table 5 a negative sign implies complementarity whereas a positive sign implies a competitive relationship. For example, $C_{\text{Labour,Milk}}$ and $C_{\text{Labour,Milk}}$ are complementary. All the other input substitutability estimates indicate a competitive relationship. When we consider the input bias with respect to regulation we find a complementary relationship between regulation and milk. This implies that there is a competitive relationship between labour and regulation, capital and regulation, and energy and regulation. As we would expect, these results confirm the results presented in Table 3, making the same point albeit in a slightly different guise. That is, once the sector has been subject to deregulation, competitive economic pressures have produced a realignment of input use that is consistent with profit maximising behaviour.

6. Conclusions

In this paper we have estimated an output distance function for the Australian dairy processing industry. Our results allow us to draw some interesting and important insights into the way in which the industry has responded to a comprehensive policy of deregulation since 1986. From a practical perspective our results provide econometric support of the views that have frequently been expressed about the impact of deregulation on the Australian dairy processing industry.

First, our results indicate that there has been a significant response by the Australian dairy processing industry to deregulation in terms of both input use and output mix. This response at the state level is in contrast to existing firm level analysis of deregulation. For example, Paul *et al*. (2000) in analysis of the New Zealand sheep and beef sector found minimal changes in input use but some change in output mix. This would suggest that at the industry level it is easier to identify changes in input use since, at the firm level, these take longer to manifest because of different constraints. It could also be the case that the industry and type of deregulation being examined would be expected to generate more change on the input side.

Second, the results reported in the paper are significant for policy analysis more generally. Our results indicate that industry regulation/deregulation does have an important impact both on input and output mix. Therefore, as micro theory would predict, there are clear structural implications that flow from policy decisions in one industry into others. Deregulation in the Australian dairy processing industry has, according to our analysis, yielded an increase in the productive contribution of capital, energy and labour. If this type of result were to be repeated across other industries that experienced a change in institutional arrangements, then we might also expect to see a secondary response in the associated input supply industries. Unless we fully understand these effects we may, when undertaking analysis of economy wide deregulation, miscalculate the potential benefits and costs of policy change.

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