Dynamic Strategic Behaviour in the Deregulated England and Wales Liquid Milk Market.

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Abstract

A model of dynamic oligopsony is estimated for the liquid milk market in the UK. The paper extends existing methods of estimating such models by allowing for the joint estimation of the market conduct equation and the input supply equation. This entails the estimation of a two equation model in which the parameters of one equation change between two regimes whilst those of the other do not. Our results provide little evidence of dynamic strategic behaviour and suggest that the farm-gate price of milk is determined competitively.

JEL codes: D4, L1, Q13

1 Introduction

Prior to deregulation in 1994, the Milk Marketing Board (MMB) was responsible for the purchase of almost all milk produced in England and Wales. The board supplied liquid milk to processors at a price determined by formula and based on the prices of processed milk products. At deregulation the position of the MMB as the monopoly supplier of milk to the milk processing industry was discontinued and Milk Marque, a farmers cooperative, was formed from the MMB. This organisation continued to be responsible for marketing the milk from the majority of dairy farmers, although the numbers declined slowly as some farmers sold to the milk processors either directly or through 'milk groups'. In 1999 Milk Marque was subject to an anti-trust investigation by the Monopolies and Mergers Commission. Noting that Milk Marque still handled around half of all liquid milk sales *ex*-farm, the commission found that Milk Marque was guilty of exercising monopoly. The commission therefore recommended that Milk Marque should be broken into a number of separate organisations. The Secretary of State initially rejected this advice but subsequently Milk Marque voluntarily decided that it should re-form as three regionally based cooperatives: Milk Link, Zenith Milk and Axis Milk. Zenith and Axis have subsequently merged with The Milk Group and Scottish Milk to form Dairy Farmers of Britain and First Milk respectively. These cooperatives have over time moved from being solely concerned with the marketing of liquid milk into milk processing. At the same time traditional milk processors have undergone a process of consolidation with, for example Unigate merging with Dairy Crest and Arla Foods merging with Express Dairies.[1]

The *ex*-farm market for liquid milk has thus been subject to considerable structural change since deregulation. This change has been accompanied by a reduction of around 21% in the real price received by farmers for liquid milk between January 1994 and September 2004. During this time the retail price of milk has been constant. Between April 2001 and September 2004 the retail price increased by 8% as the farm gate price has increased by only 4%. This price change has resulted in suspicions that the loss of market power by farmers following the demise of the MMB has led to them being subject to a price squeeze that is the consequence of monopsony power exerted by the downstream processors. The aim of this paper is to test whether this suspicion is borne out by the facts. We estimate a model of pricing at the farm level which allows for collusion (tacit or otherwise) in the downstream sectors. It is clear that the structure of the industry has been dynamic during the post deregulation period. The model we estimate explicitly allows for dynamic strategic behaviour in the downstream sectors.

[1] The latter merger was itself the subject of an investigation by the competition commission in 2003.

Richards, Patterson & Acharya (2001) estimate a model of dynamic oligopsony for potato processors in the pacific north west of the United States. The model comprises two equations of which one has parameters which vary between two distinct regimes which prevail at different and unknown times. The mixtures model adopted by Richards *et al.* (2001) allows for the estimation of such a model by estimating the classification of the data into the two regimes simultaneously with the parameters of the equation in question. Inference in their approach is classical and employs the EM algorithm. A drawback of their approach is that the two equations in the model cannot be estimated simultaneously. This paper introduces an alternative Bayesian approach to the estimation of the model which allows for the joint estimation of the two equations. In doing so the literature on Bayesian estimation of switching regression models using the mixtures approach is extended to consider a system in which the parameters of some equations remain fixed between the regimes. The paper proceeds as follows. In the following section a brief intuitive explanation of the model is given. This draws heavily on Richards *et al.* (2001) to whom the reader is referred for a thorough treatment. Section 3 sets out the method of estimation and describes the data used. The results are presented in section 4 and section 5 concludes.

2 Dynamic oligopsony

Dynamic models assume that firms interact continuously through time and that in such an approach a collusive equilibrium is a potential outcome. Firms are able to raise profits by jointly determining output so as to behave as if they were a single firm. Individual firms have an incentive to break such an arrangement provided the other firms continue with the collusive agreement. A punishment strategy may be sufficient to prevent such a break-down in some circumstances. One such strategy is for firms to respond to a single period defection by themselves reverting to the Nash equilibrium output until the collusive equilibrium is re-established. In cases where information is complete and perfect such a punishment strategy is sufficient to produce a collusive equilibrium in a repeated game. Where information is less than perfect, Richards *et al.* (2001) note that a firm is unable to distinguish between price fluctuations that are the normal consequence of varying market conditions and those which result from a deviation from collusive behaviour. In such cases firms can be expected to adopt a trigger strategy in which they revert to the Nash equilibrium when the input price rises above some predetermined level. Because information is imperfect however, firms can be expected to cheat to some extent in a collusive equilibrium. The probability of the rivals responding to cheating by adopting a punishment strategy is less than one where information is imperfect. The collusive equilibrium output is therefore at the point where the marginal benefit of increasing input purchases is equal to the marginal expected loss that results from the rivals correctly interpreting and adopting a punishment strategy accordingly. As a consequence the equilibrium is expected to vary between a less than perfect collusive equilibrium and a punishment regime of Cournot equilibrium.

The empirical model comprises two equations. The first is based on the first order condition of the monopsonist and describes their market conduct:

$$m_i = w - p(X, \mathbf{z}) = c_q + \eta\theta X \tag{1}$$

where m_i is the processor's margin, p and w are the prices of milk at the farm gate and retail levels respectively, c_q is the marginal cost, η is the inverse slope of the demand function (the flexibility) and X is the supply of milk. θ is the market conduct parameter which describes the average response of a firm to a change in a rivals output. The parameter takes the value $\theta = 2$ for perfect collusion, $\theta = 1$ for Cournot competition and $\theta = 0$ for Bertrand or perfect competition. As has been outlined the conduct parameter in equation 1 is expected to vary discontinuously according to whether the industry is in a collusive or punishment period. This is accommodated in the empirical specification by allowing all of the parameters in the equation to adjust between the two time periods. We assume a linear marginal cost function to give the following equations for estimation under the two regimes:

$$m_p = \alpha_{11} + \alpha_{21}p_f + \alpha_{31}p_l + \alpha_{41}X \tag{2}$$

$$m_c = \alpha_{21} + \alpha_{22}p_f + \alpha_{32}p_l + \alpha_{42}X \tag{3}$$

where p_f and p_l are the prices of fuel and labour respectively. The second equation is the input supply equation required to estimate η and thus to identify θ. We assume that this is linear with partial adjustment:

$$X_t = \beta_1 + \beta_2 p + \beta_3 p_f + \beta_4 X_{t-1} + \sum_{i=1}^{11} \delta_i D_i \tag{4}$$

where p_f is the price of feed barley and D_i are month dummies respectively.

3 Estimation and data.

The system to be estimated comprises two equations, a markup equation and an input supply equation. The parameters of the markup equation differ between two regimes which prevail at unknown times. The parameters of the supply equation do not differ. The estimation problem is thus to estimate the two equations simultaneously along with the classification into the two regimes.

Richards *et al.* (2001) use the mixtures model (Titterington, Smith & Makov (1985)) as the basis of this estimation. Their approach is classical and separately estimates the supply and markup equations. Our approach is Bayesian and allows for the joint estimation of these equations. Our method extends the literature on the Bayesian estimation of systems of equations in a mixtures setting because in our case one of the equations (the supply equation) is common to the two regimes.

To ease notation let us write equations 2, 3 and 7 as:

$$\mathbf{m}_p = \mathbf{z}_p\boldsymbol{\beta}_p + \mathbf{u}_p \tag{5}$$

$$\mathbf{m}_c = \mathbf{z}_c\boldsymbol{\beta}_c + \mathbf{u}_c \tag{6}$$

$$\mathbf{q} = \mathbf{p}\boldsymbol{\gamma} + \mathbf{v} \tag{7}$$

where $\mathbf{u}_p$ and $\mathbf{u}_c$ are independent of one another but correlated with $\mathbf{v}$ according to the following bivariate distributions:

$$\begin{pmatrix} \mathbf{u}_p \\ \mathbf{v} \end{pmatrix} \sim N(0, \boldsymbol{\Sigma}_p) \tag{8}$$

$$\begin{pmatrix} \mathbf{u}_c \\ \mathbf{v} \end{pmatrix} \sim N(0, \boldsymbol{\Sigma}_c) \tag{9}$$

where:

$$\boldsymbol{\Sigma}_p = \begin{pmatrix} \sigma_{11} & \sigma_{13} \\ \sigma_{31} & \sigma_{33} \end{pmatrix} \tag{10}$$

$$\boldsymbol{\Sigma}_c = \begin{pmatrix} \sigma_{22} & \sigma_{24} \\ \sigma_{42} & \sigma_{44} \end{pmatrix} \tag{11}$$

The dimensions of the matrices and vectors are as follows:

$$\left.\begin{array}{l} \mathbf{m}_i : T_i \times 1 \\ \mathbf{X}_i : T_i \times k_1 \\ \boldsymbol{\beta}_i : k_1 \times 1 \\ \mathbf{u}_i : T_i \times 1 \end{array}\right\} i = p, c \tag{12}$$

$$\mathbf{q} : T \times 1 \tag{13}$$

$$\mathbf{p} : T \times k_2 \tag{14}$$

$$\boldsymbol{\gamma} : k_2 \times 1 \tag{15}$$

$$\mathbf{v} : T \times 1 \tag{16}$$

where $T = T_p + T_c$ is the total number of observations and T_p and T_c are the number of observations when the punishment and collusive strategies respectively are played.

To simplify the notation further we define the following:

$$\mathbf{y} = \begin{pmatrix} \mathbf{m}_p \\ \mathbf{m}_c \\ \mathbf{q} \end{pmatrix} \tag{17}$$

$$\mathbf{X} = \begin{pmatrix} \mathbf{z}_p & 0 & 0 \\ 0 & \mathbf{z}_c & 0 \\ 0 & 0 & \mathbf{p} \end{pmatrix} \tag{18}$$

$$\boldsymbol{\beta} = \begin{pmatrix} \boldsymbol{\beta}_p \\ \boldsymbol{\beta}_c \\ \gamma \end{pmatrix} \tag{19}$$

and write the full model as follows:

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon} \tag{20}$$

The dimensions are as follows:

$$\mathbf{y} : 2T \times 1 \tag{21}$$

$$\mathbf{X} : 2T \times (2k_1 + k_2) \tag{22}$$

$$\boldsymbol{\beta} : (2k_1 + k_2) \times 1 \tag{23}$$

$$\boldsymbol{\varepsilon} : 2T \times 1 \tag{24}$$

In our analysis we do not wish to predetermine which of the regimes a given observation belongs to, instead we will allow the data to determine the classification. To accomplish this, the classification of a specific observation is made random. Thus, we introduce a 2×1 dimensional random vector $\mathbf{c}_i$ of which the j^{th} element $c_{ij} = 1$ if the i^{th} observation is from the j^{th} component distribution and 0 otherwise. With this view of the sampling process the joint probability density function for the i^{th} observation can be written (Diebolt & Robert (1994))

$$p\left(\boldsymbol{\beta}, \boldsymbol{\Sigma}_p, \boldsymbol{\Sigma}_c, \boldsymbol{\theta}, \mathbf{c}_i, \mathbf{y}_i, \mathbf{X}_i\right) = \left(\theta_1 p_1\left(\boldsymbol{\beta}_p, \boldsymbol{\gamma}, \boldsymbol{\Sigma}_p, \mathbf{y}_i, \mathbf{X}_i\right)\right)^{c_{i1}} \left(\theta_2 p_2\left(\boldsymbol{\beta}_c, \boldsymbol{\gamma}, \boldsymbol{\Sigma}_c, \mathbf{y}_i, \mathbf{X}_i\right)\right)^{c_{i2}} \tag{25}$$

where $p_j(\cdot)$ is a p.d.f. with parameters $\boldsymbol{\beta}$, $\boldsymbol{\gamma}$ and Σ. $\mathbf{y}_i$ and $\mathbf{X}_i$ are the rows in the matrices $\mathbf{y}$ and $\mathbf{X}$ which correspond to the i^{th} observation. The parameters θ_j satisfying $\theta_1 + \theta_2 = 1$ are the proportions of the population coming from the k^{th} component, $\boldsymbol{\theta}' = (\theta_1, \theta_2)$. For the full sample of T observations, the density is written:

$$p\left(\mathbf{c},\mathbf{y},\mathbf{X}|\boldsymbol{\beta},\boldsymbol{\Sigma}_p,\boldsymbol{\Sigma}_c,\boldsymbol{\theta}\right) = \prod_{i=1}^{T}\theta_1^{c_{i1}}p_1\left(\boldsymbol{\beta}_p,\boldsymbol{\gamma},\boldsymbol{\Sigma}_p,\mathbf{y}_i,\mathbf{X}_i\right)^{c_{i1}}\times \tag{26}$$

$$\theta_2^{c_{i2}}p_2\left(\boldsymbol{\beta}_c,\boldsymbol{\gamma},\boldsymbol{\Sigma}_c,\mathbf{y}_i,\mathbf{X}_i\right)^{c_{i2}}, \tag{27}$$

where $\mathbf{c}' = (\mathbf{c}_1,\mathbf{c}_2,\ldots,\mathbf{c}_T)$.

We adopt a Bayesian approach to inference regarding the unknown parameters. The essential feature of the Bayesian method is that uncertainty regarding the true value of the parameters is expressed with a probability density function known as the posterior. The first stage is to convert the likelihood, which is an improper density when viewed as a function of the unknown parameters, into a proper density by employing Bayes law and multiplying by a prior.

Following Zellner (1971, p. 242) we assume a diffuse prior:

$$g\left(\boldsymbol{\beta},\boldsymbol{\Sigma}_p,\boldsymbol{\Sigma}_c,\boldsymbol{\theta},|\mathbf{c}_i,\mathbf{y}_i,\mathbf{X}_i\right)\propto|\boldsymbol{\Sigma}_p|^{-\frac{3}{2}}|\boldsymbol{\Sigma}_c|^{-\frac{3}{2}}, \tag{28}$$

to give the posterior:

$$p\left(\boldsymbol{\beta},\boldsymbol{\Sigma}_p,\boldsymbol{\Sigma}_c,\boldsymbol{\theta},\mathbf{c},\mathbf{y},\mathbf{X}\right) = \theta_1^{\sum_{i=1}^{T}c_{i1}}\theta_2^{\sum_{i=1}^{T}c_{i2}}\prod_{i=1}^{T}p_1\left(\boldsymbol{\beta}_p,\boldsymbol{\gamma},\boldsymbol{\Sigma}_p,m_i,q_i\right)^{c_{i1}}\times$$

$$p_2\left(\boldsymbol{\beta}_c,\boldsymbol{\gamma},\boldsymbol{\Sigma}_c,m_i,q_i\right)^{c_{i2}}|\boldsymbol{\Sigma}_p|^{-\frac{3}{2}}|\boldsymbol{\Sigma}_c|^{-\frac{3}{2}}. \tag{29}$$

The objective of a Bayesian analysis is to report the posterior distribution of the parameters of interest and/or summary statistics for this distribution. For example we will employ the mean as a point estimate of the parameters. The posterior is of a form where the analytical integration required to compute the mean is intractable. The alternative is to use the mean of a sample drawn from the marginal distribution of the parameter as an approximation.

The Gibbs sampler (see Casella & George (1992)) allows one to sample from a marginal distribution by using the conditional distributions. The sampler can be used to obtain a sample from the marginal for a single parameter or from the multivariate marginal for a block of parameters. The latter approach is common and is employed here. Thus given the density in 29, we obtain a Gibbs sample from each of the following marginal densities[2]

$$p(\boldsymbol{\beta}) = \int\int\int\int\int\int p\left(\boldsymbol{\beta}, \boldsymbol{\Sigma}_p, \boldsymbol{\Sigma}_c, \boldsymbol{\theta}, \mathbf{c}, \mathbf{y}, \mathbf{X}\right) d\boldsymbol{\Sigma}_p d\boldsymbol{\Sigma}_c d\boldsymbol{\theta} d\mathbf{c} d\mathbf{y} d\mathbf{X} \quad (30)$$

$$p(\boldsymbol{\Sigma}_p) = \int\int\int\int\int\int p\left(\boldsymbol{\beta}, \boldsymbol{\Sigma}_p, \boldsymbol{\Sigma}_c, \boldsymbol{\theta}, \mathbf{c}, \mathbf{y}, \mathbf{X}\right) d\boldsymbol{\beta} d\boldsymbol{\Sigma}_c d\boldsymbol{\theta} d\mathbf{c} d\mathbf{y} d\mathbf{X} \quad (31)$$

$$p(\boldsymbol{\Sigma}_c) = \int\int\int\int\int\int p\left(\boldsymbol{\beta}, \boldsymbol{\Sigma}_p, \boldsymbol{\Sigma}_c, \boldsymbol{\theta}, \mathbf{c}, \mathbf{y}, \mathbf{X}\right) d\boldsymbol{\beta} d\boldsymbol{\Sigma}_p d\boldsymbol{\theta} d\mathbf{c} d\mathbf{y} d\mathbf{X} \quad (32)$$

$$p(\boldsymbol{\theta}) = \int\int\int\int\int\int p\left(\boldsymbol{\beta}, \boldsymbol{\Sigma}_p, \boldsymbol{\Sigma}_c, \boldsymbol{\theta}, \mathbf{c}, \mathbf{y}, \mathbf{X}\right) d\boldsymbol{\beta} d\boldsymbol{\Sigma}_c d\boldsymbol{\Sigma}_p d\mathbf{c} d\mathbf{y} d\mathbf{X} \quad (33)$$

$$p(\mathbf{c}) = \int\int\int\int\int\int p\left(\boldsymbol{\beta}, \boldsymbol{\Sigma}_p, \boldsymbol{\Sigma}_c, \boldsymbol{\theta}, \mathbf{c}, \mathbf{y}, \mathbf{X}\right) d\boldsymbol{\beta} d\boldsymbol{\Sigma}_c d\boldsymbol{\Sigma}_p d\boldsymbol{\theta} d\mathbf{y} d\mathbf{X}. \quad (34)$$

The marginal p.d.f. for each block of parameters is approximated iteratively by drawing on each of the conditional densities in turn. Arbitrary starting values are specified for all those parameters except those being drawn in the first step. The starting values are replaced by draws as they become available.

The posterior densities for $\boldsymbol{\theta}$ and $\mathbf{c}$ can be obtained directly from the posterior in 29:

$$p\left(\boldsymbol{\theta}|\boldsymbol{\beta}, \boldsymbol{\Sigma}_p, \boldsymbol{\Sigma}_c, \mathbf{c}, \mathbf{y}, \mathbf{X}\right) \propto \theta_1^{\sum_{i=1}^T c_{i1}} \theta_2^{\sum_{i=1}^T c_{i2}} \quad (35)$$

$$p\left(\mathbf{c}|\boldsymbol{\beta}, \boldsymbol{\Sigma}_p, \boldsymbol{\Sigma}_c, \boldsymbol{\theta}, \mathbf{y}, \mathbf{X}\right) \propto \left(\theta_1 p_1\left(\mathbf{c}_i, \mathbf{y}_i, \mathbf{X}_i|\boldsymbol{\beta}_p, \boldsymbol{\gamma}, \boldsymbol{\Sigma}_p\right)\right)^{c_{i1}} \times \quad (36)$$

$$\left(\theta_2 p_2\left(\mathbf{c}_i, \mathbf{y}_i, \mathbf{X}_i|\boldsymbol{\beta}_c, \boldsymbol{\gamma}, \boldsymbol{\Sigma}_c\right)\right)^{c_{i2}} \quad (37)$$

The conditionals for $\boldsymbol{\beta}$, $\boldsymbol{\Sigma}_p$ and Σ_c are dependent upon the unknown densities p_1 and p_2:

$$p\left(\boldsymbol{\beta}, \boldsymbol{\Sigma}_p, \boldsymbol{\Sigma}_c|\mathbf{c}, \boldsymbol{\theta}, \mathbf{y}\right) \propto |\boldsymbol{\Sigma}_p|^{-\frac{3}{2}} |\boldsymbol{\Sigma}_c|^{-\frac{3}{2}} \times \quad (38)$$

$$\prod_{i=1}^{T} p_1\left(\boldsymbol{\beta}_p, \boldsymbol{\gamma}, \boldsymbol{\Sigma}_p, m_i, q_i\right)^{c_{i1}} p_2\left(\boldsymbol{\beta}_c, \boldsymbol{\gamma}, \boldsymbol{\Sigma}_c, m_i, q_i\right)^{c_{i2}}. \quad (39)$$

Note that the structure of the matrices in 18 and 17 imply that the observations are not necessarily in temporal order as the first T_p correspond to the punishment regime and the remainder correspond to the collusive regime. Assuming that the densities are multivariate normal, 39 can be written:

$$p\left(\boldsymbol{\beta}, \boldsymbol{\Sigma}_p, \boldsymbol{\Sigma}_c|\mathbf{c}, \boldsymbol{\theta}, \mathbf{y}, \mathbf{X}\right) \propto |\Sigma_p|^{-\frac{T_p+3}{2}} |\Sigma_c|^{-\frac{T_c+3}{2}} \exp\left\{-\frac{1}{2}\left(\mathbf{u}'\mathbf{A}\mathbf{u}\right)\right\} \quad (40)$$

[2]The conditionality on the observed data ($\mathbf{x}$) is implicit in the marginals.

where:

$$\mathbf{u} = \begin{pmatrix} \mathbf{m}_p - \mathbf{z}_p\boldsymbol{\beta}_p \\ \mathbf{m}_c - \mathbf{z}_c\boldsymbol{\beta}_c \\ \mathbf{q} - \mathbf{p}\boldsymbol{\gamma} \end{pmatrix} = \begin{pmatrix} \mathbf{u}_p \\ \mathbf{u}_c \\ \mathbf{v} \end{pmatrix} \tag{41}$$

and we define $\mathbf{A}$ as:

$$\mathbf{A} = \begin{pmatrix} I_{T_p}a_{11} & 0 & I_{T_p}a_{13} & 0 \\ 0 & I_{T_c}a_{22} & 0 & I_{T_c}a_{24} \\ I_{T_p}a_{31} & 0 & I_{T_p}a_{33} & 0 \\ 0 & I_{T_c}a_{42} & 0 & I_{T_c}a_{44} \end{pmatrix} \tag{42}$$

where the elements a_{ij} are from the inverted covariance matrices as follows:

$$\boldsymbol{\Sigma}_p^{-1} = \begin{pmatrix} a_{11} & a_{13} \\ a_{31} & a_{33} \end{pmatrix} \tag{43}$$

$$\boldsymbol{\Sigma}_c^{-1} = \begin{pmatrix} a_{22} & a_{24} \\ a_{42} & a_{44} \end{pmatrix} \tag{44}$$

40 can be written:

$$p\left(\boldsymbol{\beta}, \boldsymbol{\Sigma}_p, \boldsymbol{\Sigma}_c | \mathbf{c}, \boldsymbol{\theta}, \mathbf{y}, \mathbf{X}\right) \propto |\Sigma_p|^{-\frac{T_p+3}{2}} |\Sigma_c|^{-\frac{T_c+3}{2}} \tag{45}$$

$$\exp\left\{-\frac{1}{2}\begin{pmatrix} \operatorname{tr}\left(\mathbf{U}_p'\mathbf{U}_p\boldsymbol{\Sigma}_p^{-1}\right) + \\ \operatorname{tr}\left(\mathbf{U}_c'\mathbf{U}_c\boldsymbol{\Sigma}_c^{-1}\right) + \\ (\boldsymbol{\beta} - \mathbf{b})' \mathbf{X}'\mathbf{A}\mathbf{X}(\boldsymbol{\beta} - \mathbf{b}) \end{pmatrix}\right\} \tag{46}$$

where:

$$\mathbf{U}_p = \begin{pmatrix} \mathbf{m}_p - \mathbf{z}_p\boldsymbol{\beta}_p & \mathbf{q}_p - \mathbf{p}_p\boldsymbol{\gamma} \end{pmatrix} \tag{47}$$

$$\mathbf{U}_c = \begin{pmatrix} \mathbf{m}_c - \mathbf{z}_c\boldsymbol{\beta}_c & \mathbf{q}_c - \mathbf{p}_c\boldsymbol{\gamma} \end{pmatrix} \tag{48}$$

$$\mathbf{b} = \left(\mathbf{X}'\mathbf{X}\right)^{-1}\mathbf{X}'\mathbf{y} \tag{49}$$

From 46 following conditionals can be obtained:

$$p\left(\boldsymbol{\Sigma}_p | \boldsymbol{\beta}, \boldsymbol{\Sigma}_c, \mathbf{c}, \boldsymbol{\theta}, \mathbf{y}, \mathbf{X}\right) \propto |\boldsymbol{\Sigma}_p|^{-\frac{T_p+3}{2}} \exp\left\{-\frac{1}{2}\left(\operatorname{tr}\left(\mathbf{U}_p'\mathbf{U}_p\boldsymbol{\Sigma}_p^{-1}\right)\right)\right\} \tag{50}$$

$$p\left(\boldsymbol{\Sigma}_c | \boldsymbol{\beta}, \boldsymbol{\Sigma}_p, \mathbf{c}, \boldsymbol{\theta}, \mathbf{y}, \mathbf{X}\right) \propto |\boldsymbol{\Sigma}_c|^{-\frac{T_p+3}{2}} \exp\left\{-\frac{1}{2}\left(\operatorname{tr}\left(\mathbf{U}_c'\mathbf{U}_c\boldsymbol{\Sigma}_c^{-1}\right)\right)\right\} \tag{51}$$

$$p\left(\boldsymbol{\beta} | \boldsymbol{\Sigma}_p, \boldsymbol{\Sigma}_c, \mathbf{c}, \boldsymbol{\theta}, \mathbf{y}, \mathbf{X}\right) \propto \exp\left\{-\frac{1}{2}\left((\boldsymbol{\beta} - \mathbf{b})' \mathbf{X}'\mathbf{A}\mathbf{X}(\boldsymbol{\beta} - \mathbf{b})\right)\right\} \tag{52}$$

and it is evident that the conditionals for $\boldsymbol{\Sigma}_p$ and $\boldsymbol{\Sigma}_c$ are inverted Wishart and

Parameter	α_{11}	α_{21}	α_{31}	α_{41}	α_{12}	α_{22}	α_{32}	α_{42}
Estimate	-0.124	-0.055	0.281	0.116	-0.096	-0.033	0.281	0.077
5%	-0.221	-0.103	0.233	0.065	-0.206	-0.086	0.234	0.020
95%	-0.029	-0.011	0.326	0.178	0.003	0.007	0.325	0.165

Table 1: Parameters and interval estimates for equations 2 and 3

Parameter	β_1	β_2	β_3	β_4
Estimate	1.071	0.134	-0.036	0.092
5%	0.838	0.009	-0.082	0.006
95%	1.179	0.355	0.002	0.286

Table 2: Point and interval estimates for the milk supply equation (4)

that for $\boldsymbol{\beta}$ is multivariate normal.

We use monthly data for the period April 2001 to September 2004. The margin in equations 2 and 3 is the difference between the retail and farm gate prices of milk. X is measured as wholesale milk deliveries. The source of all the preceding variables is the Milk Development Council (MDC) Datum. Feed barley prices are obtained from the Department for the Environment Food and Rural Affairs (DEFRA). The fuel price is measured as an index of prices for fuels purchased for manufacturing industry and the wage rate is the index of labour costs in the food, beverage and tobacco industries. Both of these series are obtained from the Office of National Statistics (ONS) time-series data base.

4 Results

Tables 1 and 2 give point estimates and interval estimates for the parameters from a Gibbs sample of 5000. The sample is formed by discarding 200 draws as a 'burn-in' and also by discarding draws where the slope of the supply curve (β_2) and/or the combined slope conjectural variation parameters (α_{41} and α_{42}) and/or the partial adjustment parameter (β_5) are positive. The only parameter for which the interval estimate spans zero is the coefficient on the fuel price in equation 3 (α_{22}) and the coefficient on feed barley price in equation 4. Note also that the sign on the point estimate of α_{21} and α_{22} is contrary to expectations. All the other point estimates have the expected signs. The estimated parameter for the slope of the demand curve implies that the short run elasticity of milk supply is 0.022 at the mean price and quantity. The long run slope of the supply equation is computed for each draw in the Gibbs sample. This gives a point estimate of 0.151 with $5-95\%$ interval estimate of $0.010-0.398$ which implies a long run supply elasticity of 0.024.

	Short run		Long run	
Parameter	θ_1	θ_2	θ_1	θ_2
Estimate	0.015	0.010	0.017	0.012
5%	0.001	0.000	0.001	0.000
95%	0.041	0.031	0.045	0.035

Table 3: Estimates of market conduct parameter

Table 3 reports the estimates of the market conduct parameter. These estimates are constrained to be of the right sign. In all cases the estimates indicate that the pricing strategy of purchasers of liquid milk has been close to that which would be expected in a competitive industry.

5 Conclusions

This paper has investigated the market conduct of purchasers of liquid milk from farmers in the period during which the market has been deregulated. The model estimated is sufficiently general to allow for dynamic strategic behaviour. Our results show little evidence to support the view that this type of anti-competitive behaviour has occurred in the market for liquid milk since deregulation. This suggests that the loss of market power experienced by farmers following the demise of the MMB has not been responsible for the decline in farm-gate prices for liquid to milk relative to the supermarket price. This conclusion is reached based on an estimate of the supply elasticity for milk which is somewhat lower than that which is commonly reported. Whilst the result would be different if the estimate used was closer to the conventional estimate the qualitative result would not be substantially different.

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