FINANCIAL EXPOSURE AND FARM EFFICIENCY: EVIDENCE FROM THE ENGLAND AND WALES DAIRY SECTOR

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1. Introduction

A substantial applied literature now exists on the efficiency of farms. A subset of papers in this literature also seeks to explain variations in efficiency across farms, with the typically considered explanatory variables being farm size, geographical characteristics such as regional dummies and soil quality, and farmer characteristics such as age and education. Although farm production economics issues such as technical efficiency and farm finance issues have traditionally been studied separately, a steady stream of papers over the years has argued that financial characteristics of farms may have a strong bearing upon the organisation of production (Baker (1968), Gabriel and Baker (1980), Barry, Baker and Sanint (1981), Whittaker and Morehart (1991)). In accordance with this view, a small literature has also developed that connects farm financial structure, in particular, liabilities relative to assets, with productive efficiency. Alternate hypotheses have been proposed regarding the nature of this connection between this measure of financial exposure and technical efficiency, and the implied direction of the relationship. Empirical testing has not demonstrated a common pattern regarding the direction.

In this paper, we contribute to this literature by confronting this set of hypotheses with a rich panel dataset from the dairy sector in England and Wales and applying an empirical method that arguably has some advantages over the methods used previously. The results are used along with supplementary information to enable a better understanding of the connection between financial exposure and technical efficiency in the context of British dairying. A secondary objective of the paper is to enable the first empirical analysis of some neglected production economics issues in the England and Wales dairy sector, such as technological change and returns to scale. Also, the results generated here with the benefit of a long panel enable us to critically appraise the results of previous studies of dairy farm efficiency in England and Wales that have been based on considerably smaller datasets. This study is important not only because of the insights generated on the connection between farm financial structure and technical efficiency and on the production structure of British dairying, but also because it comes at a critical time for this sector. The dairy sector in England and Wales is in the midst of an economic and financial crisis, with farm incomes dipping precariously, debt-asset ratios worsening significantly, and policy analysts forecasting that the worst is yet to come. It is hoped that the findings of this study will enhance the information base of policymakers as they take measures to assist the sector and plan for its long term health.

The paper proceeds with a brief review of the literature concerning the relationship between financial exposure and efficiency in the next section. Section three provides a historical overview of the British dairy sector, while section four presents the stochastic production frontier methodology that is applied in the paper. The data and model specification are described in section five, and the results and their implications are discussed in section six. Section seven concludes.

2. Prior Literature

Several hypotheses have been advanced regarding the process by which the extent of financial exposure of a farm (ratio of debts to assets) may exert an influence on efficiency.[1] These include:

(i) Agency costs (Nasr, Ellinger and Barry (1998)): Asymmetric information and misaligned incentives between lenders and borrowers implies monitoring of borrowers by lenders. Monitoring involves transactions costs, and lenders may pass on these costs to the farmers in the form of higher interest rates, collateral requirements, etc. It is argued therefore that more indebted farmers are 'higher-cost' farmers, and hence more technically inefficient.

(ii) Free cash flow (Nasr, Barry and Ellinger (1998)): Based on findings in corporate finance, this hypothesis postulates that large asset holdings and excess cash flows encourage managerial laxness, which translates into technical inefficiency. Therefore, in contrast to the agency cost concept, this hypothesis implies a positive relationship between financial exposure and technical efficiency.

(iii) Credit Evaluation (Nasr, Barry and Ellinger (1998)): In evaluating loan applications from farmers, agricultural lenders may partly base their evaluations upon performance measures. Lenders may be reluctant to advance funds to 'high cost' (technically inefficient) farmers. Hence, under this hypothesis, the causality runs from efficiency to indebtedness, and a positive relationship is implied.

[1] The majority of the papers in this area have used the debt-asset ratio as the variable measuring the financial exposure on the farm. In some cases, multiple debt-asset ratios (long, intermediate and short-run debts to assets) have been used.

(iv) Embodied Capital (Chavas and Aliber (1993)): Technical efficiency is measured empirically by building production frontiers where each firm is gauged relative to others in the sample. Production frontiers tend to shift upwards over time as a result of technical change. If technical change is embodied in capital (or any other purchased input), and if such capital acquisition is typically financed by debt, over time the firms with higher debt profiles tend to be the ones who fuel technical change in the industry and hence end up on the best practice frontier. This implies a positive relationship between debt-asset ratios and technical efficiency.

(v) Adjustment (Paul, Johnston, and Frengley (2000)): In a recent article in the *Review of Economics and Statistics*, Paul, *et. al.* (2000) studied the impact of regulatory reform on the technical efficiency New Zealand farms. There it was hypothesized that a transition from a subsidised agricultural system to a less sheltered atmosphere would force farmers to become more efficient, but that increased efficiency in the face of adjustment would depend upon financial exposure. Farmers with a lower debt profile relative to assets would be able to adjust more easily, and thus would be more efficient.

The Agency Cost, Free Cash Flow and Credit Evaluation hypotheses were tested by Nasr, Ellinger and Barry (1998). Data Envelopment Analysis (DEA) was used to measure efficiency, and applied year-by-year to a sample of Illinois cash grain farms observed over a seven-year period. Two measures of financial exposure were used in a second step that regressed efficiency scores on explanatory variables, the ratio of total debt to total assets, and the ratio of current debts to total assets. No significant relationship was found between technical efficiency and the *total* debt-asset ratio, while a positive relationship was found between efficiency and the *current* debt-asset ratio. Since the agency cost concept implies a negative relationship, this hypothesis was directly rejected by the data. Arguing that the total debt-asset ratio is the relevant measure for the Credit Evaluation hypothesis, while the current debt-asset ratio is most relevant for the Free Cash Flow concept, they concluded that their evidence pointed towards the latter.

In a paper more generally concerned with estimating scope efficiency in addition to technical, allocative and scale efficiencies using DEA, Chavas and Aliber (1993) also found a positive relationship between debt-asset ratios and technical efficiencies. In contrast to Nasr, *et. al*. (1998), however, the shorter term measure of debt relative to assets was not found to significantly affect efficiency, while longer-run measures were. Although their data pertained to a cross-section of Wisconsin farms and thus could not explicitly measure technical change, the authors concluded that the results were most consistent with technology being embodied in debt-financed longer-run capital, *i.e.*, the Embodied Capital hypothesis.

Interestingly, the empirical analysis of New Zealand farms by Paul, *et. al.* (2000) found a *negative* relationship between the debt-asset ratio and technical efficiency. Their dataset contained information on 32 beef and sheep farms in New Zealand over 1969-91, including the 1984-88 period when regulatory reforms were undertaken. Their stochastic distance function frontier approach estimated technical efficiency and 'inefficiency effects' simultaneously. The only variable in the inefficiency effects that was consistently significant was the debt-asset ratio. The authors explained this finding using the Adjustment hypothesis, *i.e.*, the process of adjusting to reforms is easier for farms that are more flexible financially. They indicated that this might happen because more financially stressed farms might find it difficult to maintain payments to variable inputs, farm maintenance measures, etc.

The papers reviewed above offer specific hypotheses on the manner in which a high value of debts relative to assets leads to higher technical efficiency or inefficiency. In addition, other studies also exist that find a specific, significant relationship between debt-asset ratios and efficiency without implying a specific hypothesis on why such a relationship might occur. For instance, Weersink *et. al.* (1990), found a negative relationship and noted that their results are consistent with excess capacity (the manifestation of lower efficiency) in the face of debt-financed capital (the manifestation of high debt-asset ratios). Research also exists that takes a slightly different methodological approach to the problem. For example, Whittaker and Morehart (1991) studied the connection between efficiency and farm financial structure by building DEA cost frontiers with debt and asset constraints built into the programming problems.[2] They found that one out of five US Midwestern corn farms were prevented from reaching the frontier due to debt or asset value constraints.

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[2] They also review some additional literature in this area. Instead of repeating such a review, the reader is referred to Whittaker and Morehart (1991).

In summary, there seems to be ample evidence that production structures in general, and production efficiency measures in particular, are significantly affected by financing issues. However, the following points arise:

(i) Empirical results have contradicted each other in terms of the direction of the effect. One question then worth pondering is whether the choice of empirical methods is of importance here. DEA has been the method of choice in all but one of the studies reviewed above, and we make the argument later in this paper that the stochastic production frontier method might produce more reliable results.

(ii) Although each set of authors in the above papers has offered different hypotheses, the hypotheses themselves are not mutually exclusive. For example, although Paul, *et. al.* (2000) used the Adjustment hypothesis to explain the negative relationship that they find between financial exposure and efficiency, their results could potentially also be explained by the Agency cost hypothesis of Nasr, *et. al.* (1998). It is difficult to pinpoint the exact effect that operates to produce a particular relationship, and hence each of the previous papers has (understandably) restricted itself to offering an hypothesis that seems to fit observed facts. The focus of our paper, our large dataset and the collective wisdom provided by these previous papers enables us to probe the effect behind the relationship somewhat more deeply.

(iii) Of course, explanations other than those listed above are possible. For instance, could the debt-asset ratio be proxying for some other variable, such as years spent in farming (alternatively, farmer age) in the empirical relationship with efficiency? It may be true, at least in some situations, that newer farmers tend to be more indebted relative to their asset ownership. Then, if a lack of experience translates into inefficiency, a negative relationship between debt-asset ratios and efficiency would emerge. It seems logical to explore such additional possibilities in our attempt to understand the effect underlying a financial exposure-efficiency relationship.

(iv) It would be hard to deny that the issue of technological change and the manner in which it is financed may have an important influence on both debt-asset ratios and technical efficiencies. Indeed, the Embodied Capital hypothesis is based upon this premise. Estimates of technical change may therefore contribute potentially useful information in this empirical literature. However, none of the reviewed papers have presented technical change estimates.[3] In this paper, we estimate technical change in addition to efficiency and its determinants and use such information in analyzing the link between financial exposure and efficiency.

3. The England and Wales Dairy Sector

Dairying is an important agricultural sector in England and Wales, with about 20% of gross agricultural output accounted for by milk and milk products. Only Germany and France in the EU have larger total herds than the UK, although the average herd size on UK farms (about 75 cows in 1997) is significantly larger than elsewhere in the EU (for example, Denmark: 55 cows, France and Germany: about 35 cows in 1997). Dairy farms in Britain are concentrated in Wales and the Western counties of England, particularly Devon, Cumbria, Cheshire and Lancashire. Dairy production is a relatively specialized

[3] In at least one case, this is because of a lack of sufficient data. Chavas and Aliber (1990) use a single cross-section of data, which rules out technical change estimation.

activity, with specialist dairy farms holding about 80% of all dairy cows in the UK (MAFF).

Since 1984, the sector has operated under the EU's dairy quota system. In 1984, farmers were allotted quotas based upon their production in 1981 plus one percent, and since then the rules governing quotas have been periodically revised to suit changing circumstances. A geographically limited transfer of quotas was first allowed in 1986, and unlimited transfer within the UK was introduced in 1993. Marketing of output itself was regulated by the UK Milk Marketing Scheme until 1994, under which milk output was purchased exclusively by Milk Marketing Boards. The market was deregulated in 1994, after which producers have been allowed the freedom to sell their milk without any constraints. At the EU level, milk prices have been maintained above world prices by intervention in the form of import levies and export refunds.

After a downturn over 1989-92, the sector enjoyed a prosperous phase from 1992 to 1996, buoyed by rising milk prices. However, profits have been in free-fall from 1996 onwards, and the sector now finds itself in a state of acute crisis. The most important reason for the falling incomes has been the exchange rate. EU support prices are determined in Euros, and with the UK not being among the 'Euro-Zone' countries, a stronger pound implies lower effective support for British milk products. Another reason is the general depression in world milk prices, on which EU support is based. During this period, the sector has also been affected by the BSE crisis, with the outcomes including a selective cull of animals considered most at risk in 1996. Table 1 presents information on average net farm incomes (in real terms) from 1989 to 1999. As can be seen from there, average dairy farm incomes reached an unprecedented low of £10,400 in 1998-99. A quarter of the farms recorded negative net incomes in 1998-99 (MAFF). Industry forecasts indicate that the situation will get worse over the next couple of years before stabilising or getting better. Even if an improvement is seen in two or three years' time, the EU's Agenda-2000 reforms for the dairy sector loom on the horizon. These reforms, which will be instituted in 2005-06, will cut price support for milk.

The financial side of British farming, including the dairy sector, has historically been fairly healthy. Even though the dairy sector has the second-highest values of average liabilities, interest payments relative to cash incomes, and debt-asset ratios among all farm-types in the UK, the numbers are relatively low by international standards.[4] For example, while average total debt-asset ratios in several farming areas in the US are 0.30 or higher, they have seldom exceeded 0.20 in the England and Wales dairy sector. Although terms of trade have in general gradually moved against agriculture over the last two decades, extreme indebtedness has been rare, and bankruptcy numbers have been modest (Harrison and Tranter, 1994). Since the downturn in 1996, though, the situation has worsened. For example, the average total debt-asset ratio for Welsh dairy farms was about 0.10 at the start of the 1996-97, but almost 0.14 by 1998-99 (MAFF).

Technical efficiency in this sector has previously been studied by Dawson (1987), Dawson and White (1990) and Dawson (1990). In Dawson (1987), three cross-section

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[4] Pig farming is no. 1 in this regard.

samples pertaining to 1976/7, 1980/1 and 1984/5 respectively, were used to measure technical efficiency relative to a constant returns-to-scale stochastic frontier. The results indicated that relative technical efficiency was in the mid-to-high 80s (in percentage) and had increased over this period. In Dawson and White (1990) and Dawson (1990), data for the three-year period 1984/5-86/87 were used to update the findings of Dawson (1987). Once again, relative efficiency was in the mid-to-high 80s, although there was no clear increasing or decreasing pattern. However, these papers did not seek to explain the relative inefficiencies of farms, or to measure technical change. There appears to have been no analysis of the efficiency of UK dairy farms for the 1990s.

4. Frontier Methods and Efficiency and Technical Change Measurement

Farrell (1957) first developed the notion of relative technical efficiency, where the observed output of a firm is compared to the output that can be produced by an efficient firm using the same input vector. The production functions of fully efficient firms (the frontier) are empirically constructed either by linear programming (DEA) or by econometric (stochastic frontier) methods. As noted before, most of the literature connecting farm efficiency to financial exposure has used DEA methods, with second stage regressions of efficiency scores on debt-asset ratios and other variables. One important advantage of DEA over stochastic frontiers is the absence of functional form imposition in DEA. Stochastic frontiers on the other hand score over DEA in incorporating random errors and not interpreting all deviations from frontiers as inefficiency. Additionally, conventional hypothesis test regarding production parameters are possible with stochastic frontier analysis, but not with DEA. Although the debate over the choice of methods continues, it is generally recognized that selection of an appropriate method should be done on a case-by-case basis. That said, however, compelling arguments have been made that the stochastic frontier may be the most appropriate choice in agricultural applications, where random errors due to weather and pest infestation are likely to be significant (Coelli, Rao and Battese (1998)). We take this view here, along with the implication that if stochastic frontier methods are more appropriate, the results will also better reflect the true relationship between financial exposure and efficiency.

Stochastic frontier production functions were originally proposed by Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broeck (1977). They incorporate two error terms, one to account for technical inefficiency and the other to account for random errors caused by weather, pests, etc. and measurement errors. A stochastic frontier production function may be expressed as:

$$y_{it} = f(x_{it}, t, \alpha)e^{(v_{it} - u_{it})}, \quad i = 1,2...N; t = 1,2...T \tag{1}$$

Here, y_{it} is the output of the i^{th} firm in the t^{th} year, x_{it} is a vector of inputs, α is a vector of parameters to be estimated, f(.) is a suitable functional form, such as the Cobb-Douglas or translog, v_{it} is a symmetric random error, and u_{it} is an asymmetric non-negative random error assumed to account for technical inefficiency in production. Maximum likelihood is usually used to estimate the values of the unknown parameters, after making assumption regarding the distributions of u_{it} and v_{it}, which are often assumed to be normal and half-normal, respectively.

$$u_{it} = z_{it}d + w_{it}$$

Although a part of the empirical literature has confined itself to measuring technical efficiencies, a number of studies have also gone on to explain the cross-firm variation in inefficiencies. In all DEA applications and in the previous generation of stochastic frontier applications, this has been done by regressing estimated efficiency scores on a range of explanatory variables in a second step. However, several authors (Kumbhakar, *et. al.* (1991), Reifschneider and Stevenson (1991), Battese and Coelli (1993)) have noted that such a two-step stochastic frontier approach is theoretically inconsistent. This is because in the first step the technical inefficiency effects are usually assumed to be independently and identically distributed random variables. However, in the second stage, the predicted technical inefficiency effects are regressed upon a number of firm-specific factors, implying that the predicted technical inefficiency effects are in fact not identically distributed.

The above authors who have pointed out this theoretical inconsistency have also offered single stage methodologies. These involve stochastic frontier specifications that incorporate models for the technical inefficiency effects and estimate all parameters involved simultaneously. The model specification used here is a modification of that used in Battese and Coelli (1995) that specifies technical inefficiency effects in the stochastic frontier model that are assumed to be independently (but not identically) distributed non-negative random variables. Battese and Coelli (1995) define technical inefficiency effects by:

$$u_{it} = z_{it}d + w_{it} \qquad (2)$$

where z_{it} is a vector containing a constant and firm and time-specific explanatory variables, d is a vector of parameters to be estimated, and the w_{it}s are unobservable random variables – assumed independently distributed and obtained by truncation of the normal distribution with zero mean and unknown variance, σ_u^2, and so that u_{it} is non-negative.

5. Data and model specification

5.1 Data

The farm production data is drawn from the *Farm Business Survey* (FBS) for England and Wales (MAFF, 1999) covering the production years from 1984 to 1997. The FBS is an annual survey of more than 2,800 farms that are selected from a random sample of census data that is stratified according to region, economic size of farm and type of farming. A sub sample of 601 dairy farms (defined here as those farms where 70% or more of total revenue is derived from the dairy enterprise) observed for varying numbers of years (the mean duration being 7.79 years) are extracted from this dataset to form an unbalanced panel totalling 4775 observations.

Output (y) is simply defined as the sum of all annual revenue from agricultural enterprises for each farm. Annual aggregate inputs included as explanatory variables are:

- rent and other land charges (x_1);
- hours of family and managerial labour (x_2);

- hours of all classes of hired labour (x_3) – a number of farms employ no hired labour and so to avoid zero values this variable is incorporated into the model along with a dummy variable (*Dhirlab*) which takes a value of 1 if $x_3 = 0$ and a value of 0 if $x_3 > 0$, x_3 then appears in the estimated model as x_3^* where $x_3^* = \mathrm{Max}(x_3, Dhirlab)$ (Battese, 1997);
- expenditure on livestock feed (x_4);
- veterinary and medical costs (x_5);
- crop costs (x_6), including expenditure on fertilisers, pesticides, herbicides, etc.;
- miscellaneous costs (electricity, heating fuel, etc.) (x_7);
- capital (x_8) which is constructed in an attempt to represent the flow of services emanating from capital stock items such as machinery, buildings and land improvements and which is measured by summation over these elements of maintenance and running costs, depreciation charges and interest on the capital stock;
- average annual size of the dairy herd (x_9).

All output and input variables defined in value terms are deflated to 1990 prices using the appropriate annual price indices published by MAFF. Summary statistics for these variables are detailed in Table 1.

***Table 1*.** **Summary Statistics for Sample 1984-1997**

Variable	***Mean***	***Standard Deviation***	***Minimum Value***	***Maximum Value***
Production Frontier				
y (Revenue 1990 £)	136487.03	95969.25	10557.42	809337.92
x_1 (Rent & land charges 1990 £)	13378.78	10784.72	698.01	118424.71
x_2 (Family labour hours)	3775.56	1645.05	18.00	17050.00
x_3 (Hired labour hours)	2645.31	3554.52	1.00	57610.00
x_4 (Feed costs 1990 £)	31454.39	23051.04	408.18	235984.54
x_5 (Vet & med costs 1990 £)	3091.87	2583.85	24.86	31379.50
x_6 (Crop input costs 1990 £)	10368.25	8804.01	42.08	83345.68
x_7 (Misc costs 1990 £)	7892.42	6107.46	471.95	77292.16
x_8 (Capital 1990 £)	26889.22	19052.80	1608.94	182106.04
x_9 (Dairy herd size)	98.21	62.24	4.00	579.50
Dhirlab (Hired labour dummy variable)	0.14	0.35	0.00	1.00
Inefficiency effects model				
z_1 (Time)	7.79	3.68	1.00	14.00
z_2 (Debt ratio)	0.17	0.17	0.00	1.39
z_3 (Short term debt ratio)	0.10	0.12	0.00	1.21
z_4 (Long term debt ratio)	0.07	0.11	0.00	1.07
z_5 (Farmer age)	49.30	10.66	23.00	91.00
z_6 (Less favoured area dummy variable)	0.26	0.44	0.00	1.00
z_7 (Dairy herd size)	98.21	62.24	4.00	579.50
z_8 (Tenancy ratio)	0.36	0.43	0.00	1.00

Number of farms = 601
Number of observations = 4995

A number of variables were also extracted from the *FBS* which were hypothesised as possibly having a role in explaining differences in levels of technical efficiency among farms. These are defined as follows:

- debt ratios:
  - overall debt ratio (z_2) – this is a simple measure of the gearing of the farm firm which shows the proportional extent to which total funds are supplied by

creditors and is calculated as the ratio of total debt (including current liabilities and all loans) to total assets;

- short term debt ratio (z_3) – the ratio of short term loans and debts to total assets;
- long term debt ratio (z_4) – the ratio of long and medium term loans and debts to total assets;

- farmer age (z_5)
- LFA (z_6) – a dummy variable taking a value of one if the farm is situated in a less favoured area and zero otherwise;
- dairy herd size (z_7) – the annual average dairy herd size for each farm;
- tenancy ratio (z_8) - the ratio of rented/tenanted land to total area, i.e. 0 = owner occupied, 1 = fully tenanted.

Again, summary statistics for these variables are detailed in Table 1.

5.2 Model specification

The stochastic frontier production function is specified here as a translog function with the following form,

$$\ln y_{it} = a_0 + a_0^* D_{it} + \sum_{k=1}^{9} a_k \ln x_{kit} + \sum_{k=1}^{9}\sum_{j=1}^{9} a_{kj} \ln x_{kit} \ln x_{jit} + a_t t + a_{tt} t^2 + \sum_{k=1}^{9} a_{kt} \ln x_{kit} t + v_{it} - u_{it}, \qquad (3)$$

where; ln denotes natural logarithms, y_{it} represents revenue from all enterprises for the i-th farm in the t-th year, D is a dummy variable for hired labour defined as above, the xs are inputs also defined above, t is a linear time trend (1984 = 1,.. 1997 = 14), v is a random error which is assumed independent and identically distributed $N(0,\sigma_v^2)$, and the αs are parameters to be estimated. We modify the specification of the technical inefficiency effects, u_{it}, from that defined in equation 2 to produce the non-neutral stochastic frontier model originally proposed by Huang and Liu (1994) - subsequently extended to panel data by Battese and Broca (1997) – as follows:

$$u_{it} = d_0 + \sum_{k=1}^{6} d_k z_{kit} + \sum_{k=1}^{6}\sum_{j=1}^{9} d_{kj} z_{kit} x_{jit} + w_{it} \tag{4}$$

where; the zs and xs are defined as above and the d s are parameters to be estimated.

The unknown parameters of equations 3 and 4 in addition to σ_v^2 and σ_u^2 are estimated simultaneously by maximum-likelihood using the program FRONTIER 4.1 (Coelli, 1996).

6. Results

6.1 Parameter estimates and hypothesis tests

Three models were estimated using the specification detailed above and only differing in the type of debt ratio variable entering the inefficiency effects model. Model one includes the overall debt ratio variable, z_1, as one of the variables explaining the inefficiency effects (and omits z_2 and z_3); model two includes the short term debt ratio, z_2

(omitting z_1 and z_3); and model three includes the long term debt ratio, z_3 (omitting z_1 and z_2). Maximum-likelihood estimates of the parameters of each of these three models are given in Table A1 of the Appendix.

A series of hypothesis tests were performed on each model (using likelihood ratio tests) regarding a number of restrictions placed upon the functional forms detailed above and the results of these tests (for model one) are given in Table 2 below.[5]

***Table 2*. Generalized likelihood ratio tests of hypotheses for parameters of the stochastic frontier production function and inefficiency effects model (model one)**

Test	*Null Hypothesis*	*l*	*Critical value*	*Decision*
1	$H_0 : \alpha_{kt} = 0$	118.91	16.92	Reject H_0
2	$H_0 : \alpha_{kj} = 0$	704.80	62.54	Reject H_0
3	$H_0 : \gamma = 0$	464.95	59.61	Reject H_0
4	$H_0 : \delta_1 = \delta_2 = \ldots = \delta_{kj} = 0$	231.14	57.84	Reject H_0
5	$H_0 : \delta_{kj} = 0$	198.89	50.71	Reject H_0

Note: all tests performed at 5% significance

All tests were conducted in relation to the unrestricted translog models, the log-likelihood values for which are also given in Table A1. The null hypothesis explored in test 1 is that technical change in the stochastic frontier model can be restricted to a Hicks-neutral specification; this is very significantly rejected in favour of non-neutral technical change. Test 2 tests whether a Cobb-Douglas specification of the stochastic frontier is an adequate representation of the production technology; again, the null hypothesis is very

[5] Results are only given here for model one. The same tests were undertaken for models two and three and identical results obtained, in that the null hypothesis was rejected in each case.

significantly rejected in favour of the translog form. The remaining tests are concerned with the specification of the inefficiency effects model. Test 3 assesses whether technical inefficiency in the sample data is zero; test 4 considers the null hypothesis that the variables included in the inefficiency effects model have no effect on the level of technical inefficiency; and the null hypothesis in test 5 is that the neutral stochastic frontier model (i.e. the model without interactions between the technical inefficiency effects variables and the input variables) is appropriate. All these null hypotheses are significantly rejected.

6.2 Production structure

Using the parameter estimates for the three different models given in Table A1 production elasticities for the inputs included in the specification of the stochastic frontier, the returns to scale elasticity and the rate of technical change were calculated (at the sample means). These are given in Table 3.

Calculated production elasticities are positive as expected (excepting that on veterinary and medical inputs for model one) and statistically significantly different from zero (again, with the exception of the elasticity on veterinary and medical inputs for all models) as well as being reasonably consistent in value across the three estimated models.

Table 3. **Estimates of structural coefficients derived from the parameters of the estimated models**

	Model 1		*Model 2*		*Model 3*	
	Coefficient	***S.E.***	***Coefficient***	***S.E.***	***Coefficient***	***S.E.***
Input elasticities:						
x_1 Rent & land charges	0.078	0.010	0.071	0.010	0.075	0.009
x_2 Family labour	0.055	0.008	0.056	0.008	0.056	0.008
x_3 Hired labour	0.039	0.004	0.037	0.004	0.037	0.004
x_4 Feed	0.194	0.010	0.207	0.010	0.207	0.010
x_5 Vet & med	-0.0058	0.0082	0.0065	0.0082	0.0070	0.0072
x_6 Crop inputs	0.094	0.008	0.101	0.008	0.101	0.007
x_7 Misc costs	0.099	0.011	0.086	0.011	0.082	0.011
x_8 Capital	0.096	0.012	0.095	0.011	0.098	0.010
x_9 Dairy herd	0.387	0.015	0.395	0.013	0.396	0.013
Returns to scale	1.036	0.010	1.054	0.010	1.059	0.009
Technical change	0.013	0.001	0.012	0.001	0.011	0.001

The estimate for scale elasticity signals the existence of very slight increasing returns to scale – confirmed by rejection of the null hypothesis of constant returns to scale using an asymptotic t-test for each model. Similarly, the estimated rate of technical change is found to be very significantly different from zero using an asymptotic t-test. Estimates are similar for each model and show that the annual rate of technical change was of the order of 1.2% over the sample period.

6.3 Technical efficiency

Mean technical efficiencies for models 1 to 3 are predicted as being 90.74%, 91.72% and 92.21% respectively. Overall the levels of individual farm efficiency are relatively high for this sample with over 70% of observations for model 1 having predicted technical efficiencies of 90% or more, 76% for model 2 and 79% for model 3.

6.4 *Inefficiency effects*

Given the non-neutral specification of the estimated models interpretation of individual parameter estimates for the inefficiency effects variables is difficult. A more useful manner of analysing the effects of each of the variables on levels of technical inefficiency involves partial differentiation of the technical efficiency predictor with respect to each of these firm-specific factors. These partial derivatives are shown in Table 4 – calculated at the mean of the sample data and with dummy variables set to a value of one.

Table 4 **Partial derivatives of the technical efficiency predictor with respect to inefficiency effects variables**

Variable	***Model 1***		***Model 2***		***Model 3***	
	Coefficient	***S.E.***	***Coefficient***	***S.E.***	***Coefficient***	***S.E.***
z_1 (Time)	-0.0041	0.0005	-0.00304	0.00043	-0.0022	0.0003
z_2 (Debt ratio)	-0.0548	0.0073				
z_3 (Short term debt ratio)			-0.0659	0.0064		
z_4 (Long term debt ratio)					-0.0270	0.0047
z_5 (Farmer age)	-0.000102	0.000100	-0.000097	0.000053	-0.000046	0.000051
z_6 (Less favoured area)	-0.0096	0.0031	-0.0053	0.0015	-0.0070	0.0015
z_7 (Dairy herd size)	0.00049	0.00009	0.00025	0.00006	0.00024	0.00003
z_8 (Tenancy ratio)	0.0073	0.0032	0.0125	0.0017	0.0025	0.0014

Partial derivatives with respect to time, farmer age, the less favoured area dummy variable, dairy herd size and tenancy ratio are identical in sign and broadly similar in estimated magnitude across the three different models. All coefficients are statistically different from zero (the majority at above the 1% level) excepting that estimated for farmer age in all models and the tenancy ratio in model 3.

Negative estimated coefficients are related to increases in levels of technical inefficiency; so that increases in the size of the various debt ratios, increasing farmer age, and location in a less favoured area are all likely to decrease the technical efficiency of farms. Additionally, the negative value of the estimated coefficient on time indicates that, on average, the technical efficiency of farms in this sample is decreasing relative to those farms that are pushing forward the frontier. Conversely, increases in the size of the dairy herd and the magnitude of the tenancy ratio are associated with increasing technical efficiency.

7. Discussion of early results and further work:

Of primary interest for our purposes are the estimated values of the partial derivatives for the three debt ratio variables. All are negative and, relative to the coefficients on the other inefficiency effects variables, are large in magnitude. The implication, that increased debt/asset ratios are associated with decreased technical efficiency, straightaway invalidate the free cash flow, monitoring and embodied technology hypotheses for the UK dairy farm setting. The 'monitoring' hypothesis, that there is a positive relationship between debt/asset ratios and efficiency because of banks tending to lend more to more efficient farmers, is unlikely to hold in the UK case anyway, because previous research has shown that banks in the UK have lent generously and uncaringly to farmers. In fact, the wisdom of agricultural lending in the UK has been questioned previously (Gasson, et. al., 1998). With respect to the 'embodied capital' hypothesis, i.e, that technical change is fuelled by debt-financed capital, and hence the farmers with more debt are more likely to be on the frontier, an argument in the other direction can be made as well. After all, farmers who are already saddled with large relative debt/asset ratios may be more reluctant to further worsen their indebtedness situation, and may hence be more reluctant to invest in new capital. Thus, precisely because new technology is embodied in capital, more indebted farmers may find themselves increasingly lagging behind the shifting efficiency frontier. This would be consistent with our result that while there has been significant technical change in the UK dairy industry over the last 15 years, there is falling average efficiency, i.e., a set of farms is pushing the frontier upwards, while the others increasingly lag behind.

Two of the hypotheses discussed above are consistent with the negative relationship we find between debt/asset ratios and technical efficiency: agency cost and adjustment. While the UK dairy farms have not been subject to the macro structural adjustments of the type discussed in New Zealand by Paul, et. al. (2000), one could stretch their adjustment scenario to 'good versus bad times'. During our sample period, the UK dairy industry has alternated between good and bad times. Could it be that the strong negative effect of debt/asset ratios on technical efficiency is coming through because of the process of adjusting to changed circumstances, and the ability of individual farms to do so being constrained by their debt/asset ratios? Although a test of this line of thinking has not been incorporated in this draft yet, we intend to investigate this in further versions by obtaining further data for the years from 1996-97 onwards, restricting our sample to the 90's, and looking at the temporal pattern of relative farm efficiencies over this period. This restriction to the decade of the 1990's for an investigation of this hypothesis is planned because of the sharp contrast provided within this decade. UK dairy farms had good times in the early to mid 1990's, but have slipped into bad times since 1996.

As noted before, there might be additional, simple reasons for the existence of this nexus between debt-asset ratios and technical efficiency. The ratios may simply be proxies for other variables. For example, newer farmers may inherently be relatively inefficient because of their lack of experience. Since newer farmers may also have larger debt to asset ratios (especially since they may have had to purchase quotas more recently), this may be translating into the observed negative connection between the ratios and efficiencies. Similarly, tenant farmers in the UK typically have larger debt/asset profiles than owner farmers, and tenancy is sometimes considered a determinant of farm efficiency. However, these proxy explanations are not validated by our empirical work. Firstly, a simple regression shows that age and tenancy status explain only about 7% of the variation in debt/asset ratios in our data. Secondly, age and tenancy are directly included in the inefficiency effects. While greater tenancy ratios do lead to greater inefficiency, *younger* farmers are seen to be *more* efficient than older ones.

While some further work remains to be done on this paper, the discussion of previous work and our own results highlight one important factor: while there is a nexus between debt/asset ratios and production efficiency, it is by no means clear that a ready explanation is available for any observed nexus. A variety of hypotheses and proxy effects could fit within an observed qualitative relationship. Thus, explanations of such results in further studies need to consider the interpretation of such effects more carefully.

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