EFFICIENCY AND POOLING IN WESTERN CAPE WINE GRAPE PRODUCTION

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Abstract: *This paper uses a stochastic frontier and inefficiency model to test the efficiency of grape production in the Western Cape. The data covers two panels of wine grape farms (34 in Robertson and 36 in Worcester) for 2003 and 2004 and 37 table grape farms in De Doorns for 2004 only. Tests show that Cobb Douglas stochastic production frontiers, with variables to explain the inefficiencies are an appropriate representation of the five individual samples.*

The stochastic frontier results indicate that output can be explained by land, labour and machinery and that efficiency cab be affected by labour quality, age and education of the farmer, location, the percentage of non-bearing vines and expenditures on electricity for irrigation.

These data is sufficiently good to produce reasonable results without pooling, but most applied economists would consider the possibility of improving the estimates by pooling the samples. However, pooling tests show that in this situation with small samples, when pooling is permissible it may not be helpful. More effort on determining the true distributions is needed to improve the way such samples are handled and Bayesian methods may be helpful in this respect.

JEL Codes: O13, Q12

1. Introduction

The survey by Battese (1992) shows that fitting frontier production functions to agricultural data has become common. Stochastic frontiers, of the type originally suggested by Aigner, Lovell and Schmidt (1977), discriminate between random errors and differences in efficiency. Battese and Coelli (1995) introduced the inefficiency model, in which the efficiency differences are simultaneously estimated from the stochastic frontier and explained by farm-specific variables. Their models incorporate tests that choose between functional forms and between frontier and mean regression models. This model is here applied to five small samples of grape producers in the Western Cape province of South Africa. The data covers two panels of wine grape farms (34 in Robertson and 36 in Worcester) for 2003 and 2004 and 37 table grape farms in De Doorns for 2004 only. The two years were similar, with no unusual weather and the three regions are located close together, with all farms using irrigation. These data cover outputs, inputs and farm specific characteristics that can be used to explain efficiency at the farm level. The focus of the paper is simple. The first study noted by Battese (1992) is Russell and Young (1983) whose sample included hill farms in the Pennines as well as dairy units on the Cheshire plain and other studies have included both animal and cereal farms. The majority of production frontier studies in agriculture pool cross section and time series data or use panel techniques to get sensible results. Thus, often apples and oranges are being compared (Bernard and Jones, 1996) and the recent literature on panel data (Baltagi, 2005) has begun to pay more attention to tests that determine whether data should be pooled. Here, we exploit the fact that despite the small samples, these data are good enough to produce acceptable results without pooling, to see if pooling tests are useful in determining what level of aggregation to use.

The paper proceeds as follows. The next section reviews the salient features of grape production in the three regions, with the aid of summary statistics and describes the data used for estimation. Section three outlines the stochastic frontier model with inefficiency effects and the reports on the hypothesis tests for model selection. The fourth section reports the results and is followed by a brief conclusion.

2. Western Cape Grape Production: Summary Statistics and Variable Definitions

Table I reports the summary statistics for these samples, in terms of the variables used in estimation. Thus, following the convention of keeping the inputs in physical terms, the outputs are expressed in terms of tons of wine grape equivalents, with fruit and table grapes converted to wine grapes at average relative prices. The first column shows that the average output per farm is similar for the four wine grape samples, while the table grape farms show more variance and produce almost twice as much. This is despite the average farm size, which is far smaller than Worcester, while Robertson is between. The greater input intensity of table grapes is again evident in labour use, which despite the smaller farms, is about three times that of the wine farms. Use of machinery (tractors, plus a few diggers and harvesters) is fairly uniform across the samples and machinery was the third and last input in most estimates. However, fuel costs were also recorded and for table grapes these proved a better measure of machinery use. As the Table shows, about twice as much fuel was used in table grape production, which suggests more intensive use of the available machinery. For the panel of wine farms, the best measure of machinery input proved to be the more sophisticated service flow from the capital stock, which was taken to be 10% depreciation on the machinery value, plus the running costs, represented by fuel expenditures.

TABLE 1 HERE

The next five variables are the farm-specific factors that are used to explain the efficiencies in the second part of the model. The first is the average wage, which varies as some farms employ more skilled labour. The Table shows that wages are higher in Worcester than in Robinson and highest in De Doorns. An analysis of labour differences and wages can be found in Conradie (2005), but here the wage serves to pick up the lack of quality adjustment in the labour variable. Age and education of the farmer are both uniform across the samples, but some do have an amazing 20 years of education, which is normally associated with higher degrees. Are a minority of the farmers retirees from academia, or similar employments?

The difficulty of measuring efficiency for a permanent crop like grape vines is partly captured by the percentage of the hectarage which is too recently planted to be yielding grapes. This varies from zero to two thirds of the farm in one case and as the new vines still use inputs, this must affect efficiency. Expenditures on electricity, which is used mainly for irrigation systems, is again far higher in table grape production. The next two columns report land and labour productivity. Land productivity is highest in De Doorns and lowest in Worcester, while labour productivity is lowest in De Doorns and highest in Robertson. Finally, the last two columns show factor ratios. The land/labour ratio is far lower in table grapes, while the machinery/labour is far less different across the samples.

3. Choice of Model, Functional From and Level of Aggregation

The general form of the production frontier is

$$Y_i = \alpha + \sum_j \beta\, x_{ij} + \varepsilon_i \quad where\ \varepsilon_i = V_i - U_i$$
$$with \quad U \sim |\, N(0, \sigma_U^2)\,| \quad and \quad V \sim N(0, \sigma_V^2) \qquad \textbf{1}$$

The V_i's are independently and identically distributed random error terms and uncorrelated with the regressors, and the U_i's are non-negative random variables associated with the technical inefficiency of the firm.

The technical efficiency of an individual firm is defined in terms of the ratio of the observed output to the corresponding frontier output, conditional on the levels of inputs used by that firm. Thus, the technical efficiency of firm *i* in the context of the stochastic frontier production function is defined

$$TE_i = \frac{Y_i}{Y_i^*} = \frac{f\,(x_i : \beta)\exp(v_i - u_1)}{f\,(x_i : \exp(v_i)} = \exp(U_i) \qquad \mathbf{2}$$

In Battese and Coelli's (1995) inefficiency model, the U_is, in equation (1) are defined as

$$U_i = z_i\delta + W_i \qquad \mathbf{3}$$

where z_i is a vector of explanatory values associated with firm level technical inefficiencies in production, δ is a vector of unknown parameters to be estimated and W_is are the errors.

First, the functional form of the stochastic frontier is determined by testing the adequacy of the Cobb Douglas relative to the less restrictive translog. These frontier models are defined as

$$Y_i = \beta_0 + \sum_{j=1}^{n} \beta_j x_{ji} + \sum_{j=1}^{n}\sum_{k=1}^{n} \beta_{jk} x_{ji} x_{ki} + V_i - U_i \qquad \mathbf{4}$$

where all of the variables are in logarithms and if terms under the double summation are not significantly different from zero, the translog reduces to the Cobb Douglas. Y is grape output in physical terms and the independent variables (x_i) are land, labour and machinery. This gives nine independent variables in the translog due to the addition of three squared terms and three cross products. In the inefficiency model, there are five explanatory variables, which are the wage rate, farmer's age and education, the percentage of the farm area planted with non-bearing vines and electricity expenditure. The remaining two variables are regional dummies for Worcester and De Doorns, to allow for regional variations.

First, a series of hypothesis tests were conducted to select the level of aggregation, the functional form and to choose between the frontier model and the standard average production function. The results reported in Table 2 are interdependent, in the sense that functional form and frontier test results are used in the pooling tests. For the functional form tests the null hypothesis (H0) is that $\beta_{ij} = 0$, $i,j = 1,...,n$, meaning that the Cobb-Douglas frontier is an adequate representation for these data. Generalised Likelihood Ratio (LR) tests[1] show that the Cobb Douglas is an adequate representation of the data for all five grape samples, as λ is less than the critical value. However, for the three panels that the pooling tests allow, the translog is preferred in two. The problem here is that the results for the translog do not comply with the theoretical restrictions for any production function. The basic requirement is that the coefficients of the three inputs must all lie between zero and unity, since they are output elasticities. Thus, the Cobb Douglas results are preferred, despite the tests.

TABLE 2 HERE

Having selected the Cobb Douglas functional form, the next section of Table 2 reports the results of tests that hypothesis that the technical efficiency effects are not simply random errors. The key parameter is $\gamma = \sigma_u^2/(\sigma_u^2 + \sigma_v^2)$, which is the ratio of the errors in equation (1). So, γ is defined between zero and one, where if $\gamma = 0$, technical inefficiency is not present, and if $\gamma = 1$, there is no random noise. The null hypothesis is thus that $\gamma = 0$, indicating that the mean response function (OLS) is an adequate representation of the data, whereas the closer γ is to unity, the more likely it is that the frontier model is appropriate. If γ is not significantly different from zero, the variance of the inefficiency effects (W_i in equation 3) is zero and the model reduces to a mean response

[1] *The likelihood-ratio test statistic, $\lambda = -2\{\log[Likelihood (H_0)] - \log[Likelihood (H_1)]\}$ has approximately χ^2_ν distribution with ν equal to the number of parameters assumed to be zero in the null hypothesis.*

function in which the inefficiency variables enter directly (Battese and Coelli, 1995). This test is unambiguous, with all values close to unity and all t tests indicating that the frontier is the appropriate model. The next column in this section reports χ, the LR test values for the more powerful test with the null hypothesis that $\gamma = \delta_0 = \delta_i = 0$, which means that in addition to γ being insignificant, the inefficiency effects are not present in the model. The null hypothesis, H_0, is soundly rejected in all cases at the 5% level, with DOF equal to the numbers of parameters set to zero.[2]

In the last section, LR tests determine the extent to which the five samples can be pooled, or estimated as a panel. The test is that suggested by Battese and Coelli (1988), which compares the LR for the pooled model (H0) with the sum of the LRs for the sub-samples estimated separately (H1). Thus, the LR when both years for Robertson are pooled is –1.382, compared with 8.815 (the sum of the two H0 LRs in the functional form test, below), giving a test statistic (χ) of 19.134. This is compared with the critical χ^2 value at the 5% significance level, with 12 degrees of freedom (DOF). The DOF is the number of parameters estimated, which is 12 (see Table 3) times by the difference in the number of estimating equations, which is two, minus one. The outcome is close, but the two can be pooled, as can the two years for Worcester, with greater certainty. However, the two wine regions should not be pooled in either year, which is a little surprising since the years were not very different. The three regions can be pooled for 2004 if the function is translog, but this gave unacceptable results and is not pursued further. This was also the case with pooling all five samples, so the only high level of aggregation allowed is all four wine samples, which narrowly qualifies even with a Cobb Douglas function. These tests explain why only three panels are reported in the next section.

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2 As the null hypothesis involves parameter γ, which as a ratio of two variances is necessarily positive, the test statistic follows a mixed chi-squared distribution and the critical values are from found in Kodde and Palme (1986).

4. Stochastic Production Function and Inefficiency Model Results

4.1. Output Elasticities, Returns to Scale and Farm Size

For all the five samples, the Cobb Douglas function was found to be an adequate representation of the unknown, underlying production function, meaning that the cross products and squared terms did not improve the fit sufficiently to justify inclusion. Table 3 reports the parameter estimates and t statistics for these models, beginning with the output elasticities for the inputs. For Robertson in 2003, all three elasticities are significant at the 5% level and a 1% increase in labour increases output by 0.577%.[3] Land is far less important and machinery contributes still less, so that the elasticities sum to only 0.812, which indicates that on average, there is decreasing returns to scale.

In the second year, land becomes the dominant input, labour falls and machinery is still last, but the sum is 1.207, which would suggest increasing returns to scale. With samples of only 34, it is perhaps not surprising that the results are so unstable, so forming a two-year panel to reduce the variability makes perfect sense. This results in more reasonable elasticities for land and labour and a sum that is much closer to constant returns to scale, but at the cost of machinery being insignificant. Aggregation by pooled estimation may well be inferior to simply aggregating the two previous results. The pooling test is also odd, in that it allowed pooling despite such different slope coefficients. Were the two sub-samples larger, such aggregation could well be destroying real information rather than improving the estimates.

TABLE 3 HERE

The Worcester results are less different, with land dominating both years and machinery contributing least, so it is no surprise that pooling was permitted, but in this circumstance it really isn't needed and rather than improving the significance of machinery, it makes this input insignificant.[4] Again, a simple average would perhaps have been preferable. For De Doorns, the three elasticities all have reasonable values and are significant, but the sum of 1.489 is rather too much evidence of increasing returns.

The last results are for a panel comprised of both regions in both years. The programme for the inefficiency model does not handle panels, but equivalent results are obtained by using time and regional dummies. All three inputs have reasonable elasticities and are significant at the 5% level, while there is still evidence of increasing returns to scale and the time dummy proved to insignificant.

In many papers, where the data refuses to cooperate, this panel could well have been the only results reported, but in this case the small samples gave good results, so the pooling issue could be examined. The pooling tests are somewhat useful: for instance, confirming the impression given by the summary statistics, that table grapes really are different from wine grapes. However, it is not clear how well the tests guide the researcher beyond this point.

The sum of the output elasticities provides an indication of the predominant scale effect in a sample, but it is an average and can be quite misleading, if farms that are too large and those that are too small balance out. The frontier programme calculates an efficiency level for each farm, so if the farms are then ranked according size some indication of the effect of size on efficiency can be gained. However, just as yield is a partial measure of productivity, returns to scale is output per unit of all inputs, not just land. Data envelopment analysis can be used to calculate scale efficiency, but for reasons

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[3] *The t test critical values at the 5% level are shown at the bottom of the Table. The test is one tailed as the elasticities must be positive.*

[4] The aphorism with which Samuelson used to head the banking chapter in his textbook comes to mind here.
The first law of banking and woe betide those who don't heed it
Never lend money, except to those who don't need it. *Ogden Nash*

of space this paper uses the efficiency levels from the stochastic frontier estimation and these do appear to be a monotonically increasing function of farm size. The quartile of smallest farms has an average efficiency of 65%, the next quartile 71%, the next 75% and the largest, 76%.

4.2. Explaining the Inefficiencies

The same variables are reported for each sample in explaining the inefficiencies, to facilitate comparisons, with the exception of De Doorns, where only electricity was significant. For all but De Doorns and one sample, higher average wages decrease inefficiency (hence the negative coefficients). This is to be expected, since this serves as quality adjustment for the labour input. Expenditures on electricity reduced inefficiency in De Doorns, which suggest that irrigation is important for table grapes. For Robertson the same effect dominates, but for Worcester pooled and the full pooled sample the sign is positive. This may well reflect the locations of the farms, as those on higher ground will have to spend more on pumping irrigation water.

The same type of problem arises with non-bearing vines, which increase inefficiency, in accordance with the conventional wisdom, only in Worcester in 2004. In the four cases in which non-bearing vines increase efficiency, the causality may run from efficient production to planting new vines. This follows, as any farmer who intends to continue producing has to do some replanting almost every year. If a farm is prospering, it is also likely to be investing, so it seems to be those that are not efficient that are not investing. Thus, the dynamics of the situation reverse the expected static result. Age and education often give odd results in these models and here age reduces efficiency, but so too does education, in Robertson especially. As was noted above, wine farmers with 20 years of education may have bought vineyards late in life as an attractive retirement lifestyle (the prospect certainly appeals to the authors). The last statistics are the variance parameters $\sigma^2=\sigma_u^2+\sigma_v^2$ and $\gamma=\sigma_u^2/\sigma^2$ which do not require further discussion.

5. Conclusions

This paper uses a stochastic frontier and inefficiency model to test the efficiency of grape production in the Western Cape. Data covers two panels of wine grape farms (34 in Robertson and 36 in Worcester) for 2003 and 2004 and 37 table grape farms in De Doorns for 2004 only. Tests show that Cobb Douglas stochastic production frontiers are an appropriate representation of the five individual samples.

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Table 1: Summary Statistics for the Samples

Variable	Output	Land	Labour	Machines	Fuel	Wage	Age	Education	Non-bearing	Electricity	Output/	Output/	Land/	Machinery/
Statistic	**Wine grapes**	**Hectares**	**Full Time persons**	**Number**	**Rand**	**R per month**	**Years**	**Years**	**Percent**	**Rand**	**Land**	**Labour**	**Labour**	**Labour**
	Robertson - 34 wine farms 2003													
Mean	1887.08	87.92	33.21	5.74	67.10	908.13	41.91	14.26	0.16	91.62	22.58	57.45	2.75	0.09
SD/Mean	0.73	0.79	0.75	0.58	0.92	0.24	0.25	0.14	0.52	0.99	0.44	0.42	0.48	0.55
Minimum	102.85	13.20	7.56	2.00	10.00	562.19	28.00	10.00	0.00	6.56	7.44	11.97	1.02	0.04
Maximum	5482.50	299.00	129.17	16.00	350.0	1400.7	64.00	20.00	0.41	374.62	52.70	103.60	5.79	0.20
	Robertson - 34 wine farms 2004													
Mean	1982.98	94.80	34.80	5.97	70.23	1031.65	41.91	14.26	0.16	98.43	22.59	56.97	2.77	0.09
SD/Mean	0.74	0.79	0.71	0.58	0.93	0.34	0.25	0.14	0.52	0.96	0.37	0.41	0.49	0.60
Minimum	273.13	12.20	10.12	2.00	16.00	456.08	28.00	10.00	0.00	8.50	9.04	13.47	0.60	0.03
Maximum	5845.00	330.00	113.90	16.00	380.0	1733.33	64.00	20.00	0.45	390.00	44.49	113.57	6.26	0.20
	Worcester - 36 wine farms 2003													
Mean	1675.59	101.30	35.15	6.25	79.21	923.18	41.08	14.68	0.17	80.96	16.17	47.38	2.99	0.08
SD/Mean	0.73	0.62	0.69	0.66	0.66	0.31	0.21	0.11	0.51	0.69	0.28	0.35	0.29	0.71
Minimum	100.00	6.00	4.50	2.00	8.38	267.63	24.00	12.00	0.00	7.59	7.02	17.76	1.20	0.03
Maximum	5727.05	312.00	110.00	24.00	205.4	1605.61	57.00	17.00	0.42	260.00	27.40	87.88	4.80	0.33
	Worcester - 36 wine farms 2004													
Mean	1846.82	104.23	35.87	6.58	83.72	1058.32	41.08	14.68	0.20	95.38	16.96	50.63	3.08	0.08
SD/Mean	0.76	0.63	0.70	0.64	0.73	0.30	0.21	0.11	0.54	0.72	0.25	0.31	0.32	0.72
Minimum	95.00	5.50	5.50	2.00	10.00	268.00	24.00	12.00	0.04	8.00	7.82	17.27	1.00	0.03
Maximum	7124.80	324.50	113.10	25.00	261.3	1933.94	57.00	17.00	0.67	337.00	29.48	85.79	5.25	0.36
	De Doorns - 37 table grape farms 2004													
Mean	3852.56	60.80	119.20	6.70	158.6	1239.92	41.21	14.38	0.16	175.86	69.08	36.25	0.55	0.07
SD/Mean	1.03	1.27	1.34	0.94	1.33	0.33	0.19	0.12	0.75	1.41	0.24	0.35	0.42	0.43
Minimum	965.70	15.00	24.25	2.00	15.00	352.11	27.00	12.00	0.00	4.02	35.34	16.57	0.30	0.05
Maximum	22477.50	452.00	969.76	36.00	1100	2839.01	56.00	20.00	0.50	1500.00	106.38	74.16	1.29	0.28

Table 2: Hypothesis Tests

		Log-Likelihoods		LLR Test	DOF	χ^2 Critical	Outcome
Functional Form Test		H0	H1	Statistic		Value 5%	
	Parameter Restrictions	Cobb Douglas	Translog	Statistic			
Robertson 2003	H_0: All $\beta^{jk} = 0$	0.569	4.87	8.602	6	12.59	Accept H0 - CD is adequate
Robertson 2004		7.616	8.211	1.19	6	12.59	Accept H0 - CD is adequate
Worcester 2003		5.92	12.21	12.58	6	12.59	Accept H0 - CD is adequate
Worcester 2004		16.49	17.051	1.122	6	12.59	Accept H0 - CD is adequate
De Doorns 2004		7.254	11.86	9.212	6	12.59	Accept H0 - CD is adequate
Robertson both years		-1.382	10.893	24.55	6	12.59	Reject H0- CD is inadequate
Worcester both years		19.494	25.312	11.636	6	12.59	Accept H0 - CD is adequate
All 4 wine samples		-4.454	11.88	32.668	6	12.59	Reject H0- CD is inadequate

Frontier Tests		Gamma	t stat	LLR test Statistic	DOF	Parameter Restrictions	H_0: □ = δ_i = 0
Robertson 2003		0.999	1911	40.893	7	13.401	Reject H0 - frontier not OLS
Robertson 2004		1.000	277.393	34.782	7	13.401	Reject H0 - frontier not OLS
Worcester 2003		1.000	624.090	31.835	7	13.401	Reject H0 - frontier not OLS
Worcester 2004		1.000	16.291	21.500	7	13.401	Reject H0 - frontier not OLS
De Doorns 2004		0.895	102.464	141.554	3	7.054	Reject H0 - frontier not OLS
Robertson both years		0.952	22.808	51.381	7	13.401	Reject H0 - frontier not OLS
Worcester both years		0.958	19.107	19.494	7	13.401	Reject H0 - frontier not OLS
All 4 wine samples		1.000	16017	48.461	7	13.401	Reject H0 - frontier not OLS

Pooling Tests Sample	Functional Form	H0 Pooled	H1 Separate	LLR Test	DOF		
Robertson both years	Cobb Douglas	-1.382	8.185	19.134	1*12=12	21.03	Accept H0 - can pool
Worcester both years	Cobb Douglas	19.494	22.41	5.832	1*12=12	21.03	Accept H0 - can pool
Both regions 2003	Cobb Douglas	-9.611	6.489	32.2	1*12=12	21.03	Reject H0 - can't pool
Both regions 2004	Cobb Douglas	9.55	24.106	29.112	1*12=12	21.03	Reject H0 - can't pool
All 3 regions 2004	Translog	19.045	31.36	24.63	2*12=24	49.77	Accept H0 - can pool
All 3 regions 2004	Cobb Douglas	4.511	31.36	53.698	2*12=24	36.42	Reject H0 - can't pool
All 4 wine samples	Cobb Douglas	-4.454	30.595	70.098	3*18=48	73	Accept H0 - can pool
All 5 samples	Translog	1.928	37.849	71.842	4*18=72	92.8	Accept H0 - can pool
All 5 samples	Cobb Douglas	-10.479	37.849	96.656	4*12=48	67	Reject H0 - can't pool

Table 3: Stochastic Production Frontier and Inefficiency Model Results

	Robertson 2003	Robertson 2004	Robertson 2003, 2004	Worcester 2003	Worcester 2004	Worcester 2003, 2004	De Doorns 2004	Pooled 4 wine samples
	Elasticity	Elasticity	Elasticity	Elasticity	Elasticity	Elasticity	Elasticity	Elasticity
Frontier	(t stat)	(t stat)	(t stat)	(t stat)	(t stat)	(t stat)	(t stat)	(t stat)
Intercept	0.531	0.204	0.444	0.099	0.131	2.646	0.731	3.327
	(29.977)	(1.826)	(9.171)	(1.270)	(1.340)	(18.116)	(0.749)	(0.236)
Land	0.135	0.653	0.385	0.867	0.758	0.842	0.758	0.758
	(1.694)	(9.439)	(5.875)	(7.425)	(9.356)	(12.058)	(11.743)	(12.484)
Labour	0.577	0.384	0.524	0.348	0.284	0.319	0.566	0.321
	(9.444)	(3.555)	(5.466)	(1.580)	(3.196)	(3.589)	(2.575)	(4.224)
Machinery	0.100	0.171	0.032	0.056	0.104	0.067	0.174	0.137
	(2.059)	(1.605)	(0.347)	(0.383)	(1.677)	(0.897)	(2.132)	(1.676)
Sum	0.812	1.207	0.941	1.271	1.146	1.228	1.498	1.215
Inefficiency	Parameter	Parameter	Parameter	Parameter	Parameter	Parameter	Parameter	Parameter
	(t stat)	(t stat)	(t stat)	(t stat)	(t stat)	(t stat)	(t stat)	(t stat)
Intercept	-2.751	-5.987	-6.461	0.043	1.446	0.860	0.659	-1.405
	(-2.445)	(-2.654)	(-2.318)	(0.044)	(2.055)	(0.658)	(0.436)	(-0.099)
Wage	-0.667	-0.247	-0.510	-0.222	-0.206	-0.376	-	-0.158
	(-2.512)	(-1.554)	(-1.648)	(-0.818)	(-2.368)	(-3.389)		(-2.369)
Electricity	-0.916	0.129	-0.313	0.222	-0.015	0.752	-0.868	0.441
	(-5.185)	(1.304)	(-2.228)	(0.780)	(-0.216)	(3.244)	(-3.017)	(1.507)
% Non-	-4.790	-0.386	-1.771	0.142	0.862	-0.633	-	0.635
bearing	(-3.275)	(-0.563)	(-1.839)	(0.182)	(3.033)	(-1.939)		(-3.337)
Farmer's	1.456	0.374	0.781	0.473	0.310	0.404	-	0.165
age	(2.524)	(1.362)	(2.161)	(1.497)	(2.399)	(1.172)		(4.691)
Education	2.447	2.245	3.289	-0.288	-0.331	0.198	-	-0.871
	(2.780)	(3.170)	(3.615)	(-0.597)	(-1.332)	(2.799)		(3.810)
sigma-	0.224	0.038	0.163	0.057	0.026	0.057	0.485	0.072
square	(2.807)	(2.594)	(2.985)	(2.028)	(4.335)	(3.690)	(4.565)	(8.616)
Gamma	1.000	1.000	0.952	1.000	1.000	0.958	0.895	1.000
	(1911)	(277)	(22.808)	(624)	(16.291)	(19.107)	(102.464)	(16017)
Worcester dummy								0.194
								(3.783)
Critical t 5%	1.717	1.717	1.671	1.711	1.711	1.671		1.658
Critical t 10%	1.321	1.321	1.296	1.318	1.318	1.296		1.289