

Estimates of Individual Dairy Farm Supply Elasticities

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Abstract

Milk supply elasticities were estimated for 70 farms who participated in the New York Dairy Farm Business Summary Program from 1985 through 1993. Technology was modeled as a single output, single composite input Cobb-Douglas function. The resultant supply function is the natural log of milk quantity as a function of the log of milk price to prices paid for all inputs, with a time trend added. Since random output shocks to each farm may have occurred in any of the nine data years, a dummy year variable was modeled sequentially for each year for each farm. Ignoring 12 negative estimates, elasticities averaged .65. Pooling the data with a fixed effects model produced an elasticity estimate of .47. A geometric lag pooled model produced a short-run elasticity of .2 and a long-run supply elasticity of 1.00 using instrumental variables, but an OLS short-run elasticity of .25 and long-run elasticity of .64.

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Empirical estimates of supply elasticities are essential for economic analysis involving commodity price policy. Although individual farm elasticities are needed to determine the supply response by farm type, most elasticity estimates have been estimated from aggregate market data. Supply estimates using firm level data have been fewer, and those often assume that firms have identical supply curves. In this paper individual farm supply curves are estimated from a panel of 70 New York dairy farms using 9 years of annual observations from each of those 70 farms from 1985 through 1993. These data are also pooled to estimate a single supply curve from the panel data.

Panel Data

A panel data set consists of a combination of cross-sectional, time series observations on the same farms. There are a number of statistical models that can be used to estimate relationships from a panel data set (Greene). The appropriate procedure depends upon the belief concerning the underlying economic relationship to be modeled, and the error structure of the data used to estimate that relationship.

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In much panel analysis, the assumption is made that the slope of the regression is constant across all firms. In this case, that fixes the supply elasticity constant across all farms and implies that the technology that each farm employs is identical. That is consistent with the axioms of perfect competition, where the knowledge of technology is available to all with free entry into the industry. It is ironic however, that many economic textbooks that discuss perfect competition in early chapters, and thus implicitly assumes one firm supply curve, discuss in later chapters the aggregation of a myriad of individual firm supply curves when presenting market equilibrium (Mas-Colell, Whinston, and Green).

Even if slopes are assumed to be constant across firms, it is often assumed that the intercept is not constant. That would be especially appropriate if the firms are not the identical size. The intercept is either modeled as being different for each firm, but a constant for that firm (fixed effect), or modeled as different but stochastic for each firm (random effect). The random effect model assumes that each of the firms is a random draw for the population of similar firms. If the slope of the regression is believed to be the same across firms, but subject to stochastic variation, then the random coefficient model is utilized. In any of these models, it might also be necessary to correct for non-spherical error structures (i.e. heteroscedasticity or serial correlation).

If the slopes (and intercepts) are believed to differ across firms, the estimation of those relationships can be done with individual equations. However, if coefficient restrictions, or error relationships exist across equations, then a system estimation procedure should be employed. If the coefficients of the individually estimated equations

do not differ, then it would be more efficient to estimate these coefficients from one specified equation, incorporating the necessary error structure.

In this research I first assume that supply elasticities vary by firm with no restrictions across firms, nor any relationship in the error structure across firms. Thus single equations are estimated for the supply curve for each of the 70 farms in the data set. I then estimate a single equation, but since the farms vary in size, different intercepts are estimated. Since farms are not drawn from a random sample, a fixed effects model is estimated. Finally, the model is modified to permit a geometric distributed lag.

Data and Models

The data are from 70 participants of the New York Dairy Farm Business Summary Program that participated each year from 1985 through 1993. This provides only 9 observations per farm, which severely limits model specification given the limited degrees of freedom that occur when a separate equation is fitted for each farm. Total annual milk output is available for each farm. Prices are not collected for these farms, although implicit prices can be computed by dividing revenue or expenditures by quantities. Even then quantities are only available on milk production and months of labor, but not other inputs like feed. Given these limitations, published prices are used to estimate a supply curve. The annual aggregate New York state milk price (index) is used for output price and the annual index of prices paid by New York dairy farms is used as the single input price. This approach assumes that in any year all 70 farmers faced the same output and input prices. These prices (indices) are in Table 1.

Table 1. Price Data

Year	Milk Price (1984 = 100)	Price of inputs (1984=100)
1985	94.81	93.83
1986	93.33	95.06
1987	94.07	92.59
1988	93.33	98.15
1989	105.18	103.70
1990	108.15	104.94
1991	94.07	106.17
1992	99.26	106.79
1993	96.30	109.26

The technology of each farm is modeled as a single output, single composite input Cobb-Douglas production function: $y=ax^b$, where y is output and x is the composite input. The Cobb-Douglas production is functionally separable so that multiple inputs can be aggregated into the composite input x . The elasticity of output is constant at $\epsilon=b$.

If each firm maximizes profits, then the resultant supply curve for this technology is: $y = a^{1/(1-b)}(p*b/r)^{b/(1-b)}$, where r is the price of the composite input, and p is the price of the output.

After adding a time variable and changing notation, this supply function can be specified in natural log form as: $\ln(y) = b_0 + b_1*\ln(\text{prmil}/\text{prin}) + b_2*\text{time}$, where \ln is the natural log, y is annual output of milk, prmil is the price of milk (index), prin is the price of all inputs (index), and time varies from 1 to 9 for the nine years of observations. In this estimated form b_0 represents the base output of the farm, b_1 measures the response to prices and is the elasticity of supply (for an annual period), and b_2 measures the constant annual rate of output change due to technological change and other factors. The b_2 variable could implicitly include long-run supply response to price. An alternative would be a distributed lag model.

Individual Farm Supply Elasticities

Initial estimates produced 23 negative supply elasticities. This is inconsistent with the economic theory of a non-constrained profit maximizing firm. Given the limited number of observations per farm it is believed that these negative elasticities may be the result of one year of random output shocks for each of these farms. It is not known during which of the nine years that shock may have occurred. Unlike much of crop production, where weather may be responsible and is measurable and consistent across all farms, random shocks to milk output is mostly unique to each dairy farm. Thus, it was decided to define dummy variables, each taking the value of one for each year in sequence, and run nine more regressions for each farm where one of the nine years would be defined as a dummy variable. The use of a dummy equal to one for a single year is equivalent to deleting that observation. Of the ten regressions for each farm, the regression with the highest adjusted R squared value was selected. Additional years could have been modeled stochastic for each farm by using combinations of two or more dummy variables, but that was perceived to be obvious data mining.

Results are reported in Table 2. The revised estimates produced 12 rather than 23 negative supply elasticities. These estimates ranged from a low of negative 2.77 to a high of 1.84, and averaged .38. Ignoring the negative elasticities, the average elasticity was .65 (median of .56). An histogram of the positive elasticities is shown in Figure 1. There is a considerable variation of supply elasticities across these farms. They would be expected to respond to milk prices differently. Intercepts are not reported, but varied by farm since the size (output) of farms varied significantly.

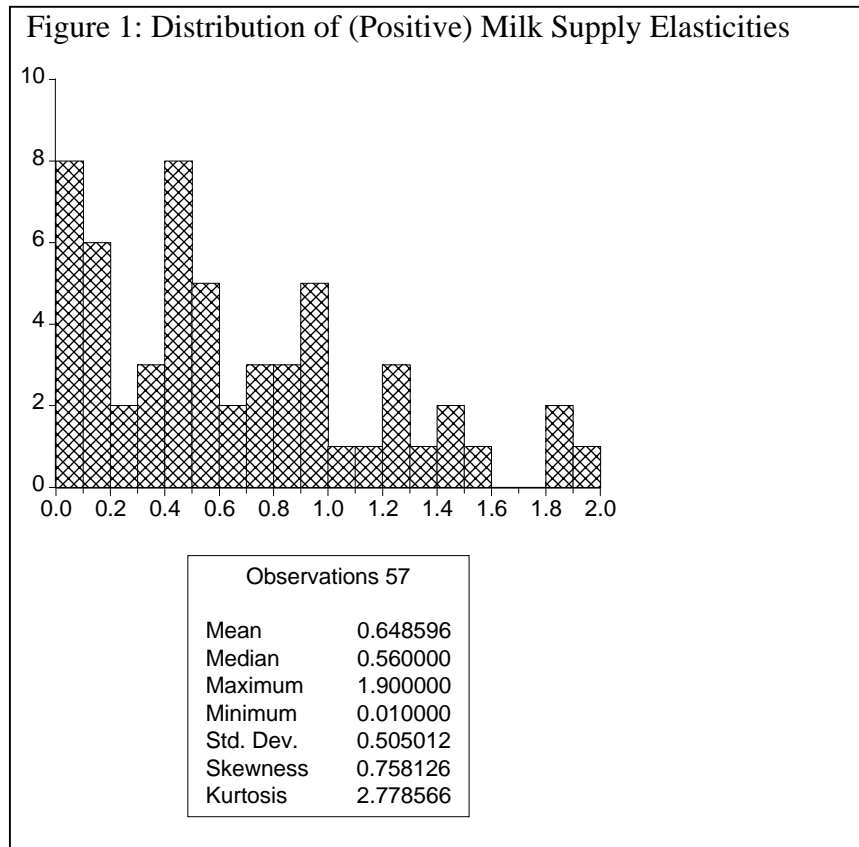
Table 2. Estimates of Individual Dairy Farm Milk Supply Elasticities

Farm	Elasticity	Output Change	Dummy Year	Adjusted R-Squared
1	0.42	0.05	3	0.85
2	1.2	0.05	8	0.59
3	0.38	0.06	4	0.95
4	-1.01	0.14	1	0.92
5	0.15	0.09	9	0.92
6	0.61	0.06	9	0.97
7	0.17	0.11	9	0.95
8	1.39	0.04	7	0.84
9	0.01	0.09	4	0.92
10	0.25	0.09	9	0.94
11	0.06	0.03	4	0.86
12	0.42	0.1	4	0.95
13	0.08	0.05	6	0.88
14	1.85	0.04	7	0.83
15	0.4	0.05	5	0.94
16	-2.77	0.09	7	0.9
17	0.59	0.05	1	0.82
18	0.94	0.05	7	0.69
19	1.44	0.09	4	0.89
20	0.38	0.06	9	0.64
21	0.16	0.04	7	0.57
22	0.81	0.02	7	0.93
23	0.45	0.02	1	0.59
24	0.15	0.06	2	0.93
25	0.57	0.04	5	0.78
26	0.31	0.04	4	0.46
27	0.06	0.06	2	0.98
28	1.29	0.03	1	0.66
29	0.71	0.07	4	0.86
30	0.56	0.07	7	0.96
31	0.93	0.09	1	0.57
32	0.49	0.02	1	0.79
33	0.75	0.03	7	0.63
34	1.24	0.05	7	0.61
35	-0.84	-0.06	9	0.91
36	0.7	0.02	7	0.5
37	0.65	0.06	3	0.95
38	0.58	0.05	4	0.91
39	0.92	0.14	5	0.98
40	0.06	0.02	6	0.6

Table 2. Estimates of Individual Dairy Farm Milk Supply Elasticities (cont.)

Farm	Elasticity	Output Change	Dummy Year	Adjusted R-Squared
41	0.45	0.03	2	0.54
42	-0.86	0.03	7	0.71
43	0.93	0.13	5	0.91
44	-1.34	0.1	3	0.97
45	0.03	0.03	4	0.75
46	0.12	0.03	9	0.55
47	-0.42	0.03	9	0.83
48	-0.17	0.04	2	0.58
49	0.04	0.03	8	0.73
50	0.07	0.02	1	0.83
51	0.43	0.03	5	0.46
52	0	0.07	1	0.86
53	1.4	0.07	3	0.91
54	0.89	0.03	4	0.91
55	0.1	0.08	9	0.85
56	1.06	0.05	4	0.76
57	-1.39	0.12	1	0.97
58	0.91	0.06	4	0.59
59	0.54	0.04	1	0.82
60	0.2	0.06	9	0.96
61	-0.66	0.02	8	0.85
62	1.12	-0.02	1	0.8
63	1.5	0.07	5	0.7
64	1.84	0.17	6	0.98
65	-0.42	0.03	1	0.94
66	1.9	0.19	4	0.92
67	-0.52	0.11	3	0.94
68	0.84	0.06	8	0.9
69	-0.17	0.11	0	0.99
70	0.47	0.06	4	0.96
Average	0.38	0.06	4.83	0.81

The adjusted R square values were relatively high, averaging .81 across all equations. The dummy year that provided the best fit (highest adjusted R square value), varied by farm, but all specifications but the one for farm number 69 included a dummy



variable for a year. The rate of output change, net of annual price effects, averaged 6 percent over the farms, and was positive for all but one farm.

It may be that farms of different sizes respond differently to milk price changes. This was tested by regressing individual farm estimated elasticities on farm size, measured by the number of dairy cows on each farm in 1993. Only farms with positive supply elasticity estimates were used. The result is reported in Table 3. Elasticities are slightly higher for larger farms, but the coefficient on size is small (although statistically significant). Thus, the estimated effect of size on elasticity is small. For instance, a dairy farm with 50 cows would have a supply elasticity of .59, while a dairy farm with 500 cows would have a supply elasticity of .77. An adjustment for the average size of 139 cows for these farms provides an elasticity value of .63.

Table 3. Regression of Supply Elasticities on Cow Numbers

Variable	Coefficient
Constant	.571
t-Stat.	(7.77)
Cows	.000403
t-Stat.	(2.23)
Adjusted R-square	.07
F-Stat.	(4.99)
Observations	57

Oi has argued that since capital intensity is likely to increase with firm size, the ability to vary output in the short-run should decrease with firm size. Here the opposite is found, although with an adjusted R squared value of only .07, there is still much variability by farm size.

Adelaja estimated farm supply elasticities for three different sizes of Northeast dairy farms, small (<40 cows), medium (40-79 cows), and large (over 79 cows). He used ELFAC data over 1971-1985, which is a record service for dairy farms in the Northeast. He estimate the one year supply response as .64 (small farm), .35 (medium farm), and .39 (large farm). My estimates for New York are similar for the small farms, but greater for the large farms.

Estimation of a Common Elasticity

The estimation of a unique elasticity for each farm is not an efficient use of data with limited observations per farm. Even if estimated elasticities differ by farm, as they do here, if characteristics of those farms considered important in policy analysis, such as size, do not determine this variation, then it is best to group the data and estimate a common elasticity. The resultant elasticity estimate may be biased but more efficient. The

57 farms with positive estimated supply elasticities from individual farm equations were pooled.

Since pooling 57 farms each with nine years of data provides 513 observations, a more complex supply curve could be estimated than the Cobb-Douglas function. In aggregate analysis the supply of milk is often decomposed into a cow number response function and a separate milk per cow response function . That is especially appropriate at the aggregate level where milk supply is influenced by farmers entering and leaving the business, which is captured in cow numbers. Individual farmers also increase and decrease their cow numbers in addition to producing more milk per cow. Yet to be consistent with the previous supply estimates, this decomposition was not done. However, a cow numbers variable was added to the supply equation.

A fixed effects model using only data from the 57 farms with positive elasticities is reported in Table 4. The common elasticity was estimated at .47. The cow numbers variable coefficient was .0008, and a common time trend variable coefficient was .05. Unique farm time trend coefficients were also estimated, but are not reported since they had no impact on the estimated elasticity. The adjusted R squared value of the fixed effects model was .99.

Short-Run and Long-Run Supply Elasticities

Given the limited number of annual observations (9 years), it is a challenge to model long-run supply response. However, if pooled data are utilized, then an aggregate long-run response may be modeled without significant loss of degrees of freedom. If a

Table 4. Estimation of a Common Milk Supply Elasticity

Variable	Coefficient
Elasticity	.4725
t-Stat.	(4.11)
Number of Cows	.0008
t-Stat.	(10.75)
Time	.0506
t-Stat.	(19.55)
Fixed Effects	Varies
Adjusted R-square	.98
Observations	513

geometric form lag is assumed for prices, where the largest response to price occurs in the initial years and this response decays geometrically, the reduced form is:

$\ln(y)_t = \alpha(1-\lambda) + \lambda \ln(y)_{t-1} + \beta(1-\lambda) \ln(\text{prmil}/\text{prinput})_t + \delta(1-\lambda)\text{time}$, where λ is expected to be between zero and one to insure a finite lag effect. Given that output and normalized prices are in log form, the short-run supply elasticity is $\beta(1-\lambda)$, and the long-run supply elasticity is β (Greene). Ofcourse, this reduced form can represent alternative models as well.

Estimating this equation with OLS may produce inconsistent coefficients if the auto-covariances are not zero.. The instrumental variables approach is often suggested. The instrument variable used here for lagged output is the lagged normalized price of milk. Results are shown in Table 5. The results produce a short-run elasticity of .2, and a long-run supply elasticity of 1.00. Dividing the sample into large farms with 100 or more cows (in 1993) and small farms with fewer than 100 cows produces a slightly larger short-run elasticity for the small farms. However, the large farms have a more higher long-run elasticity of 1.38 compared to only .55 for the small farms.

The OLS estimate using all 57 farms produces a short-run elasticity of .25 and a long-run elasticity of .64. If cow numbers are added to the OLS equation then the

Table 5. Geometric Lag Estimate of Milk Supply Elasticities

Variable	Instrumental Variable			OLS	OLS
	All Farms	< 100 cows	≥ 100 cows		
Short-run Elasticity	.20	.21	.18	.25	.28
t-Stat.	(1.77)	(1.50)	(1.08)	(2.34)	(2.66)
Lagged Output	.80	.62	.87	.61	.51
t-Stat.	(14.16)	(6.59)	(11.16)	(13.24)	(9.83)
Time	.0044	.0104	.0012	.0160	.0004
t-Stat.	(1.01)	(1.84)	(.16)	(4.14)	(4.12)
Number of Cows					.0196
t-Stat.					(5.04)
Fixed Effects	Varies	Varies	Varies	Varies	Varies
Long-run Elasticity	1.00	1.38	.55	.64	.57

short-run elasticity increases to .28 and the long-run elasticity decreases to .57. These estimates are lower short-run supply elasticities than from the earlier estimates.

Previously, price effects may have been picked up in the time coefficient. The time coefficient of the lagged model is only .0044, and statistically insignificant, contrasting to the earlier pooled estimate of .0506. Whether cow numbers should be included in the equations depends upon whether one believes farm decisions to change cow numbers are independent of milk price. Most farms have long-run growth plans dependent upon succession and other goals, which are independent of short-run prices except that short-run prices impact cash-flow. Long-run growth plans often depends upon perceptions of the long-run future of the industry.

Summary

Milk supply elasticity estimates were estimated using data from participants in the New York Dairy Farm Business Summary Program from 1985 through 1993. Individual farm

elasticities were estimated from separate farm supply curves. The data was also pooled and a common elasticity was estimated. From the pooled data, a geometric lagged model was also estimated to obtain both short-run and long-run elasticities.

The annual elasticity of supply for this group of New York dairy farms averages .65. Larger farms appear to have a slightly larger supply elasticity. Pooling the data results in a common elasticity estimate of .47. The geometric lag model produces a short-run supply elasticity of .2, and a long-run supply elasticity of 1.00 using instrumental variables, but an OLS short-run elasticity of .25 and long-run elasticity of .64. Finally, the long-run elasticity of farms with more than 100 cows was estimated at 1.38 but only .55 for farms with fewer than 100 cows using the geometric lag, instrumental variable model. Short-run elasticity was almost identical.

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