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Plant size: Capital cost relationships in the dry mill ethanol industry

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Abstract

Estimates suggest that capital costs typically increase less than proportionately with plant capacity in the dry mill ethanol industry because the estimated power factor is 0.836. However, capital costs increase more rapidly for ethanol than for a typical processing enterprise, judging by the average 0.6 factor rule. Some estimates also suggest a phase of decreasing unit costs followed by a phase of increasing costs. Nonetheless dry mills could be somewhat larger than the current industry standard, unless other scarce factors limit capacity expansion. Despite the statistical significance of an average cost-size relationship, average capital cost for plant of a given size at a particular location is still highly variable due to costs associated with unique circumstances, possibly water availability, utility access and environmental compliance.

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1. Introduction

The relation between capital costs and plant size is an important determinant of the scale of a fixed-proportions enterprise. Enterprises in many processing industries have fixed proportions production processes when a unit of a critical resource or commodity input, such as corn or petroleum, provides a constant fraction of output and requires a fixed amount of processing capacity for each unit of raw material processed.

Capital cost in a processing firm is thought to increase proportionately less than size because large containers are a dominant element of capital costs and surface area increases less rapidly than volume [1]. Considerable evidence on this point is available for the petroleum processing industry, chemical industry, and grain storage industry [2,3].

Put another way, the evidence for these three industries suggests declining average capital costs...
as the scale of the enterprise increases. This simple fact likely explains the massive scale that has evolved in all three processing industries. Similar questions about the capital cost-capacity relationship in the ethanol processing industry arose during recent expansions.

Some estimates of the capital cost-plant size relationship for dry-mill ethanol processing are presented in this paper. First, we review approaches to estimation. Second, we discuss the capital cost structure in the ethanol industry and summarize the data from a recent survey. Third, we present the results of estimation. Finally, we discuss the implications for reducing capital costs. Such estimates are critical to investors, financiers and economic analysts in their assessments of the financial viability and scale of processing investment in the ethanol industry.

2. Capital costs in the ethanol industry

Some information about capital costs in the ethanol industry is now available because the results of a recent USDA Cost of Production Survey are now available [4]. The capital cost and capacity data of the firms in this survey are used for a statistical estimate of the capital cost-capacity relationship.

There are two technologies in the ethanol industry. Most existing dry mills are small, with capacities range of 5–30 million gallons per year (MGY). However, dry mills constructed during the current expansion are from 40 to 100 MGY of capacity. Dry mills produce one composite by-product; distillers dried grains (DDG) contains the residual protein, oil and fiber after the carbohydrate is removed for starch processing and ethanol production.

The wet mills of the United States tend to be larger. The capacity ranges from 50 MGY and up to 330 MGY. Wet milling is a more complex technology; the byproduct is separated into corn gluten feed with about 20% protein, corn gluten meal with about 60% protein, and edible oil. Many wet mills of the United States are also multi-functional, with a fraction of the starch producing capacity devoted to corn sweetener production for peak summer demands. Analyses of economies of scale for variable proportions industries require other methods. Chambers discusses scale economies for a variable proportions firm [5, p.21–2, p.72–3].

Plant size-capital cost relationships are probably different for wet mills and dry mills. Some engineers would expect that a wet mill without corn sweetener production would cost about 40% more than a dry mill of the same size when both have 50 MGY capacity, because additional wet-milling and byproduct separation equipment must be installed. The sample average of capital cost and output of wet mills and dry mills from the survey, given in Table 1, confirms that average capital costs are higher for wet mills.

Our analysis focuses on the dry mill industry. One reason for this emphasis is relevance: dry mills have dominated the recent capacity expansion and the wet-mill industry has not built new plants. Also, only four wet mills participated in the survey, so data is not sufficient for estimation of cost-size relationships. In contrast, 18 dry mills participated in the survey of existing plants and one new dry mill just constructed, provided capital cost data for a total sample of 19 dry mills. A relatively homogenous capital structure may be obtained when the wet-mills are removed from the sample.

3. Estimation

The power function is the standard estimation function, an idea that emanates from early research on economies of scale for fixed proportions industries [1]. Some economists also know the inverted form of the power function as the
Cobb-Douglas production function [6, p. 106–7]. Based on some early estimates for typical industries, the power function is often referred to as the ‘0.6 factor rule’, which says that a 1% expansion in processing capacity yields a smaller 0.6% increase in capital costs. Ladd reviews estimates for several agricultural processing industries [2].

To engineers, the power function is a log-linear relationship that appears as a straight line on log–log graph paper. Factor rules have become a mainstay in process engineering and plant optimization studies. Specifically, factor rules ranging from 0.4 to 0.9 have been provided for the chemical processing industry [3].

Estimates of plant size-capital cost relationships have been estimated by two methods for other industries: econometric estimation using actual observations from survey data, and direct calculation from synthetic engineering data. Both approaches have some advantages, disadvantages and critics. The main advantage for the engineering approach is that estimates can be provided where no operating process yet exists.

The main advantage of the sample approach is also the main criticism of the engineering approach, that the cost data from an actual sample also measures outcomes of a broad set of random events due to variation in the costs of wells, utility hookups, environmental compliance and construction delays. The effects of these numerous variables could be measured with regression analysis in principle, but their predictive value would be limited due to the substantial uncertain component. Besides, the complexity of the survey would be magnified tenfold, and these are not the control variables in the plant scale problem. Finally, the regression coefficient for plant scale variable is unchanged as long as these excluded variables are not correlated with the plant scale variable [7, p. 229].

Instead, we rely on a statistical analysis, which can measure the likely range for the composite of these random events. Then prospective investors and financiers can judge when an ex ante engineering estimate for a particular size of plant lies within reasonable range, and the range of uncertain events that can still influence actual plant construction costs.

The main concern about statistical estimation is that it may be difficult to compare the costs of plants with different technology constructed at different times. Two main technology changes in dry mills have increased ethanol yields from corn by about 20 percent and reduced the heat energy required in ethanol production by about 35 percent since the 1970s [8]. The yield change results primarily from seed varieties with higher starch content and biochemistry that enables conversion of corn’s fiber [9]. These technologies likely influence operating costs, but not plant capital costs. Similarly, the heat energy reduction was achieved by re-using residual heat from the distillation column to dry byproduct feeds instead of allowing it to escape from the plant. The energy improvement was also likely achieved without a substantial increase in capital expenditure; modern plate heat exchangers are physically smaller, and require less material and space cost than previous technologies. In any event, variations of the regressions in this report also included a ‘year of construction’ variable, which was not significant and did not change the reported results. (Details of these estimations are available upon request).

The power function is convenient for estimation because plant construction costs ($K$) can increase more or less than proportionately with plant capacity ($Q$) depending on parameters:

$$K = A Q^\alpha.$$  \hspace{1cm} (1)

Statistical tests focus on the parameter $\alpha$. If $\alpha = 1$, there are constant returns to scale and capital costs increase proportionately with output. If $\alpha < 1$, there are increasing returns to scale and capital costs increase less than proportionately with output. A log-linear form of Eq. (1) is appropriate for linear regression analysis:

$$\ln(K) = \ln(A) + \alpha \ln(Q).$$  \hspace{1cm} (1a)

Estimates of unit capital costs are also useful in product pricing decisions. Also, unit costs would have a minimum and an upper limit on plant size when the economies of large containers are offset by items with rapidly increasing costs. The implied
unit cost function for the Cobb–Douglas function (1) is obtained by dividing both sides by \( Q \):

\[
K/Q = AQ^{z-1}.
\]  

(2)

Notice that unit costs are declining for \( z < 1 \) and constant for \( z = 1 \). Again, a log-linear form of Eq. (2) is appropriate for linear regression analysis:

\[
\ln(K/Q) = \ln(A) + (z - 1)\ln(Q).
\]  

(2a)

A quadratic function for unit costs was also estimated because there is a straightforward test for decreasing or increasing unit costs. Also, a minimum can exist. The unit cost function estimate is

\[
K/Q = x - \beta Q + \gamma Q^2.
\]  

(3)

The hypothesis of a range of increasing costs can be tested using a simple \( t \)-test for the hypothesis that \( \gamma = 0 \). When \( \gamma > 0 \), there is also a range of increasing costs. Further, the quadratic unit cost function can have a minimum when

\[
Q_m = \beta/2x
\]

The minimum unit cost plant size estimate has a sampling distribution. Further, the variance and standard deviation indicate the precision of the estimate. For a variance estimate, use the Taylor series approximation formulae [7, p. 65; 10, p. 444]:

\[
\text{Var}(Q_m) = \frac{\text{Var}(\hat{\beta})}{4\gamma^2} + \frac{\beta^2 \text{Var}(\hat{\gamma})}{4\gamma^2} - \frac{\beta \text{Cov}(\hat{z}, \hat{\beta})}{2\gamma^3}.
\]

4. Results

For estimation, the capital variable (\( K \)) is measured in millions of dollars and the output capacity is measured in millions of gallons. Also, the ethanol plants in this sample were constructed at different times over the last 25 years. Plant construction cost data was deflated by a cost index for process equipment plants [11]. Division by the cost index converts the capital variable to millions of real dollars in year 1988.

Three types of functions are presented below. First, the conventional expenditure-volume relation tests whether capital costs increase more or less than proportionately with output. Second, the analogous unit-capital cost estimate was calculated for confirmation. Third, the quadratic form of the unit cost function is used to explore the possible existence of a minimum in unit capital costs.

The output-capital expenditure relation was estimated using Eq. (1a). The estimate shown below was estimated using least squares:

\[
\ln(K) = 0.848876 + 0.835569 \ln(Q)
\]  

(4.53)  

(12.19)

\[
\bar{R}^2 = 0.8973 \quad \bar{x} = 0.176,
\]

Where the numbers in parentheses are \( t \)-statistics for the corresponding parameter. The goodness of fit statistic refers to residuals expressed in log form. The corresponding statistic calculated after taking anti-logs is \( \bar{R}^2 = 0.957943 \).

The hypothesis that the coefficient on the output variable is 1.0 is a test of the hypothesis of constant returns to scale. The \( t \) value for this test is \( t = 2.40 \). The critical value of the test statistic at 2.5% significance level is \( t_c = 2.11 \). Hence, the constant returns to scale hypothesis is rejected. Further, the result suggests that economies of scale are present because a 1 percent increase in plant size only increases capital cost by 0.835 percent. However, scale economies are not as extensive as in the typical processing industry; the 0.6 factor rule suggests that a 1 percent capacity increase only increases capital costs by 0.6 percent.

An output-unit capital cost estimate used Eq. (2a). The estimate shown below was estimated using least squares:

\[
\ln(K/Q) = 0.848876 - 0.164431 \ln(Q)
\]  

(4.53)  

(2.40)

\[
\bar{R}^2 = 0.2529 \quad \bar{x} = 0.17643,
\]

(2a')

Again, the goodness of fit statistic refers to the residuals expressed in log form. The corresponding statistic calculated after taking anti-logs of the above function is \( \bar{R}^2 = 0.154569 \). The hypothesis that the coefficient on the output variable is zero is a test of the hypothesis of constant capital output ratio. The \( t \) value for this
The critical value at 2.5% significance level is \( t_c = 2.11 \). Hence, the constant returns to scale hypothesis is rejected. Essentially, Eqs. (2a') and (1a') carry the same implication for scale economies. Using the estimate from Eq. (2a') for the scale parameter gives \( z = -0.164331 + 1 = +0.835669 \), which is identical to the estimate from Eq. (2a').

Another output-unit capital cost estimate used Eq. (3). The estimate shown below was also estimated using least squares:

\[
K/Q = 1.971677 - 0.034146Q + 0.000264Q^2 \\
(9.04) \quad (1.96) \quad (1.66)
\]

\[ \bar{R}^2 = 0.1724 \quad \bar{z} = 0.2885. \] (3a')

Now the goodness of fit statistic and the standard error refer to the actual residuals. The hypothesis that the coefficient on the quadratic term is zero tests the hypothesis of an increasing phase in unit capital costs. The critical value is \( t_c = 1.33 \) at a 10% significance level and \( t_c = 1.73 \) at a 5% significance level. Overall, this estimate supports the notion of a decreasing and then an increasing phase of unit capital costs.

Notice that the \( \bar{R}^2 \) statistic for Eq. (3') is higher than the corresponding statistic for Eq. (2a') when expressed in actual data instead of logarithms. Since the \( \bar{R}^2 \) statistic adjusts for degrees of freedom, we conclude that Eq. (3a') provides a better explanation of sample variation. Hence, Eq. (3a') is used in subsequent analysis.

5. Discussion of minimum unit cost estimate

The quadratic estimate of minimum unit costs suggests a range of decreasing costs followed by increasing costs (Fig. 1). The minimum unit cost estimate, \( Q_m = 64.67 \) MGY, lies within the range of the sample. The corresponding minimum cost is \$0.87/gal in 1988 dollars. In current 2004 dollars, the minimum unit cost is \$1.08/gal.

Also, the standard deviation of \( Q_m \) is 9.05 MGY, which suggests that the minimum unit (capital) cost is between 55.62 and 73.72 MGY.
with 65% confidence. The high and low bounds indicate the confidence interval for the minimum estimate. $Q_m$ does provide a rough guideline to the appropriate scale of operation. A typical dry mill can reduce unit capital costs by about $0.15/gallon by moving from the typical 40 to about 65 MGY. But other limiting factors, such as increasing corn costs, may also reduce the most profitable plant size.

The actual sample observations are shown with an ‘x’ in Fig. 1. These observations are concentrated in the capacity range of 5–30 MGY, but one plant with 100 MGY is included.

Anticipated capital expenditures for seven conventional dry mills that will be completed in 2006 or 2007 are also available [12]. Anticipated real capital expenditures for these plants are shown by a ‘□’ in Fig. 1. Data from these planned dry mills was not used for estimation. But it is useful for validation because these seven plants will have capacities in the range of 35 to 100 MGY. These data tend to confirm the quadratic function because the points near the 35 or 100 MGY extremes tend to have higher anticipated costs than the mid-range observations—notice that there are three 40 MGY plants with nearly identical values for anticipated costs. All the anticipated expenditure points also lie well within the range of deviation defined by estimated variability of the residuals. However, these are ex ante engineering estimates that do not yet include outcomes for the range of uncertain events associated with the construction process.

The extent of the sampling distribution for the estimate of $K/Q$ is also shown in Fig. 1. The upper and lower dotted lines indicate one standard deviation above and below the regression (mean) line, respectively. For instance, the average (regression line) unit cost is about $1.4/annual gal at a capacity of 15 MGY. About 2/3 of the time the typical firm’s unit capital cost for a 15 MGY plant will be between $1.75/gal and $1.25/gal, given usual normality assumptions about regression disturbances. The variance of the confidence interval widens with increasing capacity because more observations lie in the range of 10–35 MGY.

In fact, preliminary tests using regression residuals [7, p. 398] suggest that the disturbance may be non-normal. The Wald statistic for this particular sample is $W = 6.23$, which suggests non-normality at the 5% significance level. Also, the components of the W-statistic point to a positively skewed disturbance. Even with skewed disturbances however, the regression line still estimates parameters of the conditional mean without bias [13, p. 797]. But the ‘2 cases out of 3’ probability band should be shifted upward relative to the mean. Based on other regression studies with similarly skewed disturbances, 25% of the band width should be below the regression line and 75% of the band lies above the regression line [14, p. 118].

We are reluctant to abandon the normality assumption based on this test with its small sample, because one relatively large positive disturbance dominated the computed value of the test statistic—it takes a large sample to reliably measure the thickness of the tails of a probability distribution. Further investigation of non-normal disturbances with larger samples is warranted. Until then, it is important that non-normality, if it does exist, does not change the thrust of this investigation. It mainly changes the positioning of the probability band.

Regardless of the exact shape of the probability distribution for disturbances, the range of unit costs for a given size of plant shows that other factors also influence unit costs. These unmeasured factors could be variation in utility costs due to uncertain well depth, union strikes, uneven enforcement of environmental regulations, timing of construction in a recession or expansion, unforeseen local taxes or bargaining ability of buyers.

6. Conclusions

The estimates of this paper found some evidence of economies of scale arising from increasing plant size. Specifically, capital costs increased less than proportionately with plant capacity. However, the estimated power factor for dry mill ethanol plants (0.836), suggests that capital costs increase more rapidly than the average for all processing plants; the 0.6 power factor rule suggests more benefits for large plants.
Also, some estimates of unit capital costs suggest a phase of decreasing unit costs followed by a phase of increasing costs. The estimate of minimum unit capital costs suggests that dry mills could be somewhat larger than the current industry standard, unless other scarce factors limit capacity expansion. A comprehensive analysis of economic factors influencing scale decisions should build on the estimates of this report, but also include the increasing raw material costs associated with expanding processing and larger input market areas in space.

Finally, the $t$-values of all three regressions suggest that plant size is a statistically significant determinant of total capital costs and average capital costs. Further, the $R^2$ statistic from the total cost-size regression means that plant size explains most of the sample variation in total capital costs and plant size would likely predict total capital expenditure well. In contrast, the low $R^2$ statistics in the regressions with average capital costs as the dependent variable attest to the inherent variability of average capital costs, even with given plant size. Hence, competitiveness analysis for a specific location should consider plant size, but should also include careful cost analysis of unique circumstances, such as water availability, utility access, and the cost of environmental compliance, that could make a small plant profitable or a large one unprofitable.

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