Returns to Scale in Small and Large U.S. Manufacturing Establishments: Further Evidence

Sang V. Nguyen
Seong-Hoon Lee

ABSTRACT. Nguyen and Reznek (1991) used plant-level data for five 4-digit SIC industries to estimate and compare the degrees of returns-to-scale for establishments of various size classes for the years 1977 and 1982. They found that the estimated scale elasticities of all plant sizes have values approximately equal to one. They, therefore, concluded that both small and large establishments under study are equally efficient in production. The purpose of the present study is to extend and improve upon Nguyen and Reznek's work by (1) extending the data set to cover the entire U.S. manufacturing sector, (2) improving the model by including energy as a separate input in production, and (3) relaxing the assumption of homogeneity and estimating an unrestricted (non-homogeneous, non-homothetic) production model. With the improved model and data, it is found that the estimated scale elasticities for all sizes of establishment are statistically insignificantly different from one. Thus, the result confirms and strengthens Nguyen and Reznek's finding that a large establishment size is not a necessary condition for efficient production.

1. Introduction

During the last two decades, there has been a growing body of empirical research focusing on the performance of small and large establishments and firms,[1] but the empirical evidence is mixed. One set of studies found that economic performance of small firms is lower than that of large firms, regardless of whether performance is measured by productivity, efficiency (Caves and Barton, 1990), or profitability (Bradburd and Ross, 1989). Pakes and Erikson (1998), Dunne et al. (1988, 1989) and Bates and Nucci (1990) also found that the rates of entry and exit are inversely related to size for U.S. manufacturing plants and firms. Dunne (1994) found that small establishments use less advanced technology than large ones. These studies suggest that small establishments and firms in U.S. manufacturiing perform at a lower level than large establishments and firms.

In contrast, other studies provided evidence that small businesses play a significant role in the U.S. economy (e.g., see Brock and Evans, 1986) and that small businesses are not necessarily inefficient. Advocates of small businesses often contend that small firms could be more efficient than large firms because, among other things, "small firms are less likely to encounter problems that can arise from complicated multi-echelon management structures which are more common in Iarge firms."[2] Hansen (1992) found that small firms are just as innovative in terms of new products as larger firms, and perhaps more so. Acs et al. (1991) found that the increased presence of small firms is associated with the application of certain advanced technology such as numerically controlled machines. Aiginger and Tichy (1991) propose that small firms could be more efficient than large firms because they are managed by owners whose goal is profit maximization, while large firms are managed by managers who are interested in maximizing their own utility. This proposition, if true, has a very important policy implication. That is, if small businesses are as efficient as large businesses, then policies to promote and support small businesses could be carried out without sacrificing economies of scale.

To test the above hypothesis, Nguyen and Reznek (1991) used plant-level data for five 4-digit manufacturing industries,[3] taken from the

Final version accepted on August 2, 2001

Center for Economic Studies
U.S. Bureau of the Census
Washington, DC 20233
U.S.A.
E-mail: snguyen@ces.census.gov; lee00318@ces.census.gov

Small Business Economics **19**: 41–50, 2002.

U.S Bureau of the Census' Longitudinal Research Database (LRD), to estimate the degrees of returns to scale for establishments of various size classes. They then compared the estimated scale elasticities of small and large establishments and made inferences regarding economic efficiency. Their results based on a three-factor (capital (K), labor (L), and material (M)) translog model indicate that the degrees of returns to scale for all plant size classes are very similar, having values approximately equal to one. These estimates imply that both small and large establishments under study efficiently operate on constant average cost curves. They, therefore, concluded that "small establishments appear to be as efficient as large establishments" (Nguyen and Reznek, 1991, p. 198).

While Nguyen and Reznek's work makes a significant contribution to the empirical literature of small businesses, their study is based on only five 4-digit industries which may not represent the entire U.S. manufacturing sector. Moreover, their estimates of returns to scale were derived from a restricted (homogeneous) production function which may not reflect the true production technology of U.S. manufacturing. Finally, their three-factor model treats energy and materials as homogeneous inputs and lump them together as a single input.

This study attempts to extend and improve upon Nguyen and Reznek's work in several dimensions: First, this research uses a micro data set that represents the entire U.S. manufacturing sector and includes data for a more recent year, 1991. Second, it improves Nguyen and Reznek's three-factor (KLM) production function by including energy (E) as a separate input.[4] Third, in addition to estimating homogeneous production functions as in Nguyen and Reznek, this research estimates an unrestricted (non-homothetic, non-homogeneous) production function that allows estimates of the scale elasticity to take any value. Thus, the results from this study allows one to draw conclusions with more confidence regarding returns to scale in small and large establishments in the U.S. manufacturing sector.

The principal finding of this study is that the estimated scale elasticities for representative U.S manufacturing plants of all sizes are statistically insignificantly different from one. This result confirms and strengthens Nguyen and Reznek's (1991) finding that large establishment size is not a necessary condition for efficient production and that, as with large establishments, small U.S. manufacturing establishments do efficiently operate on a horizontal, industrial long-run average cost curve.

The remainder of the paper is organized as follows: Section 2 presents the model specification. Section 3 briefly discusses the data and estimation procedures. Section 4 discusses the empirical results, including hypothesis tests, the estimated production functions, and scale economies. Section 5 summarizes and concludes the paper.

2. Measuring returns-to-scale

2.1. *A production model*

In keeping with Nguyen and Reznek (1991), we use the translog functional form to specify the production function.[5] However, instead of using a three-factor (KLM) model, we specify a four-factor (KLEM) model that includes capital (K), labor (L), energy (E) and materials (M) as separate inputs in producing output (Q):

$$\ln Q = \alpha_0 + \sum_{i=1}^{4} \alpha_i \ln X_i + \frac{1}{2} \sum_{i=1}^{4} \sum_{j=1}^{4} \beta_{ij} \ln X_i \ln X_j + \sum_{k=2}^{20} \alpha_k \, IND + \sum_{r=2}^{9} \alpha_r \, REG, \tag{1}$$

where i, j = K, L, E, M and *In* is natural logarithm. The variables *IND* and *REG* are dummy variables representing industiries and regions, respectively. Industry dummies are included in the model to account for industry specific effects. Geography regions are included to accommodate region specific effects. There are 20 two-digit SIC industry groups and 9 census regions.[6]

The translog function (1), an approximation of the true production function, can be estimated directly without imposing any restriction such as homotheticity or linear homogeneity (i.e., constant retums-to-scale). However, when certain parameters are constrained to zero, this function is reduced to restricted forms such as linear homogeneous functions or traditional forms such as Cobb-Douglas and constant elasticity of substitution (CES) functions. In this paper, we use both the unrestricted and restricted translog functions to estimate the degrees of returns to scale and test for the validity of homogeneous production functions that have been widely used in previous empirical studies.

2.2. *Retums-to-scale*

The degree of returns-to-scale (also known as elasticity of scale) is simply the sum of output elasticities with respect to individual factor inputs (see, Chambers, 1988, p. 24). Thus, given the unrestiricted translog production function (1), the (unrestricted) elasticity of scale can be written as:

$$\varsigma = \sum (\partial \ln Q/\partial \ln X_i) = \sum \alpha_i + \sum \sum \beta_{ij} \ln X_{ij}. \quad (2)$$

If the production function is homogeneous of degree λ, then

$$\varsigma = \lambda = \sum \alpha_i \text{ and } \sum \beta_{ij} = 0. \quad (3)$$

The production function is characterized by constant returns to scale if $\varsigma = 1$, decreasing returns to scale if $\varsigma < 1$, and increasing returns to scale if $\varsigma > 1$. Constant returns to scale imply that establishments are operating on a horizontal (constant) average cost curve, while increasing (decreasing) returns to scale imply that establishments are operating on a declining (increasing) cost curve. A production unit is "efficient" when it operate on a constant long-run average cost curve (i.e., constant returns-to-scale). Thus, one can use estimates of returns to scale to compare production efficiencies between small and large establishments.

3. Data and estimation procedures

3.1. *Data*

This empirical work is based on a recently available micro database, integrating the 1991 Manufacturing Energy Consumption Survey (MECS) with the 1991 Annual Survey of Manufactures (ASM).[7] Both surveys are conducted by the U.S. Bureau of the Census. The 1991 MECS is a unique plant-level data set which provides an excellent opportunity for estimating a production function in which energy is treated as a separate input. This cross-section data set, containing a large number of observations, also helps to avoid the problems and biases associated with small samples used in most previous studies.

The 1991 MECS surveyed over 14,000 manufacturing plants with 20 or more employees. It collects information on quantities and expenditures of energy consumed in production for 37 energy sources. The data on energy are exactly what we need for estimating production function that includes energy as a factor of production. Quantity of fuel is reported in various measures, such as Btu, tons, cubic feet, gallons, or barrels, depending on the fuel type. In order to sum over all types of fuels, we convert the various physical units to Btu content.

While the MECS provides excellent data for energy analysis, it does not collect information on outputs and non-energy inputs, which are required for estimating a production function. Measures of output, capital, labor, materials, and size are obtained from the 1991 ASM. The nature of the data collected in the ASM places some constraints on the measurement of production inputs and output. Output is measured by the value of inventory-adjusted shipments. Capital inputs are represented by book value of equipment and structures,[8] labor is defined as total production worker equivalent man-hours, and materials are measured by the value of materials and parts used in production. Plant sizes are measured by numbers of employees.[9]

Cost shares of inputs are calculated by dividing expenses for each input by total expenses. Assuming zero excess profits, expenditures are set equal to the value of output. Expenses for labor include total salaries, wages, and other labor expenses. Energy expenditures are the sum of expenditures across all types of energy consumed in production. Material expenditures are the cost of materials, parts, and contract work. Finally, capital expenses, and therefore the capital cost share, is the residual remaining after netting out the expenses for labor, energy, and materials from total expenditures. After matching the two data sets and omitting plants with missing or imputed data values, we have 10,318 plant observations in the final data set.[10]

3.2. *Estimation procedures*

The primary objective of this study is to assess the differences, if any, in the elasticities of scale between "small" and "large" U.S. manufacturing establishments. Before proceeding, it is important to emphasize that the terms "small" and "large" are relative, and it is impossible to offer a universally accepted definitions for small and large establishments. Thus, instead of drawing a definite line between "small" and "large", following the MECS, we classify establishments into six employment size classes:

Size class 1: establishments with 20 to 49 employees.
Size class 2: establishments with 50 to 99 employees.
Size class 3: establishments with 100 to 249 employees.
Size class 4: establishments with 250 to 499 employees.
Size class 5: establishments with 500 to 999 employees.
Size class 6: establishments with 1,000 or more employees.

Note that data on establishments with less than 20 employees are not available in the MECS database. Separate translog production functions, one for each of the six size classes, were estimated. The entire data set is also used to estimate the overall production to obtain the elasticity of scale for the U.S. manufacturing sector. Our estimation procedures are as follows.

First, we estimate the unrestricted (non-homothetic, non-homogeneous) production function (1) and evaluate the degree of retums-to-scale using (2). Then, for testing purposes, as with Nguyen and Reznek (1991), we estimate the restricted production function by imposing the restrictions of symmetry and homogeneous of degree λ.[11] Thus, the following restrictions are imposed in the estimation:

$$\sum_{i=1}^{4} \alpha_i = \lambda, \ \sum_{i=1}^{4} \beta_{ij} = 0, \ \sum_{j=1}^{4} \beta_{ij} = 0, \text{ and}$$
$$\sum_{i=1}^{4} \sum_{j=1}^{4} \beta_{ij} = 0, \quad (4)$$

Monotonicity and convexity are not imposed, but are tested for after estimation. we append a random disturbance term u_i to the production function and to each share equation, i = K, L, E, M, and assume the resulting disturbance vector $u = \{u_K, u_L, u_E, u_M\}$ is multivariate normally distributed with mean vector zero and constant covariance matrix.

With the restricted model, following the standard procedure we append the system of share equations to the production function and estimate the full system subject to the parameter restrictions.[12]

Assuming cost minimization and using the generalized Euler's theorem, we derive the following cost share equation system:[13]

$$S_i = \frac{1}{\lambda}\left(\alpha_i + \sum_{j=1}^{4} \beta_{ij} \ln x_j\right). \quad (5)$$

Since the cost shares sum to one, the disturbance covariance matrix of the share equation system (5) is singular. Therefore, the material cost share equation is dropped from the estimation. We use the iterative Zellner (1963) three stage least squares method to jointly estimate the production equation (1) and the remaining three equations (5).

4. Empirical results

4.1. *The estimated production functions*

Table I reports the parameter estimates of the homogeneous of degree λ production functions, while Table II shows the estimates of the non-homogeneous, non-homothetic production functions. Although these estimates have little intuitive value because of the complexity of the translog form, they illustrate their statistical significance. In both tables, columns (1)–(6) present the estimates for the six regressions by size classes, while column (7) shows the estimates based on the entire data set. All regressions were estimated with 2-digit industry and census region dummy variables to control for differences in industry and region.

TABLE I
Regression parameter estimates by employment size class (Standard errors in parentheses)

Parameters	Weighted sample – homogeneous of degree λ production functions						
	20–50	50–99	100–249	250–499	500–999	≥1000	All
α_0	0.358 (0.050)	0.582 (0.072)	0.611 (0.051)	0.736 (0.056)	1.022 (0.086)	0.410 (0.077)	0.418 (0.015)
α_K	0.193 (0.009)	0.219 (0.008)	0.179 (0.006)	0.149 (0.006)	0.198 (0.008)	0.124 (0.008)	0.198 (0.003)
α_L	–0.096 (0.010)	–0.146 (0.008)	–0.076 (0.006)	–0.067 (0.006)	–0.074 (0.007)	–0.012 (0.009)	–0.102 (0.004)
α_E	0.022 (0.002)	0.024 (0.002)	0.026 (0.002)	0.016 (0.002)	0.014 (0.002)	0.019 (0.002)	0.022 (0.001)
α_M	0.894 (0.006)	0.900 (0.007)	0.850 (0.005)	0.867 (0.005)	0.867 (0.005)	0.857 (0.008)	0.884 (0.002)
β_{KK}	0.043 (0.002)	0.052 (0.002)	0.050 (0.002)	0.049 (0.002)	0.057 (0.002)	0.035 (0.002)	0.048 (0.001)
β_{LL}	0.108 (0.002)	0.117 (0.002)	0.095 (0.001)	0.093 (0.001)	0.094 (0.002)	0.089 (0.002)	0.108 (0.001)
β_{EE}	0.013 (0.0003)	0.014 (0.0004)	0.015 (0.0003)	0.014 (0.0003)	0.015 (0.0004)	0.015 (0.001)	0.014 (0.0001)
β_{MM}	0.167 (0.001)	0.175 (0.002)	0.175 (0.001)	0.187 (0.001)	0.187 (0.001)	0.182 (0.002)	0.172 (0.001)
β_{KL}	0.007 (0.002)	–0.0001 (0.001)	0.014 (0.001)	0.021 (0.001)	0.012 (0.002)	0.028 (0.002)	0.007 (0.001)
β_{KE}	–0.002 (0.0004)	–0.0003 (0.0004)	–0.0004 (0.0004)	–0.003 (0.0004)	–0.002 (0.0005)	–0.001 (0.001)	–0.002 (0.0002)
β_{KM}	–0.048 (0.001)	–0.052 (0.001)	–0.063 (0.001)	–0.068 (0.001)	–0.068 (0.001)	–0.062 (0.002)	–0.053 (0.0005)
β_{LE}	–0.004 (0.0004)	–0.004 (0.0004)	–0.005 (0.0004)	–0.003 (0.0003)	–0.003 (0.0005)	–0.005 (0.001)	–0.004 (0.0002)
β_{LM}	–0.112 (0.001)	–0.113 (0.001)	–0.103 (0.001)	–0.112 (0.001)	–0.111 (0.001)	–0.112 (0.002)	–0.110 (0.0005)
β_{EM}	–0.007 (0.0003)	–0.010 (0.0004)	–0.009 (0.0004)	–0.007 (0.0003)	–0.007 (0.0003)	–0.009 (0.001)	–0.008 (0.0002)
λ	1.009 (0.005)	0.997 (0.007)	0.979 (0.005)	0.965 (0.005)	0.949 (0.007)	0.988 (0.006)	1.003 (0.023)
Convexity violations	126 (7.6%)	116 (7.9%)	45 (1.7%)	12 (0.6%)	10 (0.7%)	2 (0.2%)	302 (2.9%)
Monotonicity violations	218 (13.2%)	213 (14.5%)	238 (8.8%)	117 (5.6%)	86 (6.1%)	89 (9.1%)	760 (7.4%)
N	1,652	1,473	2,706	2,099	1,410	978	10,318

All regressions include 2-digit industry and region dummy variables.

TABLE II
Regression parameter estimates by employment size class (Standard errors in parentheses)

Parameters	Weighted sample – non-homogeneous, non-homothetic production functions						
	20–50	50–99	100–249	250–499	500–999	≥1000	All
α_0	–0.046 (0.012)	0.231 (0.321)	0.135 (0.254)	–0.304 (0.320)	0.743 (0.534)	2.236 (0.402)	0.027 (0.035)
α_K	0.124 (0.018)	0.099 (0.024)	0.024 (0.020)	0.058 (0.023)	0.350 (0.037)	0.107 (0.042)	0.142 (0.006)
α_L	0.032 (0.024)	0.072 (0.052)	0.115 (0.039)	0.074 (0.045)	0.036 (0.067)	–0.181 (0.049)	–0.013 (0.007)
α_E	0.036 (0.005)	0.016 (0.011)	0.044 (0.009)	–0.003 (0.010)	–0.051 (0.015)	0.015 (0.012)	0.034 (0.002)
α_M	0.889 (0.006)	0.739 (0.029)	0.743 (0.021)	0.937 (0.026)	0.598 (0.051)	0.758 (0.046)	0.886 (0.006)
β_{KK}	0.044 (0.002)	0.050 (0.002)	0.050 (0.001)	0.053 (0.002)	0.062 (0.002)	0.036 (0.002)	0.048 (0.001)
β_{LL}	0.096 (0.003)	0.118 (0.002)	0.080 (0.003)	0.086 (0.003)	0.087 (0.005)	0.101 (0.004)	0.099 (0.001)
β_{EE}	0.013 (0.0003)	0.014 (0.0004)	0.015 (0.0003)	0.014 (0.0003)	0.015 (0.0004)	0.016 (0.0005)	0.014 (0.0001)
β_{MM}	0.168 (0.001)	0.192 (0.003)	0.184 (0.001)	0.182 (0.003)	0.210 (0.005)	0.189 (0.004)	0.171 (0.001)
β_{KL}	0.008 (0.002)	0.0005 (0.002)	0.018 (0.001)	0.021 (0.001)	0.006 (0.002)	0.027 (0.002)	0.009 (0.001)
β_{KE}	–0.002 (0.0004)	–0.0002 (0.0005)	–0.0002 (0.0004)	–0.003 (0.0004)	–0.002 (0.0005)	–0.001 (0.0009)	–0.002 (0.0002)
β_{KM}	–0.048 (0.001)	–0.043 (0.002)	–0.062 (0.001)	–0.060 (0.002)	–0.078 (0.003)	–0.059 (0.003)	–0.049 (0.0006)
β_{LE}	–0.005 (0.0006)	–0.004 (0.001)	–0.006 (0.0007)	–0.002 (0.0007)	0.0004 (0.001)	–0.005 (0.001)	–0.005 (0.0002)
β_{LM}	–0.112 (0.001)	–0.114 (0.002)	–0.105 (0.001)	–0.116 (0.001)	–0.102 (0.002)	–0.111 (0.002)	–0.111 (0.0006)
β_{EM}	–0.008 (0.0004)	–0.010 (0.0004)	–0.010 (0.0004)	–0.008 (0.0003)	–0.009 (0.0006)	–0.009 (0.001)	–0.009 (0.0002)
Convexity violations	300 (18.1%)	422 (28.6%)	378 (13.9%)	300 (14.3%)	257 (18.2%)	265 (27.1%)	515 (5.0%)
Monotonicity violations	228 (13.8%)	189 (12.8%)	210 (7.7%)	112 (5.3%)	83 (5.9%)	90 (9.2%)	868 (8.4%)
N	1,652	1,473	2,706	2,099	1,410	978	10,318

All regressions include (2-digit) industry and region dummy variables.

From the two tables, it can be seen that nearly all the parameter estimates are highly statistically significant. This suggests that these estimates are quite precise and the estimated elasticities of scale based on them are robust and reliable.

Before proceeding, it is important to report on whether or not the underlying production functions are "well-behaved". It is important because the estimated scale elasticities under consideration are derived from them. As shown at the bottom of Tables I and II, the estimated production functions based on the entire data set meet these regularity conditions fairly well. The homogeneous of degree λ production function meets the convexity conditions for 97 percent of data points, while the non-homogeneous, non-homothetic production function meets these conditions for 95 percent of data points. Similarly, monotonicity conditions are met for 92.6 percent and 91.6 percent of data points when the homogeneous and non-homogeneous, non-homothetic production functions are estimated, respectively. Note that these results are in line with previous work that estimated translog functions with plant-level data. For example, Kokkelenberg and Nguyen (1989) used plant-level data for the flat glass industry to estimate a translog cost function. They found that their cost function passed the convexity test at approximately 90 percent of the data points.

As for the regressions by plant size, the proportions of violations of both the convexity and monotonicity are also generally low. It should be pointed out that there are no statistical violations of these conditions when evaluated at the variable means. Finally, comparing the two production functions, there is evidence that the (restricted) homogeneous production function is more "well-behaved" than the (unrestricted) non-homogeneous, non-homothetic production function. This is expected because the unrestricted model contains 4 extra parameters to be estimated.

4.2. *Hypothesis test results*

To test for the validity of the homogeneous degree of λ production function, we use the Gallant-Jorgenson analog of the likelihood ratio test (1979). This test statistic is defined as[14]

$$T^0 = N^*S(\hat{\alpha}, \hat{u})_R - N^*S(\hat{\alpha}, \hat{u})_U, \quad (6)$$

where $S(\hat{\alpha}, \hat{u})_R$ denotes the minimum value of the objective function of the restricted model (i.e., model I: homogeneous of degree λ). $S(\hat{\alpha}, \hat{u})_U$ is the minimum value of the objective function of the unrestricted model (i.e., model II: non-homogeneous, non-homothetic). N is the number of observations.

T^0 is χ^2-distributed with the degree of freedom equal to the number of restrictions (i.e., the number of parameters left out of the restricted model). When the data are in accord with the null hypothesis (H_0), T^0 will be smaller than the critical chi-square $\chi^2_{(df,\,1-\alpha)}$. When $T^0 > \chi^2_{(df,\,1-\alpha)}$, H_0 will be rejected.

From Table III, it can be seen that the results are mixed: when the entire data set and data on smaller establishments are used in the estimation the homogeneous of degree λ production functions are rejected; however, it is not rejected when data on larger plants (250–999 employees) are used. These results do not uniformly reject homogeneous production functions as a valid presentation of the U.S. manufacturing production technology, at least in the long run. We note, however, that all the estimated first-order coeffficients for the labor variable, α_L, reported in Table I have the unexpected negative sign and are statistically significant. In contrast, the results obained from the unrestricted model reported in Table II show that, except for plants with 1,000 employees or more, all the estimates for α_L are positive as expected. While the negative sign of α_L does not necessarily implies that the homogeneous production model is misspecified, it appears that the non-homogeneous, non-homothetic production model yields a better set of estimates.

4.3. *Economies of scale*

Table IV reports the returns-to-scale estimates obtained from estimating separate production functions by size class. The numbers in parentheses below each estimate are $t_{0.01}$ times standard error, which are used to construct the confidence interval for the true parameter (i.e., $\lambda = \tilde{\lambda} \pm t0.01 \times$ standard error).

Consider first the estimates obtained from the homogeneous of degree λ production function model. From column (1), Table IV, it can be seen that the estimates for λ for the two smallest sizes

TABLE III
Hypothesis test results, values of T^0-statistics

Size	Model I versus Model II H_0: Homogenous of degree λ $r = 4$ $\chi^2_{(4,0.99)} = 13.28$	Not Reject(NR)/ Reject (R) H_0
20–50 employees	43	R
50–99	86	R
100–249	35	R
250–449	–21	NR
500–999	–2	NR
1000 or more	16	R
All Plants	288	R

Note: r denotes the number of restrictions.

TABLE IV
Scale parameter estimates

Size	Homogeneous of degree λ Model (1)	Non-homogeneous, non-homothetic model (2)
20–50 employees	1.009^c (± 0.012)	1.052^c (± 0.067)
50–99	0.997^c (± 0.016)	1.054^c (± 0. 112)
100–249	0.979^d (± 0.012)	1.054^c (± 0.077)
250–499	0.965^d (± 0.016)	1.019^c (± 0.028)
500–999	0.949^d (± 0.014)	0.984^c (± 0.044)
1000 or more	0.988^c (± 0.014)	1.017^c (± 0.044)
All Plants	1.003^c (± 0.053)	0.995^c (± 0.044)

Note: The number in parentheses are ± $t_{0.01}$ standard errors, which are used to construct confidence intervals for the true parameters.
[c] Denotes “insignificantly different from 1” at the 1 percent level (constant returns to scale).
[d] Denotes “significantly less than 1” at the 1 percent level (decreasing returns to scale).

(with employment less than 100 employees), the largest size (1,000 or more employees) and the whole sample are not statistically significantly different from 1, indicating that these establishments exhibit constant returns to scale. However, establishments with employment ranging from 100 to 999 employees, exhibit decreasing returns to scale (i.e., λ is statistically significantly less than 1).[15] In any event, these estimates suggest that smallest plants are as efficient as largest plants in terms of returns to scale.

Column (2), Table IV, shows that all the scale estimates for all class sizes obtained from the unretricted production functions are statistically significantly different from zero and insignificantly different from one, suggesting that representative U.S manufacturing plants of all sizes are equally efficient in their production. This result confirms and strengthens Nguyen and Reznek’s finding (1991), and strongly support the proposition that small establishments are as efficient as large establishments in producing goods.

5. Summary and conclusions

This study extends and improves upon previous work in three dimensions. First, it uses more recent data (1991) that cover the entire U.S. manufacturing sector, while previous work examined only five 4-digit SIC industries for the years 1977 and 1982. Second, it improves upon Nguyen and Reznek’s three-factor (KLM) model by specifying a four-factor (KLEM) model, incorporating energy as a separate input in production function. Finally, it relaxes the assumption of homogeneity and estimates non-homogeneous, non-homothetic production functions that provide estimates of an unrestricted measure of economies of scale.

In spite of these extensions, it is found that the estimated scale elasticities for all establishment sizes are insignificantly different from one. This result indicates that previous empirical work using homogeneous production function to study U.S. manufacturing appears to be reasonable. More importantly, it confirms and strengthens the previous finding that a large size is not a necessary condition for efficient production. Thus, policies to promote and support small businesses could be carried out without sacrificing economies of scale.

Acknowledgements

Any opinions, suggestions and conclusions herein are those of the authors, and do not necessarily reflect those of the U.S. Bureau of the Census. We thank an anonymous referee for thoughtful comments and Rebecca Turner for her skillful typing.

Notes

[1] For reviews of the literature on small and large firms, see Storey (1994) and Acs (1996).

[2] See *The 1987 Report of the U.S. President Transmitted to the Congress*, p. 107.

[3] The five four-digit industry groups: (1) SIC 2335: Women's, misses' and juniors' dresses; (2) SIC 2511: Wood household furniture, except upholstered; (3) SIC 2711: Newspapers; (4) SIC 3573: Electronic computing equipment; (5) SIC 3662: Radio and television transmitting, signaling, and detection equipment.

[4] In Nguyen and Reznek's work (1991), energy was treated as a material input and was included in their material measure.

[5] For a detailed discussion of the translog functional form, see Christensen et al. (1971). Empirical studies using the translog form include those of Berndt and Wood (1975); Burgess (1975); Christensen and Green (1976); Kokkelenberg and Nguyen (1989) among others.

[6] The 9 Census regions are (1) New England, (2) Middle Atlantic, (3) East North Central, (4) West North Central, (5) South Atlantic, (6) East South Central, (7) West South Central, (8) Mountain, and (9) Pacific. New England is used as the base case (i.e., it is omitted from the regression). As for industry dummies, in our preliminary work we estimated two sets of regressions, one set with 2-digit industry dummies and the other with 4-digit industry dummies. We found that because the number of 4-digit industries is large (about 450), some set of (iterative Zellner method) regressions did not achieve convergence. In contrast, all regressions with 2-digit industry dummies achieve convergence. We compared the regressions that "converge" with both 2-digit and 4-digit dummies and found the results are very similar. Thus, we decided to report the regression results with 2-digit industry dummies.

[7] As with all micro data collected by the U.S. Bureau of the Census, these data are confidential and cannot be released for public use. However, academics and interested researchers can obtain access to these data through the Census Bureau research fellowship program or the research program at the Center for Economic Studies (CES). For more information on access to the micro data, contact Mary Streitwieser, Center for Economic Studies, U.S. Bureau of the Census, at (301) 457-1837 or mstreitw@ces.census.gov.

[8] We use book values as a proxy for capital input because other data are not available. We note, however, that Doms' (1996) and Dwyer's (1997) work – which also use the Census Bureau's micro data – indicate that book value is a reasonable proxy for capital inputs.

[9] For a more detailed description of the MECS and ASM datasets, as well as construction of the variables, see Nguyen and Streitwieser (1998).

[10] We also omit plants in the petroleum refining industry (SIC 2911) because a significant, but unknown, portion of their fuel is derived as a by-product of the processes used to convert feedstock to marketed products. While other industries may have derived some of their fuel as a result of the production process, it is not as severe a problem as in the refining industry.

[11] Most previous studies assume homogeneity of degree one by setting $\lambda = 1$.

[12] Estimates obtained from the full system should be more precise than those obtained from a single production function and are more likely to be consistent with convexity and other restrictions.

[13] For derivation of this cost share equation system, see Nguyen and Reznek (1991).

[14] For an example of this test, see Gallant (1987), p. 459.

[15] This result appears to be somewhat puzzling. In particular, it shows that plants with 250–999 employees have decreasing returns to scale, while larger plants have constant returns to scale. We, however, tend to believe that this is a statistical aberation because the results based on the theoretically superior non-homogeneous, non-homothetic model uniformly show that plants of all sizes exhibit constant returns to scale.

References

Acs, Z. D. (ed.), 1996, *Small Firms and Economic Growth*, Cheltenham: Edward Elgar Publishers.

Acs, Z., D. Audretsch and B. Carlson, 1991, 'Flexible Technology and Firm Size', *Small Business Economics* **3**, 307–320.

Aiginger, K. and G. Tichy, 1991, 'Small Firms and Merger Mania', *Small Business Economics* **3**(2), 83–101.

Bates, T. and A. Nucci, 1990, 'An Analysis of Small Business

Size and Rate of Discontinuance', *CES Discussion Paper*, CES 90-2, Center for Economic Studies, U.S. Bureau of the Census, Washington DC.

Berndt, E. R. and D. O. Wood, 1975, 'Technology, Production, and the Derived Demand for Energy', *The Review of Economics and Statistics* **68**, 647–656.

Bradburd, R. M. and D. R. Ross, 1989, 'Can Small Firms Find and Defend Niches? A test of Porter Hypothesis', *The Review of Economics and Statistics* **71**(2), 258–262.

Brock, W. A., and D. S. Evans, 1986, *The Economics of Small Business: Their Role and Regulation in the U.S. Economy*, New York: N.Y. Holmes and Meier Publishers.

Burgess, D. F., 1975, 'Duality Theory and Pitfalls in the Specification of Technologies', *Journal of Econometrics* **3**, 105–121.

Caves, R. and D. Barton, 1990, *Efficiency In U.S. Manufacturinq Industries*, Cambridge: MIT Press.

Chambers, R. G., 1988, *Applied Production Analysis: A Dual Approach*, New York: Cambridge University Press.

Christensen, L. R. and W. H. Greene, 1976, 'Economies of Scale in U.S. Electric Power Generation', *Journal of Political Economy* **84**, 655–676.

Christensen, L. R., D. W. Jorgenson and L. J. Lau, 1971, 'Conjugate Duality and the Transcendental Logarithmic Production Function', *Econometrica* **39**, 255–256.

Doms, M. E., 1996, 'Estimating Capital Efficiency Schedules within Production Functions', *Economic Inquiry* **34**, 78–92.

Dunne, T., 1994, 'Plant Age and Technology Use in U.S. Manufacturing Industries', *RAND Journal of Economics* **25**(3), 488–499.

Dunne, T., M. J. Roberts and L. Samuelson, 1988, 'Patterns of Firm Entry and Exit in U.S. Manufacturing Industries', *RAND Journal of Economics* **19**(4), 495–515.

Dunne, T., M. J. Roberts and L. Samuelson, 1989, 'The Growth and Failure in U.S Manufacturing Plants', *Quarterly Journal of Economics* (November), 671–698.

Dwyer, D. W., 1997, 'Productivity Races II: The Issues of Capital Measurement', *CES Discussion Paper*, CES 97-3, Center for Economic Studies, U.S. Bureau of The Census, Washington DC.

Gallant, A. R., 1987, *Nonlinear Statistical Models*, New York, NY: John Wiley & Sons.

Gallant, A. R. and D. W. Jorgenson, 1979, 'Statistical Inferences for a System of Simultaneous, Non-linear, Implicit Equations in the Context of Instrumental Variable Estimation', *Journal of Econometrics* **11**, 275–302.

Hansen, J. A., 1992, 'Innovation, Firm Size and Firm Age', *Small Business Economics* **4**(l), 37–44.

Kokkelenberg, E. C. and S. V. Nguyen, 1989, 'Modelling Technical Program and Multifactor Productivity: A Plant Level Example', *Journal of Productivity Analysis* **1**, 69–90.

Nguyen, S. V. and M. L. Streitwieser, 1998, 'Factor Substitution in U.S. Manufacturing: Does Plant Size Matter?', *Small Business Economics* **12**, 41–57.

Nguyen, S. V. and A. P. Reznek, 1991, 'Returns to Scale in Small and Large U.S.Manufacturing Establishments', *Small Business Economics* **1**, 29–46. Reprinted in *Small Firms and Economic Growth*, J. Acs; (ed.), The International Library of Critical Writings in Economics Series, No. 61, 1996.

Pakes, A. and Erikson, 1998, 'Empirical Implications of Alternative Models of Firm Dynamics', *Journal of Economic Theory* **79**(1), 1–45.

Storey, D. J., 1994, *Understanding the Small Business Sector*, London/New York: Routledge.

U.S. Government Printing Office, 1987, *The State of Small Business: A Report of the President to the Congress 1987*, Washington D.C.: U.S. GovernmentPrinting Office.

Zellner, A., 1963, 'Estimators of Seemingly Unrelated Regressions: Some Exact Finite Samples Results', *Journal of the American Statistical Association* **58**, 977–992.