TECHNOLOGY, ENERGY INTENSITY, AND PRODUCTIVITY IN THE CEMENT INDUSTRY: A PLANT-LEVEL ANALYSIS

M.J. Niefer, Pacific Northwest Laboratory and
Center for Economic Studies, U.S. Bureau of the Census[a]

ABSTRACT
This paper uses plant-level data from the 1991 Manufacturing Energy Consumption Survey (MECS) for a sample of U.S. cement plants to examine the relationship between energy intensity, productivity and the use of selected industry-specific technologies. Three technologies are considered: high-efficiency classifiers, dry-preheater kilns, and dry-precalciner kilns. Based on estimation of a translog variable cost function, it is found that plants using any one of the technologies are less fossil fuel intensive than other plants. Based on an index number measure of plant-level total factor productivity, it is found that plants using both dry-precalciner kilns and high-efficiency classifiers have higher levels of productivity than other plants.

INTRODUCTION
It is widely understood that in addition to such factors as input prices, output, and capacity utilization, energy intensity in the manufacturing sector depends on technology use. Even within an industry producing a relatively homogeneous product, some plants use technology that is relatively energy efficient, while other plants use technology that is relatively energy inefficient. In short, there is significant heterogeneity in the use of energy-efficient technologies among manufacturing plants.

The adoption of energy-efficient technologies can reduce not only plant-level energy intensity, but also industry average energy intensity. The use of such technologies, which may be replacing older, less productive technologies, can also serve to increase productivity at both the plant and industry level. Estimates of the energy savings and productivity gains associated with the use of certain technologies can help forecast the penetration of such technologies, and, in turn, help forecast energy intensity and productivity trends within a given industry.

Unfortunately, many of the estimates of the impact of existing technologies on energy intensity and productivity are based on engineering estimates, laboratory tests, or anecdotal evidence, which may result in misleading estimates of the benefits associated with the technologies.[b] This is due, in large part, to the fact that there is not a readily available set of data on energy consumption and technology use. This lack of data has been overcome, in part, as plant-level responses to the 1991 Manufacturing Energy Consumption Survey (MECS), have recently made available to researchers by the Center for Economic Studies at the U.S. Census Bureau.[c]

This paper uses plant-level data for approximately 70 plants drawn from the 1991 MECS (and from other Census Bureau sources) to examine the relationship between energy intensity, productivity, and the use of selected technologies in the cement industry. Three well-defined technologies are examined: high efficiency classifiers, dry-preheater kilns, and dry-precalciner kilns.

(a) This research was conducted at the U.S. Bureau of the Census. Any opinions expressed here are those of the author and not those of the Census Bureau. Pacific Northwest Laboratory is operated for the U.S. Department of Energy by Battelle Memorial Institute under Contract DE-AC06-76RLO 1830.

(b) Reference 9 provides an example of the overstatement of benefits to be derived from the adoption of new technology: Based on laboratory tests, it was estimated by the Office of Technology Assessment that the use of best open-face sawing in the forest products industry would increase lumber recovery by more than 20 percent relative to conventional sawing. Based on actual practice, the increase was shown to be about 4%. Such uncertainty regarding the potential benefits of a new technology, Rosenberg notes, may inhibit adoption.

(c) To access the data at the Center for Economic Studies (CES), researchers must become Special Sworn Employees of the Census Bureau and agree not to violate the confidentiality of responses to surveys conducted by the Census. See Reference 10 for a description of the databases available at CES.

The economic theory of the demand for inputs resulting from cost-minimizing behavior provides a framework for the econometric estimation of the relationship between technology use and energy intensity. In particular, estimation of a translog cost function, accounting for the use or non-use of the three technologies, provides evidence on the impact of technology use on energy intensity. In addition, a measure of total factor productivity (TFP) is constructed for each plant; the correlation between plant-level technology use and TFP is examined using simple regression analyses.

The remainder of this paper is divided into four sections. The first details the plant-level data used. The second discusses the technologies examined. The third discusses estimation of the cost function and the resulting estimates of the impact of technology use on plant-level energy intensity. The fourth discusses the construction of measures of TFP and results of regression analyses of the relationship between technology use and TFP.

DATA

The estimation of a cost function and the construction of a measure of TFP requires plant-level measures of quantities and prices of inputs and a measure of plant output. Energy-related data and technology-use data are drawn from plant-level responses to the MECS, while other data are drawn from plant-level responses to the Annual Survey of Manufactures (ASM) and Census of Manufactures (CM).

Plant-level responses to the 1991 MECS provide data on energy consumption, energy price, and technology use. All fossil fuels consumed for heat, power, and electricity generation are aggregated into a single Btu measure of fossil fuel input for each plant.[a] Total expenditures on all fossil fuels divided by Btus purchased provides a dollar-per-Btu average fossil fuel price for each plant. Plant-specific consumption of electricity for heat and power is drawn from the MECS. Total expenditures on purchased electricity divided by the BTU total of purchased electricity provides a dollar-per-Btu average electricity price for each plant.

Plant-level capital input is measured as the book value of capital in place in 1991 and is constructed using data from the 1992 Census of Manufactures (CM). Plant-level labor input is measured by production worker hours drawn from the 1991 ASM. Total production-worker wages divided by production-worker hours provides an average hourly wage rate for production workers. Plant-level materials costs are drawn from the 1991 ASM.

TECHNOLOGIES

The production of cement involves three steps: 1) crushing, grinding, and mixing of raw materials (generally clay, shale, or limestone) to produce kiln feed; 2) burning of kiln feed in a kiln, generally fired by coal, oil, or natural gas, to produce clinker; and 3) finish-grinding of clinker to produce cement. The three technologies examined here are used in steps 2 and 3.

High-efficiency classifiers are generally used in the finish-grinding of clinker to separate the fine, product-quality particles from the coarser oversize particles that are recycled for further grinding. Since high-efficiency classifiers reduce the amount of product recycled relative to other classifiers, they serve to reduce overgrinding and the electric power needed for grinding. Various manufacturers have reported 15 to 50% increases in grinding mill capacity, and 12 to 25% power savings in the grinding process.[1]

The two kiln technologies are used in step 2. Dry-preheater kilns utilize a separate preheater to preheat kiln feed with waste heat before it enters the kiln.[b] Since it takes less time to burn the feed in the kiln, a dry-preheater kiln can process substantially larger amounts of feed than a kiln without a preheater. Preheaters thus provide the dual benefits of increased fossil-fuel efficiency and increased capacity. However, because they rely on fans to

(a) This would be more accurately referred to as non-electric fuel input since it includes a small percentage of non-fossil based waste fuels.

(b) There are actually two basic types of preheaters: grate preheaters and suspension preheaters. This paper examines the use of suspension preheaters only.

move waste heat to preheat raw materials, plants using dry-preheater kilns tend to be more electricity intensive. On average, plants using dry-preheater kilns use approximately 20 to 30% less fossil fuel per ton of cement and 2 to 10% more electricity than plants using conventional dry or wet process kilns.[2]

Dry-precalciner kilns utilize a separate flash furnace, in addition to a preheater, to partially burn kiln feed before it enters the kiln. Since it takes even less time to burn the feed, a dry-precalciner kiln can handle substantially larger amounts of feed than a kiln without a precalciner. Precalciners serve to increase fossil fuel efficiency and increase capacity. As with dry-preheater kilns, they also tend to be more electricity-intensive. On average, plants using dry-precalciner kilns use approximately 30% to 40% less fossil fuel per ton of cement and approximately 15% more electricity than plants using conventional dry or wet process kilns.[2]

Cement plants tend to used only one type of kiln. Thus, most plants can be expected to use either dry-preheater kilns, dry-precalciner kilns, or some other kind of kiln. High-efficiency classifiers can be used with any type of kiln.

TECHNOLOGY USE AND PLANT-LEVEL ENERGY INTENSITY

Cost Function

In order to estimate the impact of technology use on energy intensity, dummy variables indicating the use of each of the three technologies were incorporated into a translog variable cost function.[a] The cost function was estimated assuming the production of cement takes place using four inputs: capital (treated as quasi-fixed), labor, electricity, and fossil fuel; materials were assumed to be weakly separable in production.[b] More explicitly, the variable cost function took the form

$$\begin{aligned}
\ln VC = {} & \ln\beta_0 + \beta_L \ln P_L + \beta_E \ln P_E + \beta_F \ln P_F + \beta_K \ln K + \beta_Q \ln Q \\
& + 0.5[\beta_{LL}(\ln P_L)^2 + \beta_{EE}(\ln P_E)^2 + \beta_{FF}(\ln P_F)^2 + \beta_{KK}(\ln K)^2 + \beta_{QQ}(\ln Q)^2] \\
& + \beta_{LE}\ln P_L \ln P_E + \beta_{LF}\ln P_L \ln P_F + \beta_{EF}\ln P_E \ln P_F \\
& + \beta_{KL}\ln K \ln P_L + \beta_{KE}\ln K \ln P_E + \beta_{KF}\ln K \ln P_F + \beta_{KQ}\ln K \ln Q \\
& + \beta_{LQ}\ln P_L \ln Q + \beta_{EQ}\ln P_E \ln Q + \beta_{FQ}\ln P_F \ln Q \\
& + \beta_{T,L}\ln P_L T_1 + \beta_{T,E}\ln P_E T_1 + \beta_{T,F}\ln P_F T_1 \\
& + \beta_{T,L}\ln P_L T_2 + \beta_{T,E}\ln P_E T_2 + \beta_{T,F}\ln P_F T_2 \\
& + \beta_{T,L}\ln P_L T_3 + \beta_{T,E}\ln P_E T_3 + \beta_{T,F}\ln P_F T_3 \\
& + \beta_{T_1} T_1 + \beta_{T_2} T_2 + \beta_{T_3} T_3
\end{aligned} \tag{1}$$

where ln is the natural log, VC is variable cost, P_i, $i=L,E,F$, is the price of factor i, K is the capital stock, Q is output, and T_j, $j=1,2,3$, is a dummy variable for each of the three technologies taking a value of 1 if a plant used the technology and a value of 0 otherwise. The β are parameters to be estimated.

(a) The use of a variable cost function was motivated by two factors. First, capital in the cement industry is very long lived. Kilns used in the production of cement may remain in use for several decades. Given the relatively sharp, and largely unanticipated, increase in the cost of energy to the industry over the last two decades and the long life of capital, it seems reasonable to assume that the industry is not in long-run equilibrium. Second, there are no readily available plant-level measures of the rental price of capital. The fact that many plants in the industry are foreign-owned makes it difficult to obtain the necessary data for the construction of plant-level capital rental prices.
The translog was used to preserve comparability of form between this work and other work using microdata to estimate industrial energy demand.[3,4,5]

(b) Materials were assumed to be weakly separable in part because no plant-level materials prices are readily available.

Theoretically, estimation of (1) by single-equation estimation methods could provide estimates of the impact of the technologies on energy consumption. However, single-equation estimation methods neglect the additional information contained in the factor share equations derived from (1) via Shephard's lemma. More explicitly, the factor share equations derived from (1) take the form

$$S_L = \frac{P_L L}{VC} = \beta_L + \beta_{LL}\ln P_L + \beta_{LE}\ln P_E + \beta_{LF}\ln P_F + \beta_{KL}\ln K + \beta_{LQ}\ln Q + \beta_{T_1L}T_1 + \beta_{T_2L}T_2 + \beta_{T_3L}T_3 \tag{2}$$

$$S_E = \frac{P_E E}{VC} = \beta_E + \beta_{EL}\ln P_L + \beta_{EE}\ln P_E + \beta_{EF}\ln P_F + \beta_{KE}\ln K + \beta_{EQ}\ln Q + \beta_{T_1E}T_1 + \beta_{T_2E}T_2 + \beta_{T_3E}T_3 \tag{3}$$

$$S_F = \frac{P_F F}{VC} = \beta_F + \beta_{FL}\ln P_L + \beta_{FE}\ln P_E + \beta_{FF}\ln P_F + \beta_{KF}\ln K + \beta_{FQ}\ln Q + \beta_{T_1F}T_1 + \beta_{T_2F}T_2 + \beta_{T_3F}T_3 \tag{4}$$

As can be seen, the factor-share equations are the usual translog equations except that each has dummy variables for the use of the three technologies. Dropping the labor-share equation (2) so as to avoid a singular covariance matrix and simultaneously estimating (1), (3), and (4), imposing the usual homogeneity, adding-up, and cross-equation restrictions, and using Zellner's seemingly unrelated regression method yielded estimates of the impact of the technologies on the demand for electricity and fossil fuel.

The estimated parameters of the variable cost function, and mean values for prices, capital, and output, can be used to back out fitted values for the quantity of electricity and fossil fuel demanded. For example, estimated parameters for (1) can be used with sample mean values of prices to produce a fitted value for variable cost and a fitted value for the shares of electricity and fossil fuel, i.e.

$$\hat{E} = \hat{S}_E \left(\hat{VC}/\bar{P}_E \right) \tag{5}$$

$$\hat{F} = \hat{S}_F \left(\hat{VC}/\bar{P}_F \right) \tag{6}$$

where the bars denote sample means and the carats denote fitted values. Fitted values can be computed under various technology-use scenarios to compute the impact of using or not using a given combination of technologies on the demand for electricity and fossil fuel. Dividing (5) and (6) by average output gives an estimate of energy intensity for an average plant.

Results

Table 1 reports means and standard deviations for the variables entering the variable cost function. Table 2 reports estimates of the parameters of the variable cost function. Using the values of Tables 1 and 2, it is possible to estimate average energy intensity under various assumptions about technology use; these estimates are reported in Table 3.

In interpreting Table 3, it should be noted that the omitted category, (i.e., plants using none of the listed technologies) encompasses a variety of configurations of technologies. There are two other types of kilns that are

Table 1. Sample Means (Standard Deviations)

Variable	
P_L ($/production worker hour)	15.04 (2.74)
P_E ($/Million Btu)	12.47 (3.05)
P_F ($/Million Btu)	1.80 (0.46)
K (Thou $ book val, historical cost)	67846 (45076)
Q (Thousands tons cement)	747.6 (404.9)

Note:
N=69

expected to exert significant influence on energy use and productivity, but for which data are not readily available.[a] In addition, there are several other technologies expected to exert a more limited effect on energy use and productivity.[b]

Table 3 indicates that plants using dry-precalciner kilns and high-efficiency classifiers use only 3.77 million Btu per ton of cement, while plants using none of the technologies use 5.35 million Btu per ton, a difference of 30%. Average energy intensity for plants using dry-precalciner kilns and high-efficiency classifiers is 10% less than that for plants using just dry-precalciner kilns. It appears that, based on the cost function analysis presented here, the use of these technologies is associated with changes in energy intensity that are in accord with engineering estimates. Since there are a variety of unobserved factors expected to influence energy intensity and productivity, however, one cannot ascribe the reported differences entirely to technology differences.[c]

(a) These are wet kilns and long-dry kilns.

(b) See Reference 1 for a detailed list of technologies used in the cement industry. In addition to unobserved differences in technology use, there are unobserved plant and firm effects that may affect energy intensity and productivity. The usual technique for controlling for plant or firm effects is to incorporate firm- or plant-specific dummy variables (or use deviations from plant or firm mean values) into the cost function. Since this analysis is limited to a cross-section, the use of plant-specific dummy variables was not possible; the small sample size made use of firm-specific dummy variables problematic. Similar problems arise in the productivity regression results presented below.

(c) Das[6] makes the point that unobserved plant-level heterogeneity can have a significant impact on estimates of fuel intensity in the production of cement. She estimates fuel intensities across three types of kilns: wet, long-dry, and dry-preheater. She specifies fuel intensity as a function of kiln type, kiln age, and unobserved plant-level heterogeneity. She assumes that fuel intensity is independent of output, and she does not account for plant-level differences in energy prices. She finds, contrary to most estimates of fuel intensity across kiln types, that wet-process kilns have a lower fuel intensity than either long-dry or dry-preheater kilns. An advantage of the method used here over that used by Das is that it allows fuel intensity to vary with plant-level fuel prices and with plant-level output. The estimates produced here, while clearly lacking in certain respects, are still roughly in accord with prior estimates of average energy intensity across kilns.

Table 2. Translog Variable Cost Function Parameter Estimates (Standard Errors)

Parameter	Estimate	Parameter	Estimate	Parameter	Estimate
Intercept	0.772 (5.926)	β_{LE}	-0.059*** (0.019)	β_{T1L}	0.023 (0.015)
β_L	0.494*** (0.112)	β_{LF}	-0.092*** (0.022)	β_{T1E}	0.013 (0.014)
β_E	-0.075 (0.111)	β_{EF}	-0.120*** (0.021)	β_{T1F}	-0.036** (0.016)
β_F	0.581*** (0.128)	β_{KL}	.010 (0.012)	β_{T2L}	-0.009 (0.015)
β_K	-0.038 (1.041)	β_{KE}	-0.001 (0.011)	β_{T2E}	0.048*** (0.014)
β_Q	1.448** (0.667)	β_{KF}	-0.009 (0.013)	β_{T2F}	-0.039* (0.017)
β_{LL}	0.151*** (0.026)	β_{KQ}	-0.254* (0.121)	β_{T3L}	0.024 (0.017)
β_{EE}	0.179*** (0.025)	β_{LQ}	-0.083*** (0.017)	β_{T3E}	0.032* (0.016)
β_{FF}	0.212*** (0.029)	β_{EQ}	0.023 (0.015)	β_{T3F}	-0.057*** (0.019)
β_{KK}	0.169* (0.090)	β_{FQ}	0.060*** (0.019)	β_{T1}	-0.097 (0.085)
β_{QQ}	0.303 (0.180)			β_{T2}	-0.238* (0.087)
				β_{T3}	-0.249* (0.106)

System R^2 = .68
N = 69

Notes:
* Significant at 10% level.
** Significant at 5% level.
*** Significant at 1% level.
T1 High-efficiency classifiers.
T2 Dry-preheater kilns.
T3 Dry-precalciner kilns.

TECHNOLOGY USE AND PLANT-LEVEL PRODUCTIVITY

Measuring Productivity

In order to assess the correlation between technology use and plant-level productivity, a simple index number measure of total factor productivity (TFP) was constructed. This measure was regressed on dummy variables identifying users of the three technologies. A cross-sectional measure of TFP for each plant was constructed as

$$\ln TFP_i = (\ln Q_i - \overline{\ln Q_i}) - (0.5)\sum_j (\alpha_{i,j} + \overline{\alpha_{i,j}})(\ln X_{i,j} - \overline{\ln X_{i,j}}) \tag{7}$$

Table 3. Energy Intensity Estimates (Million Btu Per Ton)

Technologies Used	Average Fossil Fuel Intensity	Average Electric Intensity	Average Energy Intensity
None	4.90	0.452	5.35
High-efficiency classifiers only	4.41	0.461	4.87
Dry-preheater kilns only	3.80	0.549	4.35
Dry-precalciner kilns only	3.74	0.460	4.20
Dry-preheater kilns & high-efficiency classifiers	3.39	0.454	3.84
Dry-precalciner kilns & high-efficiency classifiers	3.32	0.445	3.77

where Q_i is output of plant i, $\alpha_{i,j}$ is the cost share of factor j, j=K,L,E,M, and $X_{i,j}$ are quantities of factor j. The bars denote arithmetic means over all plants. Two measures of TFP are constructed: ln TFP(1) measures Q by tons of cement produced, ln TFP (2) measures Q by value of production. This measure of TFP has been used by Caves et al.[7]

While there are any number of factors that might be expected to affect plant-level TFP, the focus here is on only two factors: technology use and capacity utilization. Plant-level measures of TFP are regressed on dummy variables for technology use and plant-level measures of capacity utilization. The regression models took the form

$$\ln \mathrm{TFP}_i = \beta_0 + \beta_1 D_i + \beta_2 \mathrm{CU}_i \qquad (8)$$

where TFP_i is the cross-sectional measure of TFP (1) for plant i, D_i is a vector of dummy variables for the use of various technologies by plant i, and CU_i is the level of capacity utilization for plant i.

Since average productivity of labor (APL) is also commonly used as a measure of productivity, a regression analysis identical to that for TFP was conducted in which APL_i appeared as the dependent variable in a model like (8).

Previous work has identified a correlation between plant size, ownership status (multi- versus single-plant owning firms), and plant-level productivity.[8] Since virtually all plants in the sample used here belong to multiplant firms, the impact of ownership status on productivity is ignored.

The impact of size on plant-level productivity is difficult to disentangle from the impact of the technologies examined here. Baily et al.[8] find size to be positively correlated with plant productivity levels. As noted above, there are size economies associated with the use of the kiln technologies examined here. A regression analysis including variables for technology and a measure of size will be unable to disentangle the pure impact of size on productivity from the impact of size associated with technology use on productivity. In the absence of a satisfactory method of distinguishing the two effects, the impact of size on productivity use is effectively ignored in the regression analyses.

Results

Results of the regression analyses for both APL and TFP are presented in Table 4. The variable D_i, $i=1,2,\ldots 5$, in each model is a dummy variable taking a value of 1 if a plant used the technology group in question, and a value of 0 otherwise. Plants were classified as using: 1) only high-efficiency classifiers, 2) only dry-preheater kilns, 3) only dry-precalciner kilns, 4) dry-preheater kilns and high-efficiency classifiers, 5) dry-precalciner kilns and high-efficiency classifiers, or 6) none of high-efficiency classifiers, dry-preheater kilns, or dry-precalciner kilns.

As might be expected, the level of capacity utilization is significantly and positively correlated with both APL and TFP. None of the technology groups has any significant impact on APL. An examination of the t-statistics associated with the dummy variables for each of the technology groups in Table 4 shows that the use of dry-precalciner kilns and high-efficiency classifiers is significantly and positively correlated with TFP.

Table 4. Productivity and Technology Use OLS Regressions

	APL	ln TFP(1)	ln TFP(2)
Intercept	1.069**	0.088	0.657***
	(2.208)	(0.397)	(3.163)
D1 (High-efficiency classifiers only)	-0.972**	-0.220	-0.086
	(-2.503)	(-1.236)	(-0.515)
D2 (Dry-preheater kilns only)	0.218	-0.025	-0.076
	(0.471)	(-0.120)	(-0.384)
D3 (Dry-precalciner kilns only)	-0.120	-0.475	-0.169
	(-0.147)	(-1.278)	(-0.486)
D4 (Dry-preheater kilns & high-efficiency classifiers)	0.611	-0.016	0.118
	(1.646)	(-0.093)	(0.740)
D5 (Dry-precalciner kilns & high-efficiency classifiers)	0.390	0.491***	0.345**
	(1.021)	(2.806)	(2.104)
CU	2.339***	1.035***	0.355*
	(4.991)	(4.828)	(1.766)
R^2	.42	.39	.17

Notes:
N=67.
t-statistic in parentheses.

* Significant at 10% level.
** Significant at 5% level.
*** Significant at 1% level.

D1 = 1 if use only high-efficiency classifiers, 0 otherwise.
D2 = 1 if use only dry-preheater kilns, 0 otherwise.
D3 = 1 if use only dry-precalciner kilns, 0 otherwise.
D4 = 1 if use dry-preheater kilns & high-efficiency classifiers, 0 otherwise.
D5 = 1 if use dry-precalciner kilns & high-efficiency classifiers, 0 otherwise.

These results do not necessarily imply that the use of dry-precalciner kilns and high-efficiency classifiers are the cause of higher productivity, only that plants using them are more productive. The productivity differences between users and nonusers may be the result of unobserved factors such as the quality of management. Based on the enormous technical advantages, particularly the scale economies, associated with the kiln technologies, it seems likely that at least part of the observed productivity difference is due to the use of the kiln technologies.

REFERENCES

1. Venkateswaran, S.R., and H.E. Lowitt. 1988. The U.S. Cement Industry: An Energy Perspective, DOE/RL/01830-T58. Government Printing Office: Washington, D.C.
2. Portland Cement Association. 1992. U.S. and Canadian 1991 Labor-Energy Input Survey. Skokie, IL: Portland Cement Association.
3. Woodland, A.D. 1993. A Micro-Econometric Analysis of the Industrial Demand for Energy in NSW. *The Energy Journal*, 14(2): 57-89.
4. Pitt, M.M. 1985. Estimating Industrial Energy Demand with Firm-Level Data: The Case of Indonesia. *The Energy Journal*, 6(2): 25-39.
5. Kokkelenberg, E.C., and S.V. Nguyen. 1989. Modelling Technical Progress and Multifactor Productivity: A Plant-Level Example. *Journal of Productivity Analysis*, 1: 69-90.
6. Das, S. 1991. Estimation of Fuel Coefficients of Cement Production: A Fixed-Effects Approach to Nonlinear Regression. *Journal of Business & Economic Statistics*, 9(4): 469-474.
7. Caves, D.W., L.R. Christensen, and M.W. Tretheway. 1981. U.S. Trunk Air Carriers, 1972-1977: A Multilateral Comparison of Total Factor Productivity. In *Productivity Measurement in Regulated Industries*, edited by T.G. Cowing, 47-77. New York: Academic Press.
8. Baily, M.N., C. Hulten, and D. Campbell. 1992. Productivity Dynamics in Manufacturing Plants. *Brookings Papers on Economic Activity* 2: 423-456.
9. Rosenberg, N. 1994. *Exploring the Black Box: Technology, Economics, and History*. Cambridge: Cambridge University Press.
10. McGuckin, R.H. 1990. Longitudinal Data at the Census Bureau: A New Database Yields Fresh Insight on Some Old Issues. Bureau of the Census, Center for Economic Studies Discussion Paper CES 90-1.