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The effectiveness of state technology incentives: evidence from the machine tool industry

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The effectiveness of state technology incentives:

evidence from the machine tool industry

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CHAPTER 1. INTRODUCTION

Few economic issues have captured as much attention in recent years as the apparent decline in U.S. industrial competitiveness. Michael Dertouzos and the MIT Commission on Industrial Productivity cite at least 35 studies prepared by various national commissions, policy organizations, and academics, documenting industrial decline, uncovering its causes, and proposing remedies for U.S. industry. These studies have responded to widespread charges that American factories are inefficient, that American workers are indifferent and poorly trained, and that American products are inferior to those of international competitors. Motivated by the fear of a standard of living deteriorating under the weight of a crumbling industrial base, an army of researchers has investigated the causes and possible solutions to the U.S. industrial competitiveness dilemma.

Most of the research and specially commissioned study groups have identified manufacturing as the industrial sector that has experienced the most serious erosion of cost and quality advantage. The signs of a long-term trend of manufacturing output decline are clear. While manufacturing jobs represented 38 percent of employment in 1960, the share had dropped to 16.9 percent in 1991. This decline was the result of structural changes and not cyclical swings alone. Between 1985 and 1989, a period during which total employment expanded by 10.8 million, manufacturing employment grew by only 182 thousand--less than 2 percent of total employment growth (U.S. Bureau of Labor Statistics, *Monthly Labor Review*, various issues).

Slowdowns in productivity growth often have been blamed for the decline in manufacturing. From 1948 to 1965, multifactor productivity in the manufacturing sector grew at an average annual rate of 2.26 percent, slightly below the average for the entire business sector. Multifactor productivity growth slowed considerably from 1965 to 1973, with an average annual growth rate of only 1.46 percent. Between 1973 and 1979, multifactor productivity growth in manufacturing slowed again to 0.52 percent. A considerable rebound was observed from 1979 to 1986, with a growth rate of about 2.53 percent. However, Baily and Chakrabarti (1988) point out that a great deal of this recovery was due to the computer industry. With the industry including computers (SIC 35) removed from the calculations, the growth in multifactor productivity for the remainder of the manufacturing industry was only about 1.53 percent. Dertouzos (1989) and the MIT Commission on Industrial Productivity point out that much of the gain during this period resulted from industrial restructuring during and following the 1980-1982 recession; many inefficient plants were shut down with thousands of workers laid off. Baily and Chakrabarti (1988) conjectured that after this restructuring period, the growth of productivity in manufacturing could not be sustained. Manufacturing productivity in manufacturing continued to grow at a brisk pace through 1988, but slowed considerably between 1988 and 1990. Since 1990 was a recession year, the extent to which manufacturing productivity growth has recovered from the slump of the mid-1970s will not be known until data are available over the entire business cycle.

A number of studies have attempted to explain the productivity slowdown, and Baily and Chakrabarti (1988) have grouped these studies into eight categories: education, skill and motivation of workers; capital investment; prices of energy and materials; statistical illusion created by measurement problems; failures of management; government regulatory and demand policies; and a relatively slow pace of innovation. These explanations, however, address the productivity slump from economy or industry levels. Studies of plant data have shown that productivity levels and productivity growth vary widely among industries and among plants within industries. Baily et al. (1992) found these differences to be persistent and significant; aggregate productivity measures often cited are the average of a very diverse set of economic outcomes. This diversity suggests that there may be identifiable conditions under which plants are more productive.

While much of the literature examining the performance of manufacturing has focused on productivity, studies in applied microeconomics and industrial organization often gauge the performance of industries by economic efficiency. In particular, allocative efficiency is the measure used most often to evaluate the performance of firms under differing market conditions. However, technical efficiency is more closely related to the measurement of total factor productivity, although there are important theoretical differences. As explained in the following pages, measuring technical efficiency provides a finer disaggregation of the components of economic growth than that obtainable by the calculation of total factor productivity.

Evidence from the analysis to follow suggests that the heterogeneity characterizing plant-level total factor productivity is also observed with respect to technical efficiency. This observation leads to an investigation of the characteristics of plants that might correlate with high or low efficiency. An important issue is whether inefficient plants can increase their efficiency by imitating more efficient plants.

The idea that plants might benefit from efforts to improve their efficiency has attained general acceptance among economic policy makers, particularly at the state level. As of July 1988, 43 states had at least one program aimed specifically at developing and disseminating technology to improve productivity. In fiscal year 1988 alone, state governments spent more than $550 million on such programs, including state-funded research centers, incubators and research parks, venture capital, research grants, technology transfer programs, tax incentives, and technical and managerial assistance (Minnesota Department of Trade and Economic Development 1988).

Despite such widespread efforts, there is considerable uncertainty about the impact of technology development and application policies on the productivity of the targeted plants and sectors and the well-being of a state economy. While some evaluation of these development initiatives has been attempted, the recentness of the programs, the variety of their objectives and approaches, the complex relationships between policy and economic outcomes, the political nature of the evaluation process, and the limitations of firm-, plant-, and policy-specific data have limited the availability of careful analysis based on sound experimental methods (Feller 1988;

Glasmeier 1990). Considering the fiscal crisis facing many state governments, an evaluation of development policies is needed to guide state decisions on the funding and formulation of policies to accelerate economic growth and achieve development objectives.

This study addresses some essential questions about the efficiency of manufacturing. First, what types of plants are most efficient? Identification of plant characteristics associated with efficiency can provide clues about the process by which some plants learn of and apply the more productive manufacturing techniques. Second, can less efficient plants become more efficient by imitating more efficient plants? Public policy to improve the efficiency of plants is examined as one avenue by which inefficient plants might learn to catch up to or overtake their more efficient competitors. While the empirical analysis of this study applies only to domestic plants, the findings contain lessons that might be germane to the debate addressing the competitiveness of domestic plants relative to their international rivals.

The remainder of this chapter provides background information on the issues to which this study is addressed. First, tools and approaches used by policy makers to improve the production efficiency are described. Next, industrial extension programs are examined in greater depth. Because these programs often are involved directly in the manufacturing operations of a plant, their impact on efficiency may be readily observed. Finally, alternative procedures for investigating the determinants of plant efficiency are considered, including methods for examining the impact of public intervention.

Productivity and Technology Policy

Policy efforts to strengthen the productivity of traditional industries and to expand the bases for local economies have become widespread over the past ten years, particularly at the state level. This section traces the history of those efforts, classifies the many types of initiatives and their goals, and more closely examines industrial extension programs as the tool with the most direct and immediate potential for improving manufacturing efficiency.

History

The role of the federal government in promoting civilian innovation and productivity has been extremely limited. Walter Plosila (1988) points out that despite increased interest in international competitiveness in the 1980's, the Reagan Administration took a decidedly non-interventionist approach, arguing that the federal role in the improvement of technology and efficiency should be limited to funding for basic research. For this reason, most accounts of policies directed at improving technology and productivity focus on state programs. With the exception of the University Centers Program of the Economic Development Administration and the industrial applications centers of NASA, most federal policy for manufacturing productivity has emphasized deregulation and other actions supporting the view that the "free market will handle technology" (Plosila 1988).

Early attempts by states to support the advance of science, technology, and productivity began in the 1960s and were encouraged by the establishment of the

State Technical Services (STS) program. Sponsored by the Department of Commerce between 1965 and 1969, the STS program provided grants with the purpose of improving state capacities for promoting technology transfer. The funds were used to establish science and technology commissions, appoint science advisors, and, in some cases, establish industrial extension services. Most of the established programs were discontinued in 1969 when federal funding ceased (Goldsmith 1990). Two exceptions, the New York State Science and Technology Foundation and the Pennsylvania Technical Assistance Program, are still operating (Clarke 1990).

The federal government again encouraged state technology policy in 1977 when Congress authorized the National Science Foundation to spend as much as 2.5 million dollars on the State Science, Engineering, and Technology program (SSET). During the first phase of the program, grants were made to governors' offices to initiate state plans for the development of technology programs. However, follow-up funding was never authorized, and most of the plans were never implemented (Clarke 1990).

A period of accelerated growth of state programs focusing on industrial productivity and technology began during the late 1970s and continued through the mid-1980s. Increased state activism in economic development policy during this period occurred as a response to two important developments. First, the federal government severely curtailed its economic development activities targeted to states and local areas (John 1988). Second, the need for industrial restructuring became evident to many states during the recession of 1981-82. Casual observation of the success of states such as Massachusetts, California, and North Carolina promoted the popularity of technology development and application policies and the nurturing of technology-based businesses. Technology and productivity initiatives developed in the 1980s have been almost exclusively state-funded.

Approaches to Efficiency and Improved Productivity

In response to the proliferation of state technology and productivity policies, a number of studies have described, classified, and catalogued the initiatives that have recently been developed (Jones 1986; Minnesota Department of Trade and Economic Development 1988; Clarke and Dobson 1989; Rees and Lewington 1990). These descriptions are convenient syntheses for use in discussing alternative approaches to improving efficiency and productivity.

State technology initiatives generally affect the operation of client firms in one of three ways: by introducing the firm to information about best-practice technology, thereby enabling the firm to achieve a higher level of efficiency; by taking advantage of agglomeration economies or economies of scale that exist in some types of manufacturing; and indirectly, by shifting the frontier production function, thereby increasing the highest attainable level of productivity. Many programs, because they provide more than one service, fall into more than one of these categories. Much of the descriptive material from this section is synthesized from Clarke (1990) and Minnesota Department of Trade and Economic Development (1988).

Programs Designed to Increase Firm Efficiency and Productivity

Programs for technology transfer, manufacturing extension, worker training, and technical and managerial assistance all contribute to the information set upon which the manager of a firm bases production decisions. Given the existence of a best-practice technology, firms may be technically inefficient if they lack information about that technology or its application. Information systems, machinery and production processes, input or output inventory management, and labor or financial management practices all contribute to the efficiency of a manufacturing plant.

Technology transfer programs generally are associated with a university or a national laboratory and are designed to speed the transfer of new technologies from the laboratory to the private sector. States endeavor to provide a competitive edge to citizen firms by giving them access to the most efficient technology in the industry. This effort may include awarding exclusive license to innovative technologies.

Management assistance programs provide firms with a wide variety of information, including help in locating venture capital, developing a business plan, applying for Small Business Administration grants, etc. This type of information contributes to the firm's ability to manage resources more efficiently.

Technical assistance programs focus specifically on the problems managers face in adopting a technology for commercial use. These efforts might include assisting firms with evaluation of the probable economic impact of a new technology, testing the technical specifications of new products, or tailoring information systems to user needs. Worker training programs often are combined with technical assistance or technology transfer to smooth the process of adjustment to new technology.

Manufacturing or industrial extension programs help existing manufacturers adopt technologies to improve their productivity and quality. These programs often combine technical assistance, managerial assistance, worker training, and even location of capital sources into a single program, which often is operated by state extension agents who visit firms to assess their operations and provide advice about upgrading the firm's manufacturing processes and managerial practices.

Programs to Capture Agglomeration Economies or Economies of Scale

Many empirical studies have suggested the importance of agglomeration economies or economies of scale in a number of manufacturing industries, especially those in which the technology for products or processes changes rapidly. The physical location of engineers, researchers, and managers to others studying the same problems often promotes the flow of information. Furthermore, a specialized, experienced labor force may be an important benefit of locating near other establishments similarly engaged.

Research parks are planned groupings of technology companies, often near universities, that encourage university/private partnerships. They often provide incubator services or other facilities encouraging the development of new businesses. Research parks and incubators both attempt to take advantage of the cumulative affects of the development of a market for high-technology inputs. The primary function of incubators, however, is to correct failures in the capital market.

Programs Designed to Shift the Frontier Production Function

State-funded research centers and research grants are designed primarily to advance scientific knowledge. By increasing the level of scientific knowledge, these programs are designed to create the potential for dramatic increases in productivity at the firm or plant level. However, the economic returns to scientific research are difficult to appropriate fully to the sponsoring state. The cumulative nature of technology development and the difficulty of establishing intellectual property rights for general scientific knowledge prevent guarantees that only citizen firms will benefit from the resulting technology. This difficulty impairs the process of determining economic returns from research. In order to increase appropriability, many programs that fund research centers and research grants are increasing their emphasis on technology transfer and commercial applications.

There are two types of programs that fall into this functional category. Research centers, also known as advanced technology centers or centers of excellence, usually are located in or affiliated with universities. They conduct basic or applied research and, while technology transfer may be an important component of their overall mission, their activity typically concentrates on technology development. Thus, their main contribution to changes in the economy is to advance best-practice technology. Research grants usually are made to individuals in universities working on scientific problems. Often, these projects are cosponsored by or jointly researched with private industry.

Other Programs

Two other types of programs attempt indirectly to improve productivity and efficiency. Tax policy programs provide tax deductions or credits to firms for conducting research and development, hiring technical workers, or donating technical equipment to universities. Policy development programs consider technology policy or provide science and technology advice for the governor. These include technology task forces, advisory boards, science and technology agencies, or individual science advisors.

A Closer Examination of Manufacturing Extension

Of those described, the programs most likely to have a direct and immediate impact on the efficiency and productivity of manufacturing plants are technology transfer, manufacturing extension, worker training, technical assistance, and managerial assistance. Because most of these functions are performed by industrial or manufacturing extension programs, and because several manufacturing extension programs have been in place for many years, this study focuses on these programs and their impact on efficiency, rather than attempting to evaluate programs that are less directly involved with the manufacturing process itself. The evaluation procedure focuses on plant-level responses to policy, and is well suited to the type of plant-level intervention typically provided by manufacturing extension services.

Table 1 lists industrial extension programs operating in the United States, as surveyed by the National Governors' Association (Clarke and Dobson 1989). This survey identified 43 programs in 28 states. Most of these programs have been established since 1980, and almost one-half of the programs are administered by universities. The remainder are administered by state agencies, quasi-public organizations, community colleges, or private nonprofit organizations. The staffs of these organizations are usually engineers with industrial experience, often university faculty or graduate students, who provide technology assistance to small and medium-sized manufacturers. Direct services may include:

- Review of current or proposed manufacturing methods and processes;
- Productivity and quality assessments;
- Assistance with plant layout and operations;
- Advice on acquisition and implementation of equipment, especially computer systems;
- Assistance with total quality management programs, including statistical process control (SPC);
- Access to databases and other information resources; and
- Networking.

Indirect services (i.e., those for which referrals are made to other providers) often include technical data, research and development, and training. Further details regarding program characteristics can be found in Clarke and Dobson (1991).

Table 1. State supported industrial extension programs

State	Program	Year Established
Alabama	Alabama Productivity Center	1986
	Industrial Modernization Program	1988
Arkansas	Center for Technology Transfer	1984
Connecticut	Technology Assistance Center	1984
Georgia	Industrial Extension Service	1956
Illinois	Center for Advanced Manufacturing and Production	1987
Indiana	Manufacturing Technology Service	1986
	Technology Assistance Program	1989
Iowa	Center for Industrial Research and Service	1963
Kansas	Center for Technology Transfer	1988
	Industrial Liaison Program	1990
	Mid-America Manufacturing Technology Center	1991
Kentucky	BRADD/Technical Assistance Program	1990
	Center for Robotics and Manufacturing Systems	1987
	GRADD/Industrial Extension Engineering Program	1987
Maryland	Technology Extension Service	1984
Maine	Center for Technology Transfer	1988
Massachusetts	Center for Applied Technology	1987
	Industrial Services Program	1984
Michigan	Industrial Technology Institute	1981
Minnesota	Minnesota Project Outreach	1989
	Minnesota Technology Inc.	1991
Missouri	Center for Technology Transfer and Economic Development	1987
Montana	University Technical Assistance Program	1986

Table 1. (continued)

State	Program	Year Established
Nebraska	Technical Assistance Center	1985
New Jersey	Technology Extension Centers	1986
New York	Industrial Effectiveness Program	1987
	Industrial Technology Extension Service	1990
	Northeast Manufacturing Technology Center	1989
North Carolina	Industrial Extension Service	1955
North Dakota	Center for Innovation and Business Development	1984
Ohio	Great Lakes Manufacturing Technology Center	1989
	Institute of Advanced Manufacturing Sciences	1982
	Ohio Technology Transfer Organization	1979
Oklahoma	Rural Enterprises	1980
Pennsylvania	Industrial Resource Centers	1988
	Technology Assistance Program	1965
South Carolina	Southeast Manufacturing Technology Center	1989
Tennessee	Center for Industrial Services	1963
Texas	Technology and Business Development - Technical Assistance Program	1986
Virginia	Manufacturing Action Program	1991
	Technology Transfer Program	1984
West Virginia	Center for Education and Research with Industry	1984

Source: Clarke and Dobson, 1991 and author's inquiries.

Study Methodology

Studies of the effects of interventions or events on the performance of an industry or firm are common in the industrial organization literature. This study falls in this category to the extent that it examines the influence of plant characteristics--including the presence of government intervention--on the performance of a manufacturing plants. In this section, two choices for the design of the study are discussed: the choice of a performance variable and the choice of industry.

In the past, evaluations of government interventions to improve manufacturing productivity have lacked a well defined procedure. Because such evaluations of publicly funded activities have important political implications, careful evaluation may not be the intent of the researcher (Feller 1988). However, even when it is the intention of the investigator to assess results objectively, it is often difficult to apply a sound experimental procedure to the evaluation. The relationships that technology initiatives seek to affect are extremely complex, and claims of causality between programs and macroeconomic outcomes, even when an association is found, are difficult to justify (Feller 1988). Furthermore, many evaluations are conducted after the first few years of program operation, and linkages between the programs and their objectives are likely to be formed over a period of time longer than most legislative planning horizons.

In this study, the relationship between the program goals and the performance measure is simplified considerably. Rather than trying to credit productivity programs with expanded income or employment, the direct impact of the programs on the efficiency of plants is examined. The objective is to bring the performance variable to the same level (plant) at which the program operates in order to sharpen the focus of the evaluation.

Choice of Performance Variable

Recent studies of the impact of events or interventions on plant performance have used both technical efficiency and total factor productivity as performance variables. For example, Lichtenberg and Siegel (1987) used total factor productivity as the basis for evaluating the impact of ownership changes on plant performance. Olley and Pakes (1992) used total factor productivity to examine the impact of the divestiture of AT&T on the U.S. telecommunications equipment industry. In an early application of technical efficiency analysis, Charnes, Cooper, and Rhodes (1978) evaluated the impact on efficiency of an experiment in public education. Schmidt and Sickles (1984) examined the impact of airline deregulation on technical efficiency, and Sickles and Streitwieser (1991) examined technical efficiency as a performance variable in the effect of deregulation in the natural gas industry.

The decision to use either total factor productivity or technical efficiency depends on exactly what is to be measured. The relationship between total factor productivity and technical efficiency, as well as the importance of technical efficiency in the investigation of economic growth and productivity, is well illustrated by the work of Robert Solow (1957). Solow separated economic growth into two components: that due to increases in inputs and that due to technical change.

Technical change frequently has been used synonymously with total factor productivity growth, which is the share-weighted sum of the rates of growth of output, minus the share-weighted sum of the growth of inputs (often referred to as the Solow residual). However, equating technical change with total factor productivity growth implies that all production units lie on the production frontier at all times. By dropping this assumption, increases in total factor productivity can be separated into shifts in the frontier, or best-practice, production function, and in individual firm advancement toward the frontier. Solow could have separated economic growth into three, rather than two, components: growth in inputs, shifts in the production function, and movement of firms toward the efficient production frontier.

Hence, technical efficiency is a component of total factor productivity growth that does not include output changes accountable to shifts in the production frontier. This is because, rather than being measured as share-weighted output growth minus share-weighted input growth, technical efficiency measures the distance a particular plant lies from the best practice frontier, wherever that frontier may lie. Technical efficiency is particularly relevant to this analysis for two reasons. First, the performance of a plant relative to other plants in the industry is of primary interest, and second, because the specific focus of the competitiveness debate is the ability of firms to catch up to some established "best-practice" technology, whether it be domestic or international. Hence, it is important that shifts in the frontier not be confused with movements of plants toward the frontier.

It can also be argued that technical efficiency is a performance variable that parallels the goals of the state industrial extension programs. The preceding classification of state technology programs emphasized the fact that while some programs are aimed specifically at shifting the frontier (research grants, university research centers, etc), others aim particularly to promote the use of best-practice technology. Figure 1 shows the distinction between these two objectives. Manufacturing extension services provide assistance for migration of plants from inside the established production possibilities frontier to the boundary. Since technical efficiency measures the distance a plant lies from the established frontier, it is a particularly appropriate tool for this analysis.

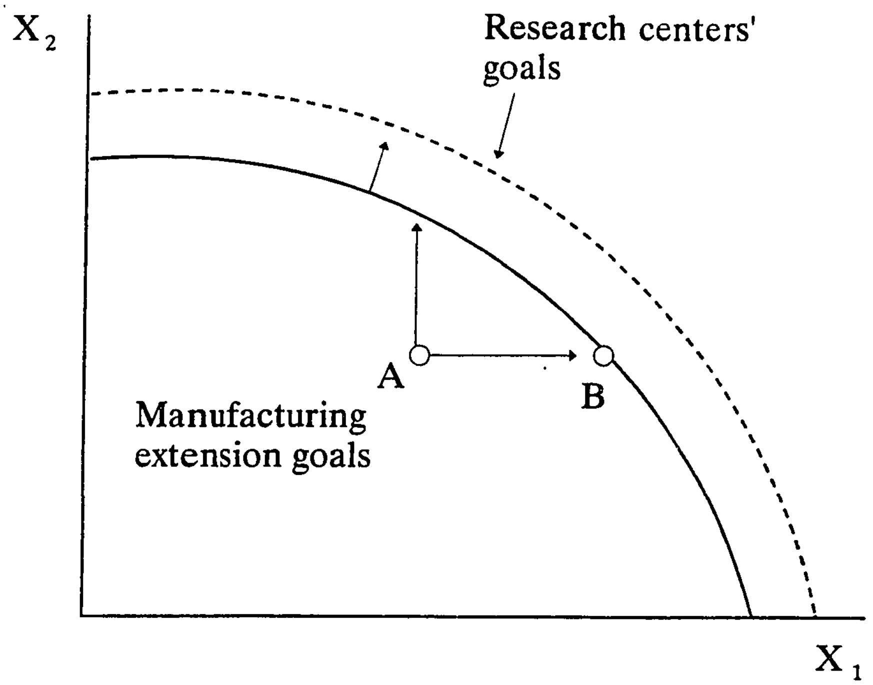

Figure 1. Objectives of manufacturing extension versus technology advancement policies

Choice of Industry--The Machine Tool Industry

The machine tool industry is composed of two four-digit Standard Industrial Classification (SIC) codes: 3541 (metal-cutting machine tools) and 3542 (metal-forming machine tools). These industries were chosen for several reasons. First, the machine tool industry has suffered from severe import penetration, as well as failure to develop an export market. Second, machine tools hold a critical and strategic position in the competitiveness and productivity of manufacturing overall. Finally, industrial decline has prompted several other studies of the industry, which provide a useful background for the present plant-level analysis, which utilizes data not available to date for the investigation of efficiency.

Industrial Decline and Import Penetration

Table 2 provides an overall picture of decline in the machine tool industry. The number of plants has fallen dramatically since 1963, as has total employment in the industry. Imports as a percentage of domestic consumption climbed from 4.7 percent in 1963 to 32.1 percent in 1987, giving an indication that industrial decline is due to loss of market share to imports. The MIT Commission on Industrial Productivity (March 1989) cited one important reason for this decline. The quality of machine tools has a direct bearing on the quality of the components built with them, and downstream manufacturers often have rejected U.S.-manufactured machine tools as inferior or inefficient, compared to foreign-manufactured machine tools.

Table 2. Economic trends in the machine tool industry

Year	Total Plants	Mail Cases:5+ Empl.[a]	Total Employ.	Value of Shipments (Millions)	Exports (Millions)	Imports (Millions)	Domestic Consum.	Exports Pct. of Shipments	Imports Pct of Consum.
1963	1,153	768	82,515	946	185	38	799	19.6	4.8
1967	1,220	818	114,998	1,826	225	178	1,779	12.3	10.0
1972	1,239	798	73,681	1,269	260	114	1,123	20.5	10.2
1977	1,334	617	79,441	2,453	452	401	2,402	18.4	16.7
1982	1,386	610	73,806	3,805	615	1,218	4,408	16.2	27.6
1987	624	597	45,395	4,586	1,011	1,689	5,264	22.0	32.1

[a]Number of plants with five or greater employees that are not administrative records cases. For details regarding the impact of administrative records on aggregate data, see the appendix.

Source: Number of plants and total employment come from the Longitudinal Research Database. Employment numbers are based on mail cases with five or more employees. Shipments and trade data are from the *U.S. Industrial Outlook*, U.S. Department of Commerce International Trade Administration, various Issues.

Strategic Importance

Machine tools are used in the transformation of metal into components that are then assembled either into end products or into capital goods that manufacture end products. The largest consumer of machine tools in 1991 was the automobile industry. Aerospace, construction and farm machinery, and specialized industrial machinery also are important users of machine tools (U.S. Department of Commerce, *Industrial Outlook* 1991). Almost every manufactured product has, at some point in the production process, involved machine tools. Direct access to the most efficient machine tools is important for domestic competitiveness in manufacturing.

There is evidence to suggest that the development of an efficient domestic machine tool industry may be required to secure access to the best and most efficient tools. American automobile manufacturers, attempting to buy the most efficient and accurate machine tools from foreign builders, often have found that their access to state-of-the-art tools lags access by their competitors by several years (March 1989). While it would seem impossible for this to occur in a perfectly competitive machine tool market, under less than perfectly competitive conditions, firms may engage in strategies that fall under the category "raising rivals' costs" (Krattenmaker and Salop 1986; Salop and Scheffman 1984). For example, an agreement between Japanese machine tool builders and Japanese automobile producers that restricts the supply of the most innovative machine tools to American manufacturers can act to raise American manufacturers' costs. In the tradition of Japanese Kieretsu, this seems a realistic scenario. Krattenmaker and Salop note that this strategy will work only if the rival cannot enter into a mutually profitable arrangement with substitute suppliers to restore its competitiveness. That is, if U.S. manufacturers cannot obtain leading-edge technology tools from American, German, Korean, or other machine tool manufacturers, then the Japanese may succeed in decreasing relative efficiency and raising the relative production costs of U.S. machine tool users.

Decline of the machine tool industry has precipitated research into its causes. A comprehensive analysis by the MIT Commission on Industrial Productivity (March 1989) has pointed to the lack of technical assistance for small and medium sized manufacturers as a barrier to innovation. Technical assistance of the type provided by industrial extension programs was recommended as a method for disseminating information about the comparative performance of new equipment and for encouraging builders to invest in new technology. This study builds upon that work by assessing the technical efficiency of the machine tool industry, by investigating relationships between efficiency and plant characteristics, and by evaluating the effectiveness of industrial extension programs in filling the need for information.

Procedures

In Chapter 2, the theoretical foundations of technical efficiency measurement are presented, and approaches to explaining variations in technical efficiency among plants are discussed. Hypotheses for the study are developed from the theoretical discussion and from the results of other empirical studies of manufacturing productivity. Chapter 3 describes the development of the data used for the study.

The Longitudinal Research Database (LRD) is a unique and rich plant level data source that is particularly suited to efficiency measurement and intervention analysis. Chapter 4 reviews different approaches to technical efficiency measurement, and describes the estimation procedures used in this study. Chapter 5 contains preliminary results, including specification test results, estimates of the frontier technologies, and an overview of the estimated efficiency scores by year and industry. Chapter 6 uses the estimated efficiency scores to investigate the relationship between technical efficiency and plant characteristics. In Chapter 7, subsets of the main data are used to address several issues: technological change in the machine tool industry, the relationship between technology adoption and technical efficiency, and the association between technical efficiency and direct intervention by manufacturing extension. Chapter 8 summarizes and concludes.

CHAPTER 2. THEORY

The use of technical efficiency as a performance measure is somewhat unorthodox among assessments of industrial performance. This is partially due to unavailability of models and empirical results explaining how and why plants might operate inside the best practice production frontier. In this chapter, the definition of technical efficiency is established, and it is contrasted with allocative efficiency, which is the efficiency concept most often applied to the analysis of firm and industry performance. A discussion of the neoclassical view of technical efficiency establishes its status as a measurement tool, rather than a theory that might explain the differences in performance between firms. A brief review of alternatives to neoclassical assumptions of firm behavior leads to a discussion of the possible sources of estimated technical efficiency (or inefficiency). The impact of efficiency on the growth and survival of plants and on the competitiveness of industries is then discussed. The discussion is summarized as a set of hypotheses for the analysis of technical efficiency in the machine tool industry.

Technical Efficiency Analysis

In a presentation to the Royal Statistical Society in 1957, M.J. Farrell proposed a method for measuring efficiency in production. His work was motivated not only by the relevance of productive efficiency in the debate over economic policy, but also by the weaknesses of productivity measures that were in use at the time.

Labor productivity, a popular efficiency indicator, did not account for the other factors of production, and efficiency indexes such as total factor productivity posed typical and highly technical index number problems. Farrell's development of technical efficiency was a response to what he saw as an important tool that had not yet been properly developed.

Defining Technical Efficiency

Intuitively, technical efficiency is the degree to which the greatest amount of output possible is produced from a given input vector, or equivalently, the degree to which as few inputs as possible are used to produce a given output level. A more formal definition is given by Lovell and Schmidt (1987) and their exposition is closely followed in this presentation. Let L(u) represent the subset of all input vectors x that can produce at least the output vector u. Using the input correspondence L(u), the isoquant and efficient subset of the isoquant are defined as

$$Isoq\ L(u) = \{x : x \in L(u),\ \lambda x \notin L(u),\ \lambda \in [0,1)\},\ u \geq 0, \tag{2.1}$$

and

$$Eff\ L(u) = \{x : x \in L(u),\ y \leq x \rightarrow y \notin L(u)\},\ u \geq 0. \tag{2.2}$$

where λ is a scalar by which all elements of x are increased. A given input vector x is technically efficient if it lies on the efficient subset of the isoquant. Placement of x on the efficient subset requires that if any elements of a point y are smaller than their corresponding elements in x, and no elements of y are larger than x, then if y lies in L(u), x cannot be on the efficient subset. Figure 2 shows the efficient subset as the thick part of the isoquant, which extends from t to s. Notice that a point such as x_2 is not on the efficient subset because point u has one element smaller than x, but is still in L(u).

Figure 2 demonstrates how Farrell measured efficiency and decomposed it into technical efficiency, F(x,u), and allocative efficiency, A(x,u). Given the input price vector $\tilde{\omega}$, production at point y minimizes cost. Production at a point such as x_1 is technically inefficient because it lies to the right of the frontier. A radial contraction of all inputs from x_1 meets the frontier at point λx_1, at which production of u is accomplished in the same input proportions as at point x_1. Technical efficiency equal to λ: the ratio of the vector of inputs used at λx_1 to that used at x_1.

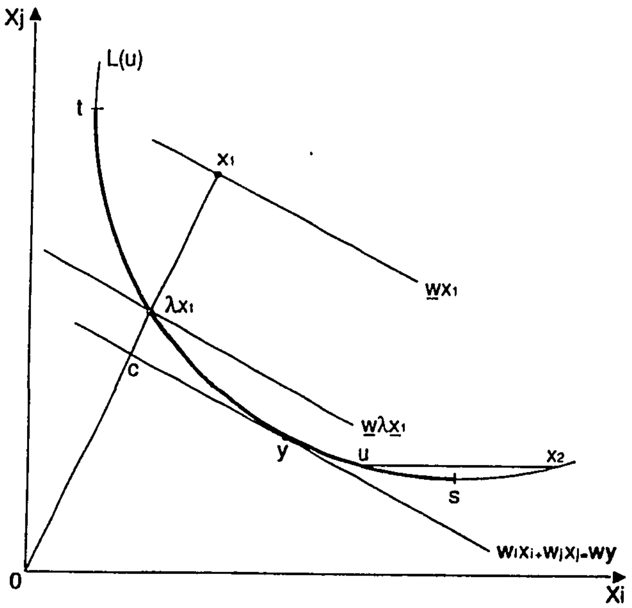

Figure 2. Farrell decomposition of deviations from minimum cost into allocative efficiency and technical efficiency

While production at λx_1 is technically efficient, it is allocatively inefficient because it uses inputs in the "incorrect" proportions, given relative input prices. Allocative efficiency is the ratio of inputs used at point c, which lies on the same isocost line as the minimum cost production point (y), and λx_1. These efficiency measures, defined relative to the point x_1 have a convenient cost interpretation. If y represents the least cost combination of inputs for the production of u, the cost of production at y is $\tilde{\omega}y$. Technical efficiency is $\tilde{\omega}(\lambda x_1)/\tilde{\omega}x_1 = \lambda$, and allocative efficiency is $\tilde{\omega}y/\tilde{\omega}\lambda x_1$.

It is instructive to note that the issue of optimal scale is not addressed in this framework. Because efficiency is defined in terms of the input requirements for a given level of output, scale can be non-optimal, but the firm can still be technically and allocatively efficient. Only cost minimization is required for both of these efficiencies to hold. If technical efficiency is defined in terms of the production possibilities set, then technical and allocative efficiency require optimal scale, because the profit function is the value dual to the production possibilities set (Lovell and Schmidt 1988).

An equivalent way to represent technology and technical efficiency can be derived from the output correspondence P(x), representing the subset of all output vectors obtainable from input vector x. There is an inverse relationship between the input correspondence and the output correspondence. Isoquants and efficient subsets can therefore be defined in terms of the output correspondence:

$$Isoq\ P(x) = \{u: u \in P(x),\ \lambda u \notin P(x),\ \lambda > 1\},\ x \geq 0, \tag{2.3}$$

and

$$Eff\ P(x) = \{u: u \in P(x),\ v \geq u \rightarrow v \notin P(x)\},\ x \geq 0. \tag{2.4}$$

Figure 3 illustrates the concept of technical efficiency using the output correspondence. For a given input vector x, the efficient output vector is y, at point A. Point B represents a plant operating with the same input vector, but with outputs that have been scaled back by γ. The technical efficiency score for the plant operating at B is $\gamma y/y = \gamma$.

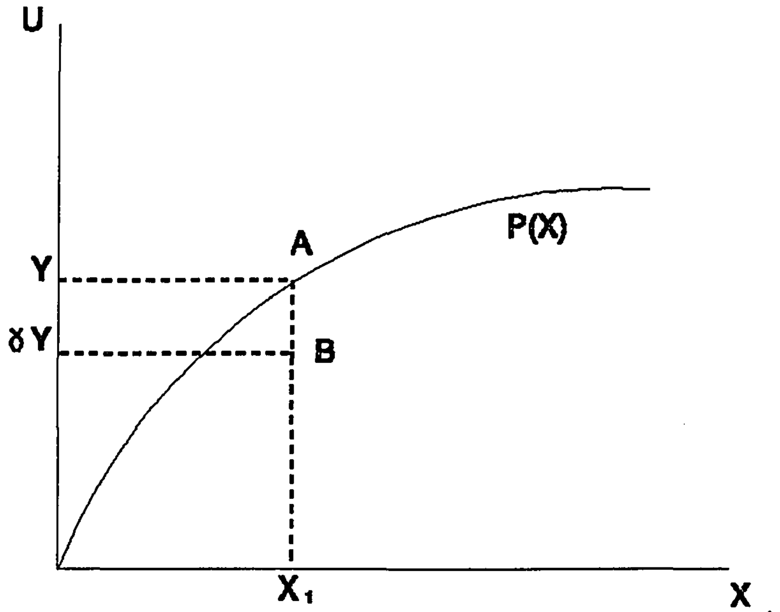

Figure 3. Technical efficiency defined in terms of the output correspondence.

Once again, the issue of scale and efficiency is not addressed. A plant that is the "wrong" size to attain maximum productivity is therefore measured as inefficient only to the extent that its falls short of the estimated output attainable in a plant of its own scale.

Sources of Technical Inefficiency

As defined above, technical efficiency is observed when plants differ with respect to their effectiveness in combining resources to attain the maximum level of output. Casual observation of the production process leads to an extensive list of reasons for these differences. This list might begin with obvious factors, such as the abilities of managers and the skills and attitudes of workers. In order to derive testable hypotheses for a study of plant performance, these observations must be organized and explained in terms of a theory of the firm. While neoclassical theory assigns a rather impotent interpretation to technical efficiency -- that it can be explained completely by errors in specifying the production decision -- alternative theories allow for heterogeneity in the objectives and organization of firms that might cause technical inefficiency in the industry.

After discussing the neoclassical interpretation of technical efficiency, alternative theories of firm behavior are explored. In particular, theories that relax the assumption of cost minimizing or profit maximizing behavior, perfect information, and the idea of the firm as a single entrepreneur are explored.

Neoclassical Economics and Technical Efficiency

As described by Farrell in 1957, technical efficiency was primarily an empirical construct. Farrell was essentially interested in solving a measurement problem, rather than developing a theory. He did warn that his measure of technical efficiency must be interpreted in relation to a given set of firms, for a given set of factors measured in a specific way. Farrell demonstrated the sensitivity of the method to the specification of the production function by showing that as more factors of production were added to the specification, the level of inefficiency declined. He acknowledged that apparent differences in efficiency may reflect factors like climate, location, and fertility that were not included in the analysis. However, he did assert that perfection of the technique, including measurement of all of the relevant variables, would lead to what he called "genuine" differences in efficiency. These "genuine" differences were attributable by Farrell to variations in the entrepreneurial ability of managers.

From the neoclassical view, technical inefficiency is inconsistent with maximizing behavior (Stigler 1976). The "genuine" differences in production efficiency referred to by Farrell are simply artifacts of failure to measure differences in entrepreneurial ability *as a factor of production that the entrepreneur chooses just as he chooses the combination of capital and labor.* Consider two farmers spending the same amount of time applying identical inputs to the same size and quality of land. Suppose one farmer elects to learn of the most innovative methods of crop rotation, fertilizer application, harvesting methods, etc., while the other chooses not to do so. He spends this time pursuing other activities, and his choice is guided by utility maximization. Although the first farmer might produce a higher level of output from a given set of physical inputs, the time that he spent acquiring knowledge that was applied to the production process must also be considered in the production function.

If this production function specification does not include the cost of knowledge production, then the second farmer has chosen a lower production frontier, because the opportunity cost of learning to reach the first farmer's frontier is higher than the value of the additional output. If the farmer's objective is to reach the same frontier as the first farmer, he can do so, even if his ability to comprehend and apply the knowledge is limited. With the value of the extra output to be earned, he can hire someone with technological ability (like the first farmer, for example) and pay him accordingly. Hence, observation of "inefficiency" is simply due to failure to allocate the foregone output correctly to the factors of production. This interpretation reduces the measurement of technical efficiency to a theoretically vacuous exercise of finding the residual effects of these failures.

Even from a neoclassical perspective, however, there is value in learning what factors are responsible for observed inefficiency and what their magnitudes might be. If the goals of society include the redistribution of resources toward improving the efficiency of production, then learning how and why production choices are made can facilitate the development of policies that provide incentives for producers to move toward this goal. For example, suppose it is possible to measure every physical input of the production function perfectly, and therefore to know that observed technical inefficiency is due completely to differences in the ability of managers to implement a given production technology. Neoclassical theory implies that the producer has chosen not to allocate resources to improving his technical knowledge, given the opportunity cost of acquiring that knowledge. Analyzing patterns of efficiency and the characteristics of firms can provide evidence as to which firms face higher opportunity costs of acquiring information.

These differences in cost are due to failure in the market for information. Such failures might define appropriate roles for public policy. For example, correcting the information market failure by equalizing the cost of information to all producers might be successful in altering the entrepreneurs' decisions about resource allocation. An example of a method for correcting this market failure might include an effective technology transfer system.

Alternative Theories of the Firm and Technical Efficiency

Neoclassical economic theory does not fully explain firm behavior and organization. In particular, it models firm behavior similarly to consumer behavior. Clearly, firm behavior is not the result of individual choice, but of a complex joint decision process within a network of agency relationships (Holmstrom and Tirole 1989). Neoclassical economics fails to explain how production is organized within the firm, how conflict between constituencies is resolved, how profit maximization, if that is the goal of the firm, is achieved, and, most fundamentally, what a firm is and why it exists (Hart 1990; Williamson 1991).

These four issues have been addressed by a diverse group of economists and organizational theorists from a number of different perspectives. Attacks on neoclassical theories of firm behavior generally originate with a repudiation of one of three key assumptions: that profit is maximized or cost is minimized; that information is perfect or can be represented by a probability distribution of future events; and that the firm acts as an individual entrepreneur (Cyert and March 1963; Williamson 1991). Violation of each of these assumptions and its implications for technical efficiency analysis are examined below.

Deviations from Profit Maximizing/Cost Minimizing Behavior

The assumption that profit maximization or cost minimization is a realistic objective function for the firm is easily challenged. Even if the notion that firm behavior can be represented by the choices of a single entrepreneur is accepted, utility maximization by that entrepreneur might not imply either profit maximization or cost minimization. The entrepreneur's utility function might include, for example, leisure, work satisfaction, or ability to provide employment for family and friends.

Furthermore, even if the profit function is the correct variable to measure, maximization might not be the correct behavioral assumption. Firms might be characterized as "satisficing" rather than maximizing agents (Cyert and March 1963). That is, they might make decisions based on some minimum acceptable level of profit. This behavior might be especially common in the case of publicly held companies in which the availability of capital is contingent upon turning a profit that will attract investors. This also could be true, however, in the case of an owner entrepreneur who is aware of his opportunity cost of operating the firm. If he can make enough profit to justify operating the business, rather than engaging in an alternative profession, then that may be "good enough." In the machine tool industry, evidence of satisficing behavior is cited by March (1989) as a reason for the failure of small, family owned firms to innovate and invest in new product development.

If not all firms minimize costs or maximize profits, then differences in the objective functions of firms might lead to observed technical inefficiency. A plant that is operated strictly for profit is likely to be more efficient than one that is maximizing the leisure of the entrepreneur subject to some minimum level of profit, unless the profit constraint is equal to the maximum. Since these differences in the objective functions of plants are not modeled in the production function, they will be manifested in the estimates of technical "inefficiency." Since there is no way to observe what the objective function of the firm is, these sources of inefficiency cannot be separated from other sources.

Imperfect Information

Two commonly cited sources of observed efficiency differences are the rate at which innovations are adopted (Baily 1988; Munnell 1990) and the lag between adoption and efficient use of the technology (Bartel and Lichtenberg, 1987; Kokkelenberg and Nguyen, 1989). Both the rate of adoption and the rate of adjustment vary among firms according to particular firm characteristics, and many of these are related to the way in which economic agents receive, process and interpret information. If information about the production process is perfect and symmetric, plant managers are simultaneously aware of the best practice technology, and are equally able to implement it. When the assumption of perfect and symmetric information is relaxed, a number of sources of technical inefficiency emerge. In particular, information asymmetries affect both the rate at which a new innovation is adopted and the lag between adoption and efficient use of the new technology.

Many models of diffusion describe the adoption decision as a function of optimization over time. An important point to remember about the application of technical efficiency in this context is that the outputs and inputs are compared to production in the present time period. Hence, when resources that are expended in one period and the returns are accrued over time, technical efficiency measures may be misleading. For example, a worker training program is an expenditure of capital and labor that may increase efficiency over a number of production periods. In the period in which resources are expended for training, efficiency will appear artificially low, while efficiency in the later periods will appear artificially high. Investment in capital equipment is generally not subject to this bias, since it is depreciated over a number of years. However, the age of existing capital can influence the decision to delay an adoption (Cabe 1989); furthermore, the time that is required to adjust to new capital equipment may put downward bias on the efficiency estimates.

Information acquisition. Many models of innovation diffusion suggest that communication is an important factor in the process of diffusion (Cabe 1989). For an agent to have knowledge upon which to act, information regarding the innovation must have been received and incorporated into the agent's beliefs. Information about an innovation is communicated in a number of ways, for example, contact with prior adopters, advertisement, or government efforts to communicate the attributes of the innovations (Cabe 1990). The probability of contact with prior adopters increases with the level of interaction an agent has with others in the same business.

Agglomeration economies. Contact with prior adopters is one source of agglomeration economies (Calem and Carlino 1991). A plant located in an area heavily populated by other establishments engaged in the same business has the opportunity to observe and exchange information with prior adopters. Spatial diffusion theories suggest that innovation is adopted in the largest cities first, and then diffuses to smaller cities. Radial diffusion theories also favor early adoption by firms in large cities, since new technologies often are first introduced in large cities where they are developed (Beeson 1987). Once new technologies are developed, the rate at which they are adopted by firms depends on the rate at which knowledge of the technology is diffused through the economy.

Ability to learn. Firms that receive the same information might not derive equal benefit. That is, firms might differ in their ability to process information about an innovation. The information capacity hypothesis (ICH) (Jensen 1982) asserts that a greater capacity or ability to obtain and process information about an innovation should shorten the delay of adoption of a profitable innovation, since the firm learns sooner of the innovation's profitability.

Jensen developed a model to show how the probability of adoption is affected by the acquisition of information. The model shows that the probability of adoption varies directly with the number of favorable signals received by the firm, where favorable signals are bits of information indicating that the innovation would be profitable. The firm's original estimate of the probability that the innovation will be profitable also affects the rate of adoption. This original estimate depends upon the agent's previous experience with similar technology and his attitudes towards risk.

Risk aversion. Risk aversion has been mentioned often as a source of differences in innovation rates (Mansfield 1961). An innovation with the potential to lower costs significantly or to increase price, but with a high fixed cost, might be rejected by risk averse firms while risk neutral or risk loving firms are more likely to adopt the innovation. Furthermore, agents might differ in their prior beliefs about the attributes of an innovation. Even if agents receive similar information about the innovation, these beliefs might not be changed (Cabe, 1989). The ability of information to change beliefs depends upon how reliable the agent view the source of information.

Information cost. Failures in the market for information might lead to differences in the cost of information between firms. As stated earlier, the cost of acquiring information about the existence, effectiveness, and application of a technology can affect the agent's decision to adopt. Factors that might raise the cost of information to a given plant include the firm's organization, the firm's relationship with other firms in the industry, its location relative to other firms, and its access to low cost sources of information such as government extension services.

A theory that allows for heterogeneity in a firm's exposure to new technology, ability to adapt to new technology, attitudes toward risk, and cost of information, is consistent with the idea that technical inefficiency might exist as a result of this heterogeneity. Plants with the greatest exposure to new technology, with the greatest amount of experience with similar technologies, and with more favorable attitudes toward risk are more likely to adopt a technology that is required to achieve technical efficiency.

The Firm as a Group of Individuals

Neoclassical theory assumes that the firm is characterized by a single entrepreneur. Once this assumption is relaxed, the firm can be modeled as a set of contracts between agents. The complexity of contracting models of the firm varies from the simple principal-agent model, associated most often with the work of Holstrom (1979), to the much more complex model of the firm as a nexus of contracts, often associated with Jensen and Meckling (1976). These models have in common the idea that the behavior of the firm is the result of a complex set of decisions among a number of agents with different sets of objectives. Profit maximization, even if it is the objective of the owners, will not always be the end result of the optimizing decisions of this complex group of individuals.

Principal-agent theory. Principal-agent theory diverges from neoclassical microeconomic theory first by dropping the assumption that the firm is a unified agent. Once this assumption is dropped, the assumption that firms maximize profits is an easy target, since the objectives of different agents within the firm diverge.

Principal-agent theory introduces conflicts of interest between different economic actors through the inclusion of asymmetries of information or observability problems (Hart 1990). Most firms are controlled by managers, who usually have more information about the technology and daily operations of the firm than the owners. Owners rarely can observe the input efforts of the manager, and have little control over the actions that managers take. Under these conditions, some authors argue (Leibenstein 1978) that the objectives of the owners are not served by the managers, who have their own priorities. Subject to the incentive structures erected by owners, managers might seek their own objectives such as a minimum amount of slack time, job perks, or maximizing the breadth of his control.

The source of divergence between the objectives of owners and the actions of managers is the asymmetry of information between owners and managers. Managers typically have more information about the production technology than do the owners. Thus, the owners cannot contract based on that technology, and cannot require the manager to produce a specific amount of product from a given set of inputs. Furthermore, the owners cannot observe the degree of effort that the manager expends in production. This information asymmetry might be a source of observed technical efficiency. For example, a manager might lead the owners to believe that the best technology possible can only lead to x amount of output with a specified level of inputs. The manager might know, however, that some greater amount of output is possible, but conceals the truth so that he has slack time, or in order to facilitate side contracts with workers that allow them to shirk.

Information asymmetries might be more prevalent worse in some firms than others. This depends on the structure of the board of directors, for example, and their experience in the production process. It also depends on how actively the board is involved in the operations of the firm. For privately held companies, ownership and control might coincide perfectly. In this case, principal-agent asymmetries of information would not be a source of technical inefficiencies.

In the context of this study, principal-agent problems cannot directly be observed, but they may manifest themselves in technical inefficiency. In light of the above discussion, we expect this to be a problem in larger plants that are part of multi-plant firms. In this case, the management system is fragmented, further removing the profit maximization objectives of the owners from the management of the plant.

Two-tier agency structure. Principal-agent theory operates under the assumption that the firm consists of owners and managers and a "black box" exogenous production function (Hart 1990). The manager's decisions are transformed into output. However, the problems of observability and information asymmetry that plague the owner manager relationship also apply to the manager-worker relationship. Workers' actions can rarely be observed completely, and contracts between firms and workers are incomplete. Much of the theory regarding the two-tier agency structure is related to the subject of hierarchies and their role as provider of information and incentives. Leibenstein (1975) explains that because labor contracts are incomplete, information flowing through hierarchies to clarify the intent of the owners, to evaluate the performance of the worker, and to provide incentives to workers are crucial. Any distortion of these signals can result in a nonoptimal level of output, since the worker will either misinterpret the intent of the owners, or will further his own objectives without the managers' knowledge.

If the effectiveness of information channels within hierarchies differs among firms, then technical efficiency might result. Unless the effectiveness of these hierarchies can be reflected in some obtainable variable and the process modeled, then firms with a more effective information and incentive mechanism may appear technically efficient.

Of course, even if two firms have equally effective information channels between owners, managers, and workers, the incompleteness of contracts leaves them open to interpretation by the contractors. Differences in attitudes toward work and leisure are likely to affect how a worker interprets and executes his responsibilities. Workers do not have homogeneous utility functions with respect to their tradeoffs between effort and slack. Unless these utility functions are somehow included in the firms's objective function, then differences in the general attitude of workers toward work and slack will affect the observed level of technical efficiency.

Relaxing some of the neoclassical assumptions of the theory of the firm results in three general sources of inefficiency: non profit maximizing or cost minimizing behavior, information asymmetry, and conflict between agents within the firm. While many of these characteristics affecting efficiency cannot be observed--for example, objective function, attitudes toward risk, and attitudes toward slack--these characteristics may vary systematically with other, observable characteristics. For example, small, single unit plants might have fewer principal-agent problems, since management and ownership might be more closely in contact. However, cost minimization of profit maximization might not be the correct objective assumption for these plants.

The testability of hypotheses depends to a great extent on what data are available. Because behavior and attitudes cannot be observed, proxy variables must be developed that represent conditions under which these behavior and attitudes are assumed to exist. Hypotheses about the relative efficiency of plants with differences in observable characteristics are developed in the final section of this chapter.

Efficiency and Survival, Growth, and Competitiveness

While many studies have focused on the relationship between industrial structure and efficiency, both allocative and technical, few have examined the causality between industry and efficiency in other direction. The relative efficiency of firms in the short run might affect the structure of the industry as evolutionary forces such as the "creative destruction" process mentioned by Joseph Schumpeter work to move the system toward an equilibrium in which the most efficiency plants capture the largest market share, while the least efficient plants cannot survive.

Efficiency and Survival

What predictions does neoclassical theory hold for the effect of efficiency on the survival of firms? Referring to Figure 2, and abstracting from the issue of optimal size, and assuming all costs are variable, inefficiency implies that for a given level of output Q, the inefficient firm must use a vector of inputs equal to x, while an efficient plant needs only λx. Hence, when input markets are perfect, the inefficient plant's total cost and average cost are both higher by a factor of λ. In a perfectly competitive output market, in which price is equal to average cost, and in which consumers with perfect information buy only from the lowest price producer, the inefficient plant could not continue to operate, since its average cost is in excess of the lowest price of the output.

However, several key assumptions in the above argument might be altered to make room in the market for plants that are not efficient. In fact, inefficient plants might be expected to flourish in several types of environments. Large fixed costs might make a plant appear less productive in the short run, if investment cannot be depreciated over time. Investments in worker training and research and development are prime examples.

Violations of a perfect input market might allow a seemingly inefficient firm to continue operating because it has lower input costs. For example, a plant with a monopsony over the local labor market might face lower labor costs than its competitors. The cost advantage allows the plant to waste some resources and remain competitive. If the cost advantage is large enough, the plant might continue to operate for a long period of time despite its apparent inefficiency.

Similarly, if the output market is not characterized by perfect competition, inefficient producers might be able to retain market share. Product differentiation might encourage consumers to pay a higher price for a product that is perceived as superior. Tacit agreements among producers to charge an artificially high price might allow an inefficient producer to take fewer profits that the other parties to the cartel, allowing him to retain his inefficiency.

The assumption that all costs are variable implies that the efficiency referred to above is strictly short term efficiency. As explained above, firms make decisions considering a multi-period time horizon. Plants that appear inefficient in a given year may have made investments that improve efficiency in the long run.

Finally, it is likely that plants are observed in some condition other than equilibrium. That is, if a plant is inefficient but surviving, it may be working toward sustained efficiency following a shock due to investment or reorganization of production. Similarly, a plant may be in the final stages of life, but still operating, at the time it is observed. While market forces may eventually bring these plants to their steady state of either efficiency or nonexistence, they might be observed at a single point in time before markets have cleared.

Efficiency, Growth, and Competitiveness

Under the assumptions of perfect competition, only efficient plants will survive in equilibrium. Any state in which inefficient plants exist cannot be a stable equilibrium; eventually the inefficient plants will die and the efficient plants will capture their market share. Hence, if inefficient plants exist, it is expected that market forces eventually will drive them out of business, and their market share will be captured by efficient plants.

However, perfect competition has been assumed in this argument. As explained above, plants that appear inefficient might be able to gain market share through price competition, despite inefficiency, because of an input cost advantage. Other plants might gain market share through investments in advertising or product development that lead to product differentiation. Similarly, plants that appear efficient in the short run could be taking a fatalistically short-run view of profits, failing to invest in long-run efficiency. In fact, a common criticism of U.S. manufacturing industries is that the pressure to produce short term profits, brought about by the frenzy of takeover activity, has forced managers to abandon long term strategies (Dertouzos 1989). There is evidence, however, that manufacturing plants that lead productivity in an industry tended to remain more productive than other plants over a long period of time (Baily et al. 1992).

Summary and Hypotheses

Several testable hypotheses for the study follow from the above review of theories of technical efficiency. Three sets of hypotheses are derived: hypotheses relating firm and plant characteristics to efficiency; hypotheses relating efficiency to survival and growth; and hypotheses about the efficiency of the machine tool industry in general, and differences between the metal-cutting and metal-forming machine tool industries.

Sources of Inefficiency

Neoclassical and alternative theories of the firm were invoked to explain why differences between firms might exist and how these might lead to technical inefficiency. Neoclassical theory attributes all inefficiency to measurement error. Hence, any plant characteristic or input that differs between firms but cannot be specified or measured accurately might manifest itself as inefficiency. The alternative views of firm behavior cite deviation from optimizing behavior, information asymmetries, and the conflicts between the agents that comprise the firm as sources of heterogeneity. In this section, each of these theories is cited to develop hypotheses about how efficiency might vary according to observed plant characteristics.

Size

Larger plants are expected to exhibit higher efficiency for a number of reasons. First, large plants are more likely than small, family owned and operated plants to pursue a profit maximization or cost minimization strategy. Second, the owners and managers of large plants are less likely to be averse to risk, since the risk probably involves little personal loss. Furthermore, large firms are likely to have better access to markets that allow hedging to offset risk. Third, large plants are likely to have better developed information networks, and are more likely to generate on-the-floor innovation, simply by virtue of having more workers to develop more efficient production processes. Finally, large plants are more likely to invest in new, expensive technology because they are able to spread large fixed costs over a greater quantity of output and are able to benefit from specialization in production.

However, small plants might have fewer principal-agent problems, promoting the communication of the objectives of the owner to the managers. Their small size is also likely to minimize worker supervision problems. Furthermore, employees may be less likely to shirk if they feel that they have a personal stake in the success of the firm. This is more likely for small, family-owned and -operated firms.

Age and Investment

It is expected that a pattern of efficiency will be observed over the life of a plant in which new plants are inefficient at first, until the initial adjustment to the plant is complete. Beyond the initial adjustment period, the age of the plant itself is much less important than the vintage of the equipment. Hence, investment is likely to be associated with efficiency in a pattern similar to that observed for new plants. The effect of investment on efficiency should be greatest once the adjustment has been made, but before the efficiency advantage has been relinquished to newer technology.

Ownership

Plants that are part of multi-plant firms should exhibit higher efficiency for several reasons. First, multi-plant economies exist due to coordination of production and distribution and economies of scope (Caves 1990). Second, plants that are part of multi-unit firms might acquire information from other divisions of the firm that is not available to single unit plants. Finally, measurement error might artificially inflate efficiency for multi-unit plants, since they often have lower overhead costs because administrative functions are handled by the corporate office.

However, plants that are part of multi-unit plants might have more serious principal-agent problems than single unit plants. Furthermore, since the plant is only one unit of the firm's operation, profit maximization for the firm might not necessarily imply that the plant will be run efficiently. Other firm objectives, such as vertical integration, control over a strategic resource, or the need to attract capital might affect the efficiency of the operations of the plant.

Average Production Worker Wage

Because production labor is measured in hours, it does not reflect differences in worker skill that might be reflected in salaries. Plants with higher average production worker wages should have workers of higher skill and education, if labor markets are efficient. These higher skill workers should contribute to efficiency not only because they can perform established tasks more efficiently, but also because they increase the information available to the firm about technology and production. Finally, higher wage workers may be less likely to shirk since they might enjoy a higher level of job satisfaction.

Metropolitan versus Nonmetropolitan Location

Plants located in metropolitan areas probably will exhibit higher efficiency due to agglomeration economies. Some of the factors that contribute to agglomeration economies include proximity to suppliers and customers, access to a diverse and skilled labor force, and proximity to other producers. Proximity to customers and other producers is especially important because it facilitates the exchange of information regarding the needs of the customers and recent innovations in products and processes.

The advantage of metropolitan location might be reduced if nonmetropolitan plants can find ways to acquire information that do not require proximity to other manufacturing plants, customers, or suppliers. For example, they might form consortia or other associations with other manufacturing plants that replace the informal contact that follows from proximity. Government programs such as industrial extension might be an important catalyst for these associations and consortia. Furthermore, input prices, including land and labor, might be lower in nonmetropolitan areas.

Access to Industrial Extension

Industrial extension services act as a source of inexpensive information for manufacturing plants. While the availability of extension services in a state does not necessarily imply direct intervention by the extension agent in the activities of firms, there are indirect activities performed by extension agents that increase the flow of information to all manufacturing firms in the state. For example, most extension offices circulate a newsletter to all manufacturing plants in their constituency. These activities might serve to correct for market failure in information. Furthermore, extension assistance to one plant might have spillover benefits to other plants that transmit the information by word of mouth and the formal and informal associations mentioned above.

There may be a reverse causation dampening the efficiency effect of access. That is, states in which manufacturing is suffering from severe problems of competitiveness and survival might be more likely to institute extension program sin response to these problems. If some period of time is required between the establishment of the service and the positive benefits of the flow of information, then some states with more recently established extension programs might have less efficient plants, even after the extension service has been established.

Direct Intervention by Extension Agents

A subset of the data is analyzed for the impact of direct intervention by extension agents. The impact of the extension on the efficiency of that plant is expected to be positive; however, self selection bias taints any analysis comparing assisted firms with non-assisted firms. This is because plants that come to the attention of extension service, or those that actively seek extension assistance often are the least efficient plants, in danger of shutting down, and searching for help out of a crisis situation (Clarke and Dobson, 1991).

A comparison of the efficiency of plants before and after assistance is provided is probably the best way to examine the direct effects of assistance while controlling for selectivity bias. In order to perform this analysis, a time series of manufacturing data that spans the period of intervention, as well as the exact dates of intervention, would be needed. Unfortunately, the data available for this study are not detailed enough to allow this level of analysis.

Use of Advanced Technologies

While new investment will reflect the vintage of the capital equipment used in the production process, it will not reflect the level of technology embodied in the equipment. Information on the number of advanced technologies used by a plant is available for a small subset of plants from the 1988 Survey of Manufacturing Technology. It is expected that plants using a larger number of advanced technologies in production will be more efficient. However, this is likely to depend on how extensively the technology is used in production. That is, if the technology is being used primarily for demonstration and training, or has been integrated into only a small portion of the production process, the efficiency impact of the technology will be reduced.

Effects of Inefficiency

Martin Baily et al. (1992) found that one feature of the productivity of manufacturing plants over time was the persistence with which plants on the top remained productive. We expect a similar patter to emerge with respect to the efficiency of plants in the machine tool industry. Efficient plants are likely to survive longer, to remain efficient, and to capture a larger market share than inefficient plants. Exceptions to this might occur in the case of young plants which, while they may be equipped with recent technologies, skilled workers, and knowledgeable managers, are likely to be relatively inefficient until they have adjusted to the production process.

Inter-industry Differences

The two industries that make up the machine tool industry will be examined separately. Although plant, rather than industry, characteristics that affect technical efficiency are the main focus of this study, the characteristics of the industries will be compared, and their implications for efficiency will be examined.

Three factors are likely to contribute to differences in the average efficiency of an industry: competitive conditions, product differentiation, and the rate of technological change (Caves and Barton 1990). An industry with highly competitive input and product markets will force out inefficient firms. However, deviations from perfect competition might allow for firms that appear less efficient.

Demand for machine tools is highly cyclical. Because the industry uses highly skilled labor with skills that are firm-specific, firms often hesitate to fire workers during slack times. Capacity utilization is also highly volatile. This is likely to show up as a fall in efficiency during recessions. These conditions are fairly uniform in both the metal-cutting and metal-forming tool industries.

While the metal-cutting tool firms are the core of the industry, they both are comprised of many small firms, and few large producers exist in the industry. However, the range of customers of metal-forming tools is much more limited. While metal-cutting tools are used by thousands of machine shops and metal product manufacturers, demand for metal-forming tools comes mainly from automobile and appliance manufacturers that use sheet metal in production (Baily and Chakrabarti 1988). Hence, the fate of the industry is strongly tied to the fate of durable goods manufacturing. This could show up in differences in the timing of average efficiency changes.

Policies for Improving Efficiency and Competitiveness

The categories given above for sources of inefficiency can be used to classify recommendations for improving efficiency. For example, policies to improve input quality include worker education and training, which have been given high priority by an number of commissions that have studied the competitiveness issue (Dertouzos, 1989). Improving the quality of the nation's fixed capital stock, both private and public, has also become a high priority for policymakers, including Congress and the mayors of large cities. Policies that improve the flow of information include the encouragement of consortia and the development of industrial extension services. State venture capital programs have tried to ensure that small firms can obtain the capital they need to invest in emerging technologies and remain competitive, and they encourage risk sharing.

This study aims to identify the most important and persistent sources of inefficiency, and thereby suggest policies that may be successful in eliminating sources of inefficiency. While this study focuses on the machine tool industry, patterns of inefficiency in other traditional manufacturing, particularly durable goods manufacturing, are likely to be similar. If the sources of inefficiency in plants can be identified, and if policies to counteract these weaknesses can be constructed, efficiency and competitiveness might be improved in a number of declining industries.

CHAPTER 3. DATA

This analysis of efficiency and factors affecting it employs three plant-level data sets. Production data are derived from the Longitudinal Research Database (LRD), which is a detailed account of the products produced and the inputs used by U.S. manufacturing plants, collected and maintained by the U.S. Census Bureau. Information about the participation of manufacturing plants in technology extension activities was collected from several state manufacturing extension services. Data reporting the technologies used by plants are obtained from the 1988 Survey of Manufacturing Technology, also collected by the U.S. Census Bureau. In this chapter, each data source is described, variables used for the analysis are defined, data editing procedures are explained, and basic statistics for the U.S. machine tool industry are discussed.

The Longitudinal Research Database

Production data are from the Longitudinal Research Database (LRD), created and maintained by the Center for Economic Studies at the U.S. Bureau of the Census. The LRD is a panel data set constructed by linking individual establishment records from the Census of Manufactures (CM), which occurs every five years, and the Annual Survey of Manufactures (ASM). The longitudinal linking of plant-level observations across years makes it possible to monitor the history of a plant's production activities.

Census of Manufactures

The Census of Manufactures is a complete enumeration of all manufacturing plants that had one or more persons employed at any time during the census year. Because the plant is the basic unit of observation, firms that operate more than one plant are required to file separate reports for each plant. Associated with each establishment record is a permanent identification number and location. Both of these items are associated with the establishment from its birth until it permanently ceases operations. The plant-level data include shipments, materials by detailed (seven-digit) product code, inventories, employment, wages, salaries and fringe benefits, energy use, cost of contract work, investment, book value of capital, capital rentals, ownership, and the legal form of organization of the owning firm. Each of the censuses from 1963 to 1987 contains between 300,000 and 350,000 manufacturing plants (U.S. Department of Commerce 1991).

An establishment is classified in a particular industry on the basis of its major activity during the year of record, i.e., production of the products primary to the assigned industry exceeds, in value, production of the products primary to any other single industry. Hence, the disappearance of an establishment from an industry does not necessarily imply that it has ceased operation. Rather, it may have reorganized its production to result in a different industrial classification. All plants classified in either of the machine tool industries at any time during the sample period were examined. Thus, plants that change industries can be distinguished from plants that cease operations. Coverage codes identify establishments that have a change of status from the previous year that affects identifiers for their data on the LRD for the year of reference. For example, plants that change to a non manufacturing industry and plants that are temporarily out of operation are assigned coverage codes to indicate their status.

Not all establishments actually report data to the Census Bureau. Beginning in 1967, the reporting burden for some small establishments was reduced by developing statistics for these establishments from records of the Internal Revenue Service and the Social Security Administration. The administrative statistics obtained from these records include the firm's name and address, payroll, and gross business receipts. Other statistics for these smaller firms are estimated using industry averages in conjunction with the administrative information. The impact of administrative records cases on industry aggregates is slight; they represent less than two percent of total value added in manufacturing (McGuckin and Pascoe 1988). However, when analysis is being conducted on an individual establishment level, as in this case, the existence of imputed data can be troublesome. For this reason, administrative records cases are eliminated from the analysis. The percentage of plants eliminated from the census data for this reason is about 25 percent in 1972 and 50 percent in 1977 and 1982. However, the percentage of shipments represented by the eliminated plants is never greater than 5 percent.

Annual Survey of Manufactures

The Annual Survey of Manufactures is conducted in each of the four years between the censuses. It is administered to a sample of establishments drawn from the universe of establishments in the Census of Manufactures. The sample is selected during the year following each census and is used for data collection for 5 years. After 5 years, a new sample is drawn from the most recent census.

All establishments with more than 250 employees are sampled in the ASM. The probability of inclusion for smaller establishments is proportional to their size. Prior to 1979, company affiliation also played a role in sample selection; that is, if a plant owned by a multi-establishment company was included in the sample, all of the company's other plants were required to report their data, regardless of size. Thus, all firms in the ASM sample for these years were complete in the sense that all their manufacturing establishments were included.

In each of the years following the selection of a panel, some changes were made in the panel to reflect similar changes in the general population. A sample of new plant births, as identified by social security records, was added to the panel, and plant deaths were represented as they occurred. Although these procedures were followed in an effort to maintain the statistical properties of the sample in relation to the general population, it is likely that, over the sample period, the panels became less and less representative of the general population.

Although an annual survey has been taken every year since 1949, the linkage between plants across years and between the Census and the ASM extends back in time only to 1972. The period covered by the data for this study includes four ASM panels: the 1969-1973 panel, the 1974-1978 panel, the 1979-1983 panel, and the 1984-

1988 panel. The procedures for sample selection and panel evolution that were used in the 1969 panel were followed for the 1974 panel. However, in 1979, a new procedure for sample or panel selection and calculation of survey statistics was adopted. In 1984, more changes in the procedure, although relatively minor compared to the revisions of 1979, were incorporated into the procedure.

Changes in sampling procedures and probability weights across ASM panels suggest that if the ASM data are to be partitioned for any reason, the years for a given panel should be kept together. Changes in the number of plants over the sample period then can be interpreted as representing changes in the general population, rather than changes in the sampling procedure. Evidence of changes in the general characteristics of the panels is provide by Tables 3 and 4. The ASM panel for 1974-1978 was based on the 1972 census, and the panel for 1979-1983 was based on the 1977 census. Despite an increase in the number of plants in the census in the metal-cutting machine tool industry, the number of plants in the ASM sample declined from 1978 to 1979. In the metal-forming machine tool industry, the number of ASM plants increased from 1978 to 1979 by 73, even though the number of plants in the census increased by only 44. Clearly, changes in the sampling procedures between panels have affected the makeup of the ASM sample.

Census-ASM Differences

Aside from obvious differences due to the sample selection probabilities for the ASM (i.e., the ASM is skewed toward larger plants, and has no administrative

Table 3. Effects of data editing procedures on sample sizes for industry 3541, metal-cutting machine tools

	Number of Observations					TVS Percent of Full Sample TVS[a]	
Year	Total	Mail Cases	Mail, 20+ Empl.	Final Sample	Panel Sample	Final Sample	Panel Sample
Census Sample							
1972	864	599	264	299	198	93.1	81.6
1977	915	460	297	306	247	94.9	89.8
1982	939	395	288	300	241	94.9	88.2
1987	417	417	232	245	174	90.9	79.2
ASM Sample							
1972	864	202	153	162	151	85.1	84.2
1973	227	227	162	165	160	99.0	98.9
1974	135	167	135	135	133	99.4	99.1
1975	172	172	129	134	134	99.6	99.7
1976	164	164	134	135	135	98.7	99.7
1977	915	160	124	122	122	79.9	80.4
1978	171	171	134	131	126	99.2	99.0
1979	139	139	128	128	131	99.8	99.5
1980	139	139	131	131	136	99.9	99.9
1981	152	152	138	137	127	99.6	99.8
1982	939	155	133	132	115	81.1	79.4
1983	143	143	118	122	131	98.2	95.9
1984	146	146	131	132	127	99.6	99.3
1985	148	148	135	130	95	96.7	96.3
1986	141	141	122	--	--	--	--
1987	417	119	105	107	95	73.6	70.9

[a]TVS = total value of shipments.

Table 4. Effects of data editing procedures on sample sizes for industry 3542, metal-forming machine tools

	Number of Observations					TVS Percent of Full Sample TVS[a]	
Year	Total	Mail Cases	Mail, 20+ Empl.	Final Sample	Panel Sample	Final Sample	Panel Sample
Census Sample							
1972	375	285	160	175	112	95.4	79.6
1977	419	201	158	162	132	93.3	88.5
1982	447	253	156	172	135	92.7	81.5
1987	207	207	120	133	95	93.7	73.8
ASM Sample							
1972	375	120	102	104	102	83.5	82.9
1973	131	131	106	107	104	99.2	98.3
1974	118	118	103	104	103	99.7	99.4
1975	107	107	97	101	101	99.9	99.9
1976	115	115	101	106	103	99.9	99.1
1977	419	100	86	88	87	80.4	80.0
1978	104	104	88	90	89	99.5	99.4
1979	177	177	105	110	107	97.7	93.4
1980	167	167	101	109	108	98.0	97.9
1981	160	160	92	102	102	97.6	97.8
1982	447	115	78	87	84	73.3	72.8
1983	116	116	76	83	79	94.2	93.2
1984	66	66	60	59	59	98.4	98.4
1985	65	65	59	60	60	99.1	99.1
1986	62	62	56	--	--	--	--
1987	207	63	57	57	49	70.0	64.5

[a]TVS = total value of shipments.

records cases), there are other differences between the content and quality of the two data sets that might affect the quality of the estimates derived from them. Data from ASM plants are more detailed with respect to assets; in fact, asset data are imputed from industry averages for all non-ASM plants for all years except 1987.

Imputation

Two important differences between the data from the ASM plants the non-ASM plants are the level of imputation and the imputation method. Aside from the administrative records cases already mentioned, data from the Census of Manufactures tends be particularly subject to imputations. Since the ASM plants are, on the average, larger, and since the plant managers are required to complete a survey every year, their own knowledge of their operations tends to be more detailed and reliable. Furthermore, since ASM plants are surveyed every year, variables that are missing for a particular year are imputed from the same plant's information from the previous year. For non-ASM plants, imputation is based on key industry ratios for the plant's industry and its size. The result of this type of imputation is that much of the heterogeneity in the operations of plants is obscured, particularly with respect to the capital stock.

An examination of plant-level ratios of output to capital stock provides evidence of imputation: ratios that are identical for groups of plants in a given size class. The impact of these imputations on the empirical results is not completely clear. However, in Chapter 5, inconsistencies in the estimates of stochastic frontiers for the two samples imply that the census data obscure plant heterogeneity, resulting in underestimates of technical inefficiencies at the plant level. This problem for the use of census data in efficiency analysis is discussed in more detail in Chapter 5.

Data Editing Procedures

Two samples were developed for each machine tool industry. The first sample included census year observations for 1972, 1977, 1982, and 1987. The second sample consisted of observations for ASM plants from 1972 to 1987. Data for 1986 were not used because serious problems with inconsistency in the capital stock data for that year were discovered.

Tables 3 and 4 show how the data editing process affected the number of observations in each sample for each year. Column 2 in each table shows the total number of observations for the industry and year. In census years, this represents the total population of plants in the industry. In non-census years, it represents the total number of plants in the ASM sample.

The total number of establishments in industries 3541 and 3542 was questionable. The probability that many of these plants were misclassified was brought to the attention of the Census Bureau by the National Machine Tool Builders' Association, which asserted that there was some minimum number of employees required to manufacture machine tools. In 1987, to decrease the number of misclassifications, the Census Bureau reclassified all administrative records cases. All plants classified in industry 3541 or 3542, returned a census form explicitly indicating that it manufactured products in that industry. All administrative records cases were placed in industry 3545 (machine tool accessories) for 1987. The result of this change was that the number of establishments was not strictly comparable between 1987 and earlier years; however, industry aggregates are barely affected (McGuckin and Pascoe 1988).

Despite this adjustment, there still existed a number of very small plants that returned forms indicating 3541 or 3542 as their industry. Based upon the advice of William Brennan, Industry Economist for the National Machine Tool Builders' Association, all plants that never employed more that 20 workers were deleted from the sample. Mr. Brennan suggested that any plant with fewer than 20 employees had probably incorrectly been identified as a machine tool builder, when it actually operated a tool and die shop or manufactured machine tool accessories.

Rather than simply deleting all observations in which total employment fell below 20, plant histories were examined, and cases in which a plant's employment fell below 20 temporarily were identified. These observations were kept in the sample in order to maintain a complete time series of observations on such a plant.

Column four of Tables 3 and 4 lists the number of mail cases with 20 or more employees. The number of observations in each of the final samples is listed in column five. The difference between columns four and column five is due to the number of observations added-back for selected small plants, as described above, the observations removed because they had zero values for input or output variables, and the observations removed because they were outliers. The identification of outliers was based upon the size of several key ratios: capital-labor, output-labor, and materials-output. A plot of the distribution of each ratio for each sample was used to delete observations lying in the extreme ends of very thin tails.

Because some of the econometric procedures applied required panel data, a sample was developed that contained only plants observed at least twice. The number of plants satisfying this criteria in each year in each sample is listed in column six of Tables 3 and 4. The final columns of Tables 3 and 4 indicate what percentage of the total value of shipments the final samples represent. Note that despite the elimination of a number of observations, most of the value of shipments is still accounted for by the plants retained in the sample.

Variable Construction

The inputs and outputs are calculated separately from the LRD for each manufacturing establishment. The LRD data are supplemented by deflators from Gray (1989) and the Bureau of Economic Analysis, and by capital cost measures from the Bureau of Labor Statistics. Table 5 provides a list of the variable abbreviations.

Output

Nominal output, VQ, is defined at the plant level as the total value of shipments, adjusted for changes in inventories of finished goods (FGI) and work-in-process (WIPI), as shown in equation 3.1:

Table 5. Abbreviations for key variables

Variable Name	Description[a]
Q	Real output
M	Real value of materials
VQ	Nominal output
TVS	Total value of shipments
endFGI	Finished goods inventory, end of year
begFGI	Finished goods inventory, beginning of year
endWIPI	Work-in-process inventory, end of year
begWIPI	Work-in-process inventory, beginning of year
APWW	Average production worker wage
PWW	Total production worker wages
PWH	Total production worker hours
NPWW	Total Non-production worker wages
L	Labor (production worker equivalent hours)
K	Capital stock (net, in constant dollars)
GBV	Gross book value of the capital stock
NSTKCON	Net industry capital stock (2 digit), constant dollars
GSTKHIS	Gross industry capital stock (2 digit), historical dollars
BR	Building rent
BRR	Building rental rate (2 digit industry)
MR	Machinery rental
MRR	Machinery rental rate (2 digit industry)

[a]all dollar denominated variables are reported as thousands of dollars; labor is reported as thousands of hours.

$$VQ = TVS + (endFGI - begFGI) + (endWIPI - begWIPI). \quad (3.1)$$

Real output is computed by dividing the nominal output by the industry shipments deflator for the given year. The four digit shipments and materials deflators are described by Gray, 1989. This deflator series only exists through 1986. Deflators for 1987 were developed by calculating the ratio of the Producer Price Index (PPI) for 1987 for the four digit industry to the PPI for 1986 from the Bureau of Labor Statistics. This ratio was then applied to the 1986 Gray deflator.

Labor

Total hours is a more accurate measure of actual labor input than the number of employees; however, because data on the number of hours for nonproduction workers are not available, some estimate must be developed. The Census of Manufactures provides data on the number of production and nonproduction employees, production and nonproduction salaries and wages, and, for production employees, the number of total hours actually worked. Two estimates of nonproduction worker hours were considered. For the first, a 2000 hour work year was assumed for nonproduction employees, and the number of nonproduction workers was multiplied by 2000. An alternative estimate, used by both Lichtenberg and Siegel (1987) and Nguyen and Reznek (1991), measures production worker equivalent hours, assuming that relative wages are proportional to marginal productivity. The average production worker wage rate is the ratio of total production worker wages to total production worker hours. Total plant worker hours then can be estimated as the ratio of total wages for all workers divided by the average production worker wage rate, as shown in equation 3.2.

$$
\begin{aligned}
APWW &= \frac{PWW}{PWH} \\
L &= \frac{PWW + NPWW}{APWW}
\end{aligned}
\tag{3.2}
$$

Two factors motivated a decision to use the average production worker wage rate. First, the number of nonproduction employees is collected on March 12; fluctuations occurring throughout the year are not observed. However, total wages are reported for the entire year, and will reflect these fluctuations. Furthermore, many nonproduction workers may work part-time; assuming a 2000 hour work-year for every worker clearly overestimates some actual contributions.

Materials

Total materials consists of five components: parts and materials, electricity, contract work, resales, and fuels. All materials data are adjusted for inventory, reflecting the actual value of materials used in the production process. To build a materials measure that was comparable over time, the total value of materials was deflated by the materials deflators developed by Gray (1989). This deflator was created by averaging together price deflators for 529 inputs, using as weights the relative size of each industry's purchases of that input in the Census Bureau's input-output tables (Gray 1989). This deflator has not been constructed for 1987. For 1987, a procedure similar to that used for the shipments deflator was used. A weighted average of the change in the PPI for the materials used in each industry was constructed, with weights assigned according to the percentage of total materials that each materials category represented. This weighted average was applied to the 1986 Gray materials deflator.

Capital

Capital services are measured ideally as machine hours per year, with adjustments for the vintage of machinery and the intensity of its use. For most practical applications, the common practice is to use the perpetual inventory method to deflate the value of the gross capital stock, and then to adjust this by a utilization rate (Usher 1980). In this study, capital input is the plant's net stock of capital in constant dollars, which is estimated by the same algorithm used by Lichtenburg and Siegel (1987):

$$K_{i,j,t} = GBV_{it} * \left(\frac{NSTKCON_{j,t}}{GSTKHIS_{j,t}}\right) + \left(\frac{BR}{BRR}\right) + \left(\frac{MR}{MRR}\right) \tag{3.3}$$

where i represents the plant, j represents the industry, and t represents the year. GBV is the gross book value of the capital stock as given on the LRD. GSTKHIS is the gross stock of industry assets for the two-digit industry, valued on a historical basis; NSTKCON is the net capital stock of the two-digit industry, valued in constant

(1982) dollars. Both of these are obtained from the Bureau of Economic Analysis. Applying the adjustment ratio converts the gross, current dollar measure of capital, GBV, to a net of depreciation, constant dollar measure that approximates a perpetual inventory measure of the capital stock, with the proviso that the adjustment for depreciation is taken at the two-digit industry level, rather than on an individual plant basis. Additions to the capital stock due to building and machinery rental are constructed by dividing the rental expenditure from the LRD by the building and machinery rental rates from the BLS.

This measure of capital input clearly is imperfect and several problems are worth noting. First, the combination of machinery and buildings into one capital input measure implies that they are homogenous factors; arguments against this undoubtedly have merit. Second, no adjustment is made for vintage or intensity of use. Finally, the adjustment for depreciation is the same for all plants in a given two digit industry.

Unfortunately, these problems are unavoidable, given the constraints on the data and the desired sample. Separate data for equipment and structures are available only for plants that are in the ASM sample; individual plant capacity or intensity of use measures are virtually unobtainable. Perpetual inventory methods of capital measurement are available only for firms in the ASM sample that are observed continually from 1972 to 1987. This would severely limit the data on small establishments.

Concerns about the capital measurement problem are mitigated somewhat by studies suggesting that gross capital stock may be a reasonable proxy for real capital input. Doms (1992) has estimated capital efficiency schedules by inserting a parameterized investment stream for a capital variable in the production function. This specification allows the data to dictate the rate at which the capital depreciates. Estimation of the production function together with the capital efficiency schedule was compared to a baseline case in which the capital variable was constructed with economic depreciation rates similar to those used for this analysis. The results for Cobb-Douglas technology indicated that the estimated geometric rate of deterioration of the capital stock was nearly identical to the baseline case. Other functional forms for the efficiency schedule, i.e., Box Cox and polynomial models, nearly replicated the geometric results.

The results from Doms (1992) did not include an adjustment for capacity utilizations, but an attempt was made to assess the impact of capacity utilization on the efficiency schedules and the parameters of the estimated production function. Plant specific capacity utilization rates are not available from public sources, but Doms obtained private estimates of capacity for the raw steel industry. The collection of capacity utilization for the raw steel industry was facilitated by the small number of plants in the industry. Doms constructed capacity utilization by dividing these capacity estimates by the actual output for each plant. When this measure was included in models to estimate efficiency schedules, the output elasticity of capital increased, but the parameters for the efficiency schedules remained unchanged. Failure to include capacity utilization in the measurement of capital is likely to bias the output elasticity of capital downward.

However, the seriousness of this limitation depends on how efficiency is viewed. Given that capital is a fixed factor of production, and given that capital located in a machine tool plant cannot be reallocated to other uses when it is not in service in the short run, the estimates of technical efficiency resulting from a specification that does not adjust for capacity utilization includes this "waste" of productive resources. This waste is likely to be overestimated, since buildings and machinery depreciate more slowly when they are not used. When interpreting the results of the technical efficiency measures, it is important to recognize that they include effects of allowing resources to be idle.

Basic Industry Statistics

Tables 6 and 7 show the average values for the input and output data used for the analysis of the machine tool industry. As expected, the average size of a plant is higher in the ASM sample than in the census sample for both industries. Plants in metal-cutting machine tools are, on the average, larger than plants in metal-forming machine tools.

The cyclical nature of the industry is apparent from the rise and fall of the real value of output, which reached a trough in 1983. Both labor hours and materials rose and fell fairly consistently with output. The real value of the capital stock, however, rose through 1983. This reflects the continuation of increases in investment in new machinery that began in the industry in the late 1970s (March 1989).

Table 6. Average values of variables for production function estimation by year for metal-cutting machine tools

Year	Plants	Output	Labor	Materials	Capital
Census Sample					
1972	299	4,406	366	1,583	4,973
1977	305	5,274	411	1,942	4,992
1982	299	4,416	369	1,962	6,264
1987	245	3,322	273	1,660	5,135
ASM Sample					
1972	164	7,341	598	2,638	8,463
1973	171	9,332	706	3,561	8,072
1974	137	12,192	924	4,821	9,781
1975	136	10,732	813	4,404	10,103
1976	137	9,347	770	3,352	10,095
1977	127	10,739	819	3,972	10,246
1978	134	11,400	840	4,683	9,779
1979	128	13,083	970	5,569	11,087
1980	131	12,904	987	5,703	11,567
1981	141	11,961	897	5,172	11,577
1982	133	8,425	684	3,701	12,906
1983	122	5,306	514	2,384	12,244
1984	135	6,150	518	2,879	10,713
1985	133	6,275	519	2,945	10,487
1987	105	6,232	506	2,996	9,977

Table 7. Average values of variables for production function estimation by year for metal-forming machine tools

Year	Plants	Output	Labor	Materials	Capital
Census Sample					
1972	175	3,747	303	1,491	4131
1977	162	3,725	316	1,536	4048
1982	172	2,231	222	1,172	4359
1987	133	2,856	220	1,428	3946
ASM Sample					
1972	104	5,490	444	2,218	6283
1973	107	6,980	519	2,733	6338
1974	104	7,256	537	3,137	6333
1975	101	5,825	465	2,525	6246
1976	106	4,664	375	2,042	5437
1977	88	5,917	488	2,517	6470
1978	90	6,014	497	2,747	6299
1979	110	5,261	424	2,518	5655
1980	109	4,693	405	2,333	5834
1981	102	4,105	370	2,000	7326
1982	87	3,469	335	1,827	5840
1983	87	2,677	249	1,339	7520
1984	59	4,455	368	2,205	8055
1985	60	5,279	414	2,417	7025
1987	57	4,955	372	2,391	7025

The U.S. machine tool industry response to cyclicality has had an important impact on competitiveness. Typically, U.S. machine tool builders allowed backlogs of orders to accumulate during busy times and worked off the backlog during slow times. While this strategy was effective for smoothing the cycle before the onset of foreign competition, the boom of the late 1970s was met with a significant rise in imports which did not diminish once the U.S. industry had worked off its backlog. Japanese suppliers were able to capture a share of the U.S. market, at first by filling orders more quickly, and then by continuing to impress customers with improving quality (March 1989).

Tables 8 and 9 provide traditional simple productivity statistics, averaged by year. Output per labor hour remained fairly stable throughout the period. This reflects the ability to spread orders over time, and to some extent, to layoff workers to adjust for changes in demand. Note, however, that in 1983, output per labor hour fell to a minimum, reflecting the resistance of the machine tool firms to lay off workers with specific skills that were not easily replaced. Output per labor hour recovered strongly in 1984 in both industries.

The time trend of capital per labor hour reflects not only the rise in the capital stock over the period, but also the problem of capacity utilization. The traditional idea that increasing the amount of capital for a fixed amount of labor will increase productivity cannot hold if that capital is idle. This point is underscored by the trend in output per unit of capital. Clearly, the existing capital stock was not declining in productivity, but was not being used to full capacity.

Table 8. Basic productivity statistics by year for metal-cutting machine tools

Year	Output/ labor hour	Capital/ Labor hour	Output/ Capital	Total Factor Productivity
Census Sample				
1972	12.26	11.43	1.28	0.116*
1977	12.46	11.12	1.22	0.107*
1982	11.86	13.44	1.08	-0.080*
1987	11.72	16.31	0.95	-0.180*
ASM Sample				
1972	13.71	13.23	1.41	0.090*
1973	14.95	10.94	1.76	0.132*
1974	15.35	9.94	1.95	0.111*
1975	13.95	11.62	1.49	0.030
1976	13.58	12.37	1.36	0.057*
1977	15.74	12.94	1.39	0.101*
1978	13.96	10.56	1.69	0.047*
1979	14.00	11.02	1.52	0.021
1980	13.27	10.97	1.41	-0.036
1981	13.69	13.20	1.33	-0.040
1982	13.08	18.92	0.87	-0.086*
1983	11.74	23.15	0.65	-0.147*
1984	14.35	19.63	1.03	-0.092*
1985	13.90	19.05	0.96	-0.122*
1987	12.71	19.32	0.89	-0.169*

* indicates that the mean of total factor productivity is significantly different from zero.

Table 9. Basic productivity statistics by year for metal-forming machine tools

Year	Output/ labor hour	Capital/ Labor hour	Output/ Capital	Total Factor Productivity
Census Sample				
1972	12.90	12.52	3.10	0.196*
1977	11.66	12.73	1.15	0.040
1982	9.29	15.54	1.07	-0.187*
1987	12.09	16.74	0.94	-0.065*
ASM Sample				
1972	13.32	13.79	1.18	0.116
1973	14.65	11.92	1.54	0.196
1974	14.54	11.68	1.57	0.171
1975	12.42	13.25	1.23	0.067
1976	13.04	14.09	1.21	0.074
1977	12.47	14.00	1.19	0.039
1978	12.18	13.06	1.20	-0.007
1979	11.78	11.54	1.30	-0.018
1980	10.39	12.03	1.10	-0.142
1981	9.98	12.89	1.06	-0.157
1982	10.26	19.31	1.27	-0.186
1983	9.82	21.73	0.65	-0.182
1984	12.35	18.69	0.91	-0.053
1985	13.42	18.35	0.93	-0.007
1987	14.38	19.83	1.06	0.003

* indicates that the mean of total factor productivity is significantly different from zero.

Total factor productivity (TFP) was calculated simply as the average of the residuals from estimation of a traditional three factor Cobb-Douglas production function. These averages are a measure of the productivity of plants in each year relative to the average (Lichtenburg and Siegel, 1987). That is, the expectation of the residuals for all observations is equal to zero, and deviations from zero represent productivity above or below the average for all observations.

Figures 4 and 5 provide a visual representation of the productivity measures in Tables 8 and 9. Total factor productivity was been multiplied by 100, and output per dollar of capital was been multiplied by 10, so that the statistics could be displayed on a single plot.

Despite a fairy steady trend for both labor and capital productivity in industry 3541, TFP trended downward from 1977 to 1987. The short recovery following the 1982-83 recession probably reflected the shutdown of low-productivity plants as the industry adjusted to a lower market share. Despite this adjustment, TFP resumed its decline after 1984. Apparently, these fluctuations in TFP were not due solely to cyclical factors.

In industry 3542, the post-recession TFP recovered rapidly and continued to rise through 1987. The sharp rise between 1983 and 1984 reflected downsizing of the capital stock, as well as increased orders. The strong recovery of TFP relative to industry 3541 occurred despite very modest improvements in labor productivity and a decline in capital productivity.

The aggregate productivity measures plotted in Figures 4 and 5 fail to provide

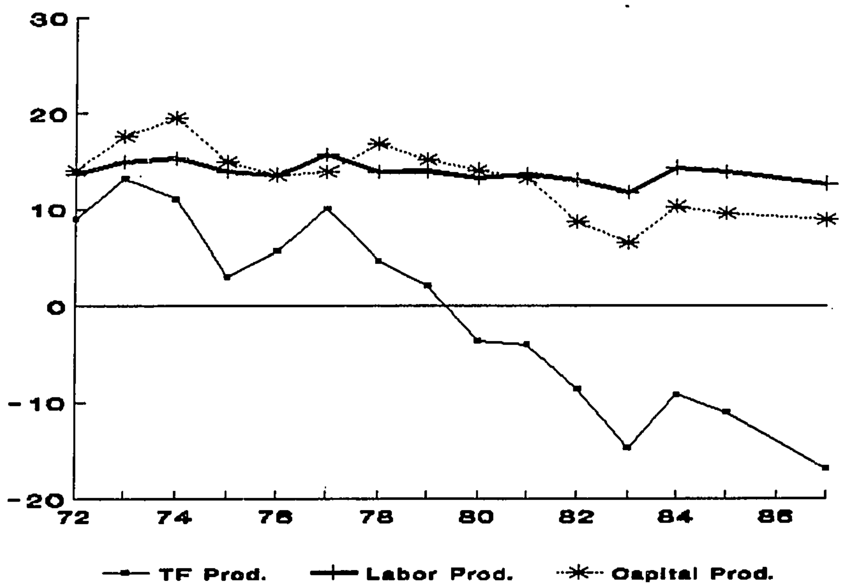

Figure 4. Traditional productivity measures for metal-cutting machine tools

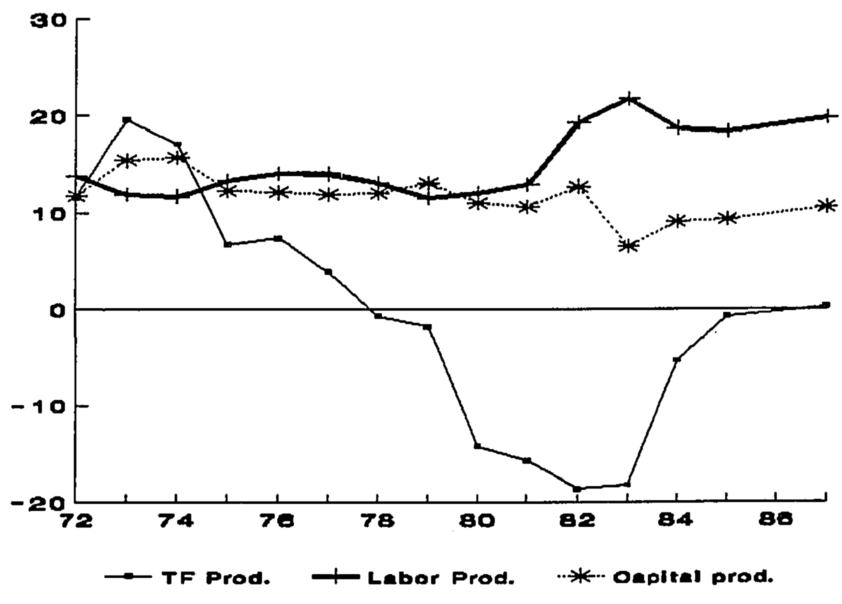

Figure 5. Traditional productivity measures for metal-forming machine tools

important information about the structure of changes in TFP. Declines occur despite steady labor and factor productivity. Has there been some essential change in production technology that has decreased labor's marginal product? Furthermore, do changes in TFP reflect changes in the composition of the industry between high- and low-productivity plants or changes that affect all plants equally? These questions can only be addressed by a plant-level decomposition of changes in technology and changes in efficiency.

Tables 10 and 11 provide traditional productivity statistics for plants by several attributes. Metropolitan plants are located in a Census-designated standard metropolitan statistical area (SMSA). Multi-unit plants are owned by firms that operate more than one plant. Large plants have total employment greater or equal to the median for that industry and year. High wage plants have higher average production worker wages than the median for that industry and year.

Labor productivity is not always correlated with total factor productivity. These divisions raise questions relevant to the problem of productivity improvement. For example, if agglomeration economies contribute to productivity in the machine tool industry, then metropolitan plants might be more productive. If multi-plant firms benefit from economies of scope and plant specialization, then plants that are part of multi-unit firms might be more efficient. Wages might proxy for the level of worker skill; this would result in higher production for high-wage plants. For example, large plants in the industry 3541 ASM sample have higher TFP but lower labor productivity.

Table 10. Average plant productivity by selected plant attributes for metal-cutting machine tools

Attribute	Plants	Output	Output/ Labor Hour	Capital/ Labor Hour	Output/ Capital	Total Factor Productivity
Census Sample						
Metropolitan	973	4,344	12.27	12.95	1.15	0.002
Non-metropolitan	175	4,764	11.13	12.71	1.09	-0.013
Single unit	623	1,405	10.56	10.92	1.13	-0.013
Multi-unit	525	7,971	13.92	15.27	1.16	0.016
Large	578	8,010	12.64	14.11	1.100	0.004
Small	570	755	11.54	11.71	1.18	-0.004
High Wage	576	6,163	14.34	10.90	1.16	0.006*
Low Wage	572	2,640	9.84	14.91	1.13	-0.006*
ASM Sample						
Metropolitan	1,721	9,219	14.16	14.27	1.36	-0.000
Non-Metropolitan	311	10,830	12.49	14.20	1.20	0.001
Single-Unit	555	3,003	11.51	12.20	1.32	-0.025
Multi-Unit	1,477	11,893	14.81	15.03	1.34	0.009
Large	1,023	16,811	13.61	15.04	1.16	0.004
Small	1,009	2,017	14.21	13.46	1.51	-0.004
High Wage	1,020	12,483	16.43	15.87	1.38	0.077*
Low Wage	1,012	6,423	11.36	12.63	1.29	-0.077

* denotes statistical significance at $\alpha = .05$.

Table 11. Average plant productivity by selected plant attributes for metal-forming machine tools

Attribute	Plants	Output	Output/ Labor Hour	Capital/ Labor Hour	Output/ Capital	Total Factor Productivity
Census Sample						
Metropolitan	518	3,164	11.66	14.47	1.73	0.018
Non-metropolitan	124	3,096	10.61	13.20	1.13	-0.075
Single unit	313	1,397	10.46	12.39	1.05	-0.002
Multi-unit	329	4,820	12.40	15.97	2.14	0.002
Large	322	5,559	12.09	15.35	2.20	0.010
Small	320	728	10.81	13.09	1.03	-0.010
High Wage	323	4,027	13.03	16.44	2.03	0.068*
Low Wage	319	2,263	9.86	11.98	1.20	-0.069*
ASM Sample						
Metropolitan	1,127	5,181	12.40	14.69	1.21	0.010
Non-metropolitan	240	5,307	11.73	11.73	1.10	-0.046
Single unit	425	2,134	10.98	12.45	1.24	-0.030
Multi-unit	942	6,587	12.87	15.48	1.16	0.014
Large	688	8,960	12.53	15.06	1.04	0.005
Small	679	1,395	12.03	14.01	1.34	-0.005
High Wage	687	7,138	13.69	16.85	1.05	0.049*
Low Wage	680	3,248	10.86	12.21	1.32	-0.049

* denotes statistical significance at $\alpha = .05$.

Metropolitan plants typically have higher averages for labor and capital productivity, and a higher capital-labor ratio. However, differences in TFP are not significant. Either agglomeration economies are not important to productivity in the machine tool industry, or total factor productivity is too blunt a measure to reveal these differences.

A limitation of total factor productivity as a measure of productive efficiency is that it cannot show how changes in overall productivity can be decomposed into changes in the technology and changes in relative efficiency. For example, consider the change in TFP from 1977 to 1982 in industry 3541. Several process likely contributed to the fall in total factor productivity during this period. First, as old capital equipment was replaced, the technology in the manufacture of machine tools advanced. However, because of problems with capital utilization, the total factor productivity did not reflect this shift in the production frontier technology. Technical efficiency measurement allows observation of the technology of the most efficiency plants--those that have modernized and have the greatest rate of capacity utilization--and measures the remainder of the plants against this standard, rather than against the average for the entire industry.

A reexamination of the relative efficiency of plants with different attributes, based on technical efficiency rather than total factor productivity, will reflect this difference in the methodologies and permit associated interpretations. In Chapter 7, changes in efficiency are decomposed into changes in technology and improvements in the efficiency of individual plants relative to a fixed standard.

Industrial Extension Participation Data

The industrial extension services of Iowa, North Carolina, and Michigan provided names, addresses, and other identifying information for companies that had been provided with direct intervention from the extension service. These names and addresses were matched against the name and address file of the Longitudinal Research Database, which provides the permanent plant number, the record for linking the plant longitudinally over time. The matching process is imperfect; changes in name and other problems sometimes make a plant impossible to identify. Twenty seven plants was identified as industrial extension clients. With observations over a number of years, the total number of client observations was 39 in industry 3541 and 17 in industry 3542. The total number of machine tool manufacturers in these states is 305 in industry 3541 and 106 in 3542. The majority of these plants is located in Michigan. The impact of this direct intervention on the efficiency of these plants can be assessed using data from the three states. Details on the results of the analysis are provided in Chapter 7.

Only a small number of states provided data on the direct intervention of industrial extension (all industrial extension services that have operated since 1980 were approached; those from Iowa, North Carolina, and Michigan were the only three that were both willing and able to provide plant level data). Therefore, a proxy variable was developed for use with the full data set to take advantage of the richness of the national data set, and to augment the assessment of industrial extension that is based only on data from three states. A plant is classified as having access to industrial extension if there is an industrial extension service operating in the state in the given year. The data for each state are taken from Table 1 in Chapter 1.

This environmental variable, while admittedly a poor proxy for actual extension service intervention, does control for activities of the extension services aside from direct intervention. For example, many extension services circulate newsletters, perform demonstrations, and hold workshops and seminars (Clarke and Dobson 1991). While most of these would not be considered direct interventions, they may contribute to the flow of information about technologies in the industry. Considering the importance of information in technology adoption and adjustment, and considering the number of states with extension programs for which data could not be obtained, the use of this proxy variable was a second best solution.

Technology Adoption Data

Technology usage data are extracted from the 1988 Survey of Manufacturing Technology (SMT). The SMT provides data from approximately 10,000 manufacturing establishments about the use of 17 individual "advanced technologies." These technologies are general innovations primarily used in the design and production of manufactured products. The 17 technologies can be classified into five broad technology groups including design and engineering, fabrication/machining and assembly, automatic material handling, automated sensors, and communication and control. These data are merged with the LRD to develop a single data set containing both production and technology information. This data set is used to examine patterns of technology adoption in the industry and to assess the impact of these technologies on technical efficiency. Chapter 7 provides detail about the specific technologies listed on the survey.

Since only 62 of the machine tool plants in either the census or ASM samples were sampled in this survey, the methods for calculating technical efficiency scores were adapted to fit the small number of observations, as explained in Chapter 7.

CHAPTER 4. ESTIMATION

Measurement of efficiency in production has been the subject of many methodological and empirical studies, for example, Farrell (1957), Färe, et al. (1985), Schmidt and Sickles (1984), and Caves and Barton (1990). A rich alternative of models and methods have been developed for measuring the efficiency of decision making units. For empirical analysis of efficiency measurement, choices in developing the associated model and estimation procedures must be made. These choices should reflect the details of the application, the available data, and the objectives of the analysis. This chapter will discuss these choices in reference to the particular application and data used for the machine tool industry.

The chapter opens with a discussion of issues relevant to the choice between parametric and nonparametric analysis of technical efficiency. The cross section stochastic frontier model is then discussed, along with the implications of the necessary assumptions, and early variations of the basic model. Panel data models are explored as a way of relaxing the assumption necessary for the cross section model. The chapter concludes with a summary and plan for applying the methodologies discussed.

Parametric and Nonparametric Analysis

Determining the position of the frontier technology is the major point of controversy surrounding technical efficiency measurement. In his first analysis of technical efficiency measurement (1957), Farrell acknowledged that few production relationships are simple enough to be represented by a theoretical engineering function. Rejecting this approach to finding the best-practice technology, he suggested instead the construction of the frontier from observed data. Since that time, two competing methodologies for measuring efficiency have emerged: those utilizing linear programming techniques (the nonparametric approach) and identified with the work of Färe and his colleagues (1985), and those emphasizing econometric estimation (the parametric approach) and identified with the work of Aigner, Lovell, and Schmidt (1977).

Nonparametric Approach

Linear programming techniques for measuring technical efficiency were first proposed by Farrell (1957) and have been further developed by Charnes, Cooper, and Rhodes (1978), and by Färe, Grosskopf and Lovell (1985). Often referred to as data envelopment analysis (DEA), this method constructs the frontier by finding a piecewise-linear, convex, weak-disposal hull that "envelops" the sample data; it is the smallest set that includes all of the observations in the sample and satisfies the properties of any well-behaved input set. In terms of the notation of the Chapter 2, technical efficiency is calculated in two steps; first, by constructing L(u) as described above, and second, by solving the associated programming problem:

$$F(x,u) = \min\{\lambda : \lambda x \in Isoq\ L(u)\}. \qquad (4.1)$$

Details on the formulation of the linear programming problem can be found in Lovell and Schmidt (1987).

Proponents of the nonparametric approach argue that since no a priori assumptions are imposed on the form of the production function, the distribution of technical efficiency, or the correlation between efficiency and inputs, this method comes closer to defining the true frontier than parametric methods that require such assumptions. Furthermore, nonparametric analysis is possible even if few observations are available, whereas parametric approaches require large sample sizes (Lovell and Schmidt 1987).

However, there are at least two major drawbacks to the linear programming approach to technical efficiency measurement. First, the frontier is deterministic; hence no allowance is made for variations from the convex hull for reasons other than efficiency, such as random external shocks, measurement error, omitted variables, etc. The constructed frontier is very sensitive to outliers in the sample data. Furthermore, since the frontier and efficiency measures are computed rather than estimated, no standard errors are produced and there is no way to make reliability statements about the shape and placement of the frontier or the consistency of the estimators of technical efficiency. However, some progress has recently been made toward providing goodness of fit statistics for optimizing models such as DEA (Varian 1990).

Parametric Approach

Early attempts to develop an econometric interpretation of Farrell's propositions include the Aigner and Chu (1968) deterministic frontier model. They suggested a Cobb-Douglas kernel with a technical efficiency term that entered multiplicatively:

$$\begin{aligned} Q_i &= AX_{1i}^{\beta_1}X_{2i}^{\beta_2}U_i, \\ &= Q_i^{*}U_i. \end{aligned} \tag{4.2}$$

where U_i is a random disturbance between 0 and 1. Taking logs,

$$\begin{aligned} y_i &= \alpha + \beta_1 x_{1i} + \beta_2 x_{2i} + \epsilon_i, \\ &= \alpha + \beta_1 x_{1i} + \beta_2 x_{2i} - u_i. \end{aligned} \tag{4.3}$$

where y_i is the log of output, $\alpha = \ln A$, $x_{ki} = \ln(X_{ki})$, and $\epsilon_i \equiv -u_i \equiv \ln U_i$; u_i is a non-negative random variable. The "kernel" on the right hand side is deterministic; the error term is attributed entirely to inefficiency. In keeping with the Farrell framework defined earlier, technical efficiency, U, is the ratio $Q_i/Q_i^{*} = U_i \equiv \exp\{-u_i\}$.

The stochastic frontier, proposed independently by Aigner, Lovell, and Schmidt (1977), Meeusen and van den Broeck (1977) and Battese and Corra (1977), emerged as a response to criticism of existing methods that attributed all deviations from the frontier to technical inefficiency. These criticisms fall under two headings. First, production itself, even if planned efficiently ex ante, is subject to random influences that are not under the control of the producer. These random events such as equipment failures, weather, the quality of inputs, etc. should not be attributed to inefficiency. Second, errors in variable measurement, associated with technical inefficiency in a nonparametric or deterministic frontier framework, should not be counted as inefficiency. In order to separate the random components of deviation from the frontier from inefficiency, a two part composed error term was proposed. In keeping with the notation used above, consider a generalized single equation production function model:

$$\begin{aligned} Y_i &= F(X_i;\beta) + \exp(\epsilon_i), \\ \epsilon_i &= v_i - u_i. \end{aligned} \tag{4.4}$$

The first part of the composed error term, v_i, represents statistical noise, and is generally assumed to be normally distributed. The second part of the error, u_i, represents inefficiency, and was originally assumed to follow a particular one sided (positive) distribution. Recent developments allow these assumptions about distribution to be avoided and tested (and are discussed below).

The parametric approach to finding the production frontier is intuitively appealing due to its allowance for the stochastic nature of production. This is the main benefit of the stochastic frontier method: deviations from the frontier are attributed to technical inefficiency only after random noise and measurement error are appropriately and systematically reflected.

However, this benefit of the parametric method does have a cost. A number of restrictive assumptions are required for stochastic frontier estimation: a functional form for the production function, an assumption on the distributions of both portions of the composed error term, and the assumption that the regressors (X_i) and inefficiency are not correlated. While assumptions on distribution of the error terms and orthogonality may be relaxed if panel data are available, the estimates still hinge on the assumed functional form, and how closely it approximates the underlying technology.

Choice of Technique

To summarize, the choice between parametric and nonparametric analysis of technical efficiency rests on a number of factors. The quality and quantity of data available are an important consideration. Data with significant noise or subject to excessive measurement error are not well suited to data envelopment analysis. If few data points are available, stochastic frontier estimation will have more limited properties. The availability of panel data adds to the appeal of stochastic frontier estimation, since some of the restrictive assumptions are avoidable. These include the error distribution assumption and the orthogonality assumption. Finally, the objectives of the analysis should be considered. If estimates of output elasticities of elasticities of substitution are required, parametric methods must be used.

The comparative accuracy and usefulness of the two methods is an empirical question. Several studies have contrasted the methods (e.g., Gong and Sickles 1991, and Sickles and Streitwieser 1991), and one conclusion is common to all -- the reliability of the efficiency estimates from a stochastic frontier model hinges on the ability of the chosen functional form to approximate the underlying technology. Several functional forms should be tested for fit when the stochastic frontier method is employed.

A number of factors are supportive of the stochastic frontier approach for this analysis of the machine tool industry. First, panel data are available, and the number of observations for each industry is relatively large, as shown in Tables 3 and 4 in Chapter 3. Second, the Census of Manufactures and Annual Survey of Manufactures data are quite likely to contain measurement errors due to imputation, transcription error, and error by respondents. The stochastic frontier methodology is more likely to screen out the errors. Finally, the data construction approaches imply variations with concept and reality that are likely to introduce other sources of measurement error.

The Basic Stochastic Frontier Model

Several refinements of the stochastic frontier production function model in the preceding section have more recently appeared in the econometric literature. These innovations in modeling can be classified by the type of data used to estimate them: cross section or panel data. The original models were formulated for cross section data; applications to panel data are more recent. In this section, the original model and estimation methods applicable to cross section data are reviewed.

The Original Model

Aigner, Lovell and Schmidt (1977) began with the basic stochastic frontier production function model:

$$\begin{aligned} Y_i &= F(X_i;\beta)\exp(\epsilon_i), \\ \epsilon_i &= v_i - u_i, \\ TE &= \exp(-u_i). \end{aligned} \tag{4.5}$$

where Y_i and X_i are in levels. The multiplicative error term, $\exp(\epsilon)$, is composed of v_i, the log of random deviations from the stochastic frontier, and $-u_i$, the log of technical efficiency. The range of v_i is not restricted, but u_i is restricted to be greater than or equal to zero. Hence, technical efficiency has a range defined as $TE \in (0,1]$. A score of one indicates that the production unit is on the frontier; as technical efficiency approaches zero, u_i becomes large, diminishing production.

Aigner, Lovell, and Schmidt used maximum likelihood estimation (MLE), with the following assumptions on the distribution of each element of the disturbance term, and the correlation between the regressors and the disturbance:

$$\begin{aligned} v_i &\sim N(0,\sigma_v^2), \\ u_i &\sim |N(0,\sigma_u^2)|, \\ E(X_i\epsilon_i) &= 0. \end{aligned} \tag{4.6}$$

u_i has a normal distribution truncated at zero from below. The log likelihood function was derived for this set of assumptions, producing estimates for ß, the ϵ_i, and ρ (the ratio of $\sigma^2{}_v$ to $\sigma^2{}_u$).

The slope parameters can be estimated consistently using ordinary least squares (OLS), although these estimates are inefficient compared to the maximum likelihood estimates (Greene 1992). However, since the expectation of the composed error term is less than zero, the intercept cannot be estimated consistently with OLS. As demonstrated by Greene (1980), the moment equations of the residuals can be used to correct the constant term and derive estimates of the variance components.

Because the residual $\ln Y_i$ - $\ln F(X_i;\beta)$ estimates ϵ_i, not u_i, the firm level efficiency estimates must be determined indirectly. Under the assumptions set out in the basic model, Jondrow and his colleagues (1982) derived an explicit form for the conditional expectation of u_i, given ϵ_i:

$$\hat{u}_i = E(u_i|\epsilon_i) = \frac{\sigma_u^2\sigma_v^2}{\sigma^2}\left[\frac{\phi(\epsilon\rho/\sigma)}{1 - \Phi(\epsilon\rho/\sigma)} - \left(\frac{\epsilon\rho}{\sigma}\right)\right], \tag{4.7}$$

where ϕ (.) is the standard cumulative normal density function and Φ(.) is the standard normal distribution function. This estimate of u is unbiased, but is not consistent. While the estimate of the entire residual, v_i - u_i is consistent, the variance of $\hat{u}_i$ alone remains nonzero regardless of the number of observations. No improvement has been made on this measure in the context of a cross section single equation framework.

Within the limits imposed by cross section data, most variations of the basic model have modified the distribution of the one sided component of the disturbance; models assuming exponential, gamma, and truncated normal distributions with means other than zero have been developed. Greene (1992) provides a review of these variations, specifying the log likelihood functions as well as the moment equations and intercept corrections for corrected least squares. Kopp and Mullahy (1990) explore the generalized method of moments technique for frontier estimation which requires fewer distribution assumptions. However, this method does not produce definable estimates of u_i, and so is not considered a viable alternative for the estimation of technical efficiency.

Panel Data Models

Several deficiencies of the basic stochastic frontier model have been noted: first, that the estimate of u_i is not consistent; and second, that strong assumptions on the distribution of the error terms and correlation between the errors and the regressors are required. Schmidt and Sickles (1984) have shown that if panel data are available, consistent estimates of u_i can be obtained that do not depend on the distribution or correlation assumptions required for the cross section model. In this section, two types of panel data models and estimators of technical efficiency are described: those assuming technical efficiency is constant over time, and those allowing technical efficiency to vary over time.

Assuming N firms are observed over T periods, the panel data model can be written:

$$Y_{it} = F(X_{it};\beta)\exp(v_{it} - u_{it})$$
$$i = 1,2,...,N \tag{4.8}$$
$$t = 1,2,...,T$$

The model can be restricted by the assumption that $u_{it} = u_i$; that is, while technical efficiency is specific to each firm, it does not vary over time. Assuming that the u_i are random variables, the model can be estimated by the method of maximum likelihood or feasible generalized least squares (FGLS). If the u_i are treated as firm specific constants, rather than random variables, then a fixed effects model is used, and a least squares dummy variable (LSDV) estimator is employed. The instrumental variables method of Hausman and Taylor (1981) can be used when technical efficiency is treated as a firm-specific constant, but other firm-specific effects appear in the model as well.

If the assumption that $u_{it} = u_i$ is not feasible, then additional parameters can be specified that allow technical efficiency to vary over time in a particular way; these parameters can be added to the specification for any of the four aforementioned estimators. Allowing for variations in efficiency over time provides a method for analyzing changes in relative efficiency when the frontier technology has remained constant.

Time Invariant Technical Efficiency

Beginning with maximum likelihood estimation, which requires the greatest number of assumptions, the assumptions are relaxed, and the estimation method appropriate to each set of assumptions is described. Specification tests that facilitate the choice among these models are then presented.

Maximum likelihood estimation. The application of maximum likelihood methods to panel data stochastic frontier models was first accomplished by Pitt and Lee (1981). They maintained the following assumptions:

- v_{it} ~ iid with density f(v);
- u_{it} ~ iid with density g(u);
- u_{it}, v_{it}, independent of each other;
- u_{it}, v_{it}, independent of the regressors.

In keeping with the assumptions of the basic model, f(.) is concentrated on $(-\infty, \infty)$, while g(.) is concentrated on $[0, \infty)$. With $\epsilon_{it} = v_{it} - u_{it}$, the joint density of $(\epsilon_{i1} \ldots \epsilon_{iT})$ is

$$h(\epsilon_{i1},\ldots\epsilon_{it})=\int_0^\infty g(u)\prod_{i=1}^{T} f(\epsilon_{it} + u)du, \tag{4.9}$$

and the likelihood function is

$$L = \prod_{i=1}^{N} h[Y_{i1} - f(X_{i1};\beta), \ldots, Y_{iT} - f(X_{iT};\beta)]. \tag{4.10}$$

Maximizing this equation gives estimates of α, ß, and the parameters in the density functions of u and v.

Battese and Coelli (1988) derived the analogue to the Jondrow, et al. (1982) estimate of technical efficiency for panel data. This estimate is consistent as $T \rightarrow \infty$. However, this is not a very useful property for two reasons: first, the assumption of fixed technical efficiency becomes less plausible as T rises; second, the availability of a large number of time periods is not a likely situation.

Generalized least squares. Maintaining assumptions that the regressors are not correlated with technical efficiency and are independent of each other, generalized least squares estimation can proceed without maintaining the distribution assumptions required under maximum likelihood estimation. Technical efficiency is still assumed to be a random variable, but its distribution is not fully specified. Where the variance components are not known, they can be estimated using the usual procedure for feasible generalized least squares (FGLS) (Greene 1990). Efficiency for a specific plant can be captured as the mean of the residual over time, and then normalized so that the most efficient firm is counted as 100% efficient. The index of efficiency adjusts for the log form of the equation:

$$\begin{aligned} \bar{u}_i &= \frac{1}{T}\sum_{t=1}^{T} \epsilon_{it} \\ \hat{u}_i &= \max(\bar{u}_i) - \bar{u}_i \\ TE &= 100\exp(-\hat{u}_i). \end{aligned} \tag{4.11}$$

Estimates of the u_i are consistent as $T \rightarrow \infty$, given the consistency of β; the assumption that the most efficient firm is 100% efficient is true as N becomes large. Estimates of ß are consistent as $N \rightarrow \infty$; hence estimates of u_i are consistent as N and $T \rightarrow \infty$.

Fixed effects model. Problems arise with the maximum likelihood and FGLS estimators if the assumption that the regressors and u_i are not correlated is called into question. One way to avoid this assumption is to employ a fixed effects model estimated by the least squares dummy variable method (Hsiao 1986). This model can be written as

$$y_{it} = \alpha_i^* + \beta' X_{it} + v_{it}, \tag{4.12}$$

where α_i^* is a scalar constant representing the effects of variables particular to firm i in the same fashion over time. The v_{it} still represents the normal random residual, but the α_i^* is treated as a constant.

Estimation proceeds as usual for a fixed effects model, with a least squares dummy variable (LSDV) estimator. That is, either a dummy variable is included for each plant, or, if the number of cross sections is large, the data are transformed by mean differences (Hsiao 1986). The firm effects are separated from the overall intercept through normalization, as described above for the FGLS model. If α_i is the estimate of the intercept for firm i, then,

$$\begin{aligned} \hat{u}_i &= \max(\hat{\alpha}_i) - \hat{\alpha}_i \\ TE &= 100\exp(-\hat{u}_i). \end{aligned} \tag{4.13}$$

While the LSDV estimate of the ß is unbiased and consistent as either N or T

$\to \infty$, the estimators for the individual intercepts are consistent only as $T \to \infty$. As N gets large, the overall intercept can be separated consistently from the one-sided individual effects, allowing measurement of efficiency relative to an absolute standard. Hence, consistency of the individual efficiencies requires large T and N.

Use of the fixed effects model has an important drawback: all time invariant variables are swept into the individual firm intercept. Thus, firm specific, but time invariant factors besides technical efficiency cannot be separated from technical efficiency. For example, if the capital stock for a given plant is fixed over time, the fixed effects model cannot separate the fixed effect of the capital stock from the fixed effect of technical efficiency. Hence, if observed time invariant independent variables are important in the production process, the LSDV estimates may be biased. Furthermore, the LSDV estimator may not be as efficient as either MLE or FGLS estimators, because it does not take advantage of variation between cross section units.

Instrumental variables. Hausman and Taylor (1981) responded to the above criticisms of the fixed effects model by developing an estimator that allows unobserved fixed effects (i.e., technical efficiency) to be separated from observed factors that do not vary for a single cross section over time (i.e., capital stock, in the example above). The model can be written as

$$y_{it} = X_{it}\beta' + Z_i\gamma + u_i + v_{it}, \tag{4}$$

where u_i is treated as a fixed effect, and Z represents a vector of independent observed variables that are fixed for a particular plant over time. Some of the columns of both X_{it} and Z_i are assumed correlated with the u_i. The columns of X_{it} that are not correlated with u_i can serve two functions because they vary both across time and cross sections. First, they can produce unbiased estimates for the ß using deviations from the individual means; second, the individual means can be used to provide instruments for the columns of Z_i that are correlated with the u_i.

Once the instruments are found, technical efficiency estimation proceeds in the same manor as FGLS estimation. These estimates are consistent as T and N $\rightarrow \infty$.

Specification Tests

Deciding between the estimators described above involves testing the maintained assumptions. Several specification tests are useful in this respect. The Hausman test (1978) can be used to test either correlation assumptions, distribution assumptions, or both simultaneously. The Hausman test statistic is based on the assertion that under the null hypothesis of no misspecification, there will exist a consistent, asymptotically normal and asymptotically efficient estimator, ß. Under the alternative hypothesis of misspecification, ß will be biased and inconsistent. Hausman's test involves finding another estimator b, which is consistent under both the null and alternative hypothesis. Under the null hypothesis, b will be inefficient, since ß is the minimum variance estimator; b will not attain the asymptotic Cramer-Rao lower bound. The test consists of analyzing the difference q = b - ß under the null and alternative hypotheses. Under the null hypothesis of no misspecification plim q = 0 while under the alternative hypothesis of misspecification plim q ≠ 0, and, if the power of the test is high, q will be large in absolute value relative to its standard error (Fomby et al. 1984).

For example, consider the choice between a fixed effects and random effects model. Recall that a random effects FGLS estimator requires the assumption that the regressors and errors are orthogonal, while the LSDV estimator of the fixed effects model eliminates this assumption. The specification test can be stated:

$$\begin{aligned} &Ho\colon E[X_{it}u_i = 0] \\ &Ha\colon E[X_{it}u_i \neq 0]. \end{aligned} \tag{4.15}$$

Under the null hypothesis, both the FGLS and within estimators are consistent, but the within estimator is inefficient. Under the alternative, the within estimator is consistent, but the FGLS estimator is not. The test statistic is

$$\begin{aligned} W &= [\hat{b} - \hat{\beta}][var(\hat{b} - \hat{\beta})]^{-1}[\hat{b} - \hat{\beta}]' \\ W &\sim \chi^2_{(k)}, \end{aligned} \tag{4.16}$$

where b is the FGLS estimator, ß is the FGLS estimator, and k is the number if slope parameters. Large values of W place doubt on the null hypothesis, providing evidence that the regressors and the error term are correlated. This finding suggests that a fixed effects model or a Hausman estimator may be more appropriate than either maximum likelihood or FGLS estimators of the u_i.

Similarly, the distribution assumptions can be tested with the Hausman test by comparing the MLE with the FGLS estimator, provided the assumption of orthogonality is maintained, since it is required for correct specification for both the MLE and FGLS estimator. Distribution and orthogonality can be tested jointly by comparing the MLE estimates with the LSDV estimates from the fixed effects model.

The significance of the variance of technical efficiency estimate with respect to the total variance can be tested with a lagrange multiplier test (Breusch and Pagan, 1980):

$$\begin{aligned} Ho&: \sigma_u^2 = 0 \\ Ha&: \sigma_u^2 \neq 0. \end{aligned} \tag{4.17}$$

The test statistic is

$$\lambda = \frac{NT}{2(T-1)}\left(\frac{\sum_{i=1}^{N}\left(\sum_{t=1}^{T} e_{it}\right)^2}{\sum_{i=1}^{N}\sum_{t=1}^{T} e^2_{it}} - 1\right)^2 \tag{4.18}$$

$$\lambda \sim \chi_1^2.$$

Large values of λ imply that the numerator of the term in brackets is greater than the denominator. Under the maintained hypotheses that the v_{it} are independent across time and cross section, and that the u_i are independent from each other and from the v_{it}, the numerator can only be greater than the denominator if the u_i have nonzero variance. Another test of the significance of the one sided component of the error term can be derived from moments of the least squares residuals. Without inefficiency in the model, the disturbance will be symmetric and normally distributed. Hence, deviations from symmetry and from the kurtosis of the normal distribution can be used to detect non-normality. Greene (1990) derives the Wald statistic for testing normality. The test statistic is

$$W = n\left[\frac{b_1}{6} + \frac{(b_2 - 3)^2}{24}\right] \sim \chi^2_{(2)}, \tag{4.19}$$

where $\sqrt{b_1}$ is the estimate of skewness and b_2 is the estimate of the kurtosis. Large values of W place doubt on the hypothesis of normality of the OLS residuals.

Time Varying Technical Efficiency

Each of the estimators described above for panel data models maintains the hypothesis that technical efficiency is constant over time. This assumption is difficult to justify in light of the fact that consistency of each of the estimators requires $T \to \infty$, as well as $N \to \infty$. Over a longer time period, it becomes more likely that technical efficiency for a given firm will change. Improvements over time may be due to investment in new capital, research and development, or the acclamation of workers to new manufacturing processes. Technical efficiency can also decline over time, if the relevant frontier shifts out but the individual firm does not take advantage of the advance in technology.

This concern has been addressed by Cornwell, Schmidt, and Sickles (1990) by specifying technical efficiency as a quadratic function of time:

$$u_{it} = \gamma_i + \delta_i t + \theta_i t^2. \tag{4.20}$$

The parameters γ, δ, and θ can be estimated along with the ß and variance components by either fixed effects, FGLS, or Hausman estimators presented above.

Battese and Coelli (1991) specified a different functional form. Let:

$$\begin{aligned} Y_{it} &= F(X_{it};\beta)\ \exp(v_{it} - u_{it}) \\ u_{it} &= \eta_{it} u_i \\ \eta_{it} &= \exp(-\eta(t-T)), \end{aligned} \tag{4.21}$$

where T is the number of time periods. Maximum likelihood estimation proceeds in the same way as in the time invariant TE models, with the required adjustments to the log likelihood function. Battese and Coelli derive the estimator of technical efficiency analogous to their time invariant estimator presented earlier.

Note that the exponential specification of the behavior of the firm effects over time is a rigid parameterization. The technical efficiency must either increase at a decreasing rate ($^n > 0$), decrease at an increasing rate ($^n < 0$), or remain constant ($^n = 0$). A two parameter specification could be helpful, and it is currently being developed by Battese and Coelli.

Summary

Building a model for the estimation of technical efficiency involves a number of choices and modeling decisions. First, the choice must be made between statistical and nonparametric methods. This choice must be based on the particular application, the characteristics of the available data, and personal choice of the researcher. Given the choice of a statistical methodology, the preferred model depends on whether panel data are available. Without panel data, estimates of technical efficiency are inconsistent, and hinge on strong assumptions. If panel data are available, many of these assumptions can be dropped, and the particular estimator that is best suited to the data can be found by testing these assumptions. If a long time series of data are used, models that allow technical efficiency to change over time should be considered.

For this study, the following procedures will be followed. First, functional form will be investigated by estimating both transcendental logarithmic (translog) and Cobb-Douglas production functions, and testing the restrictions imposed by the Cobb-Douglas form. Given the functional forms selected, fixed effects, generalized least squares, and maximum likelihood estimators will be produced. The specification tests described above will be used to determine the appropriateness of the assumptions implied by each estimator. The technical efficiency estimates from each procedure will be correlated to determine the impact of different assumptions on the technical efficiency estimates.

The stochastic frontier method produces estimates of the best practice technology, as well as technical efficiency estimates. The parameter estimates of the frontier technology will be used to note variations in the production technology over time and between industries. The technical efficiency estimates will be used as a performance variable for evaluating the comparative performance of different groups of plants over time. These comparisons lead to observations about the conditions amenable to efficient production.

V. EMPIRICAL RESULTS I

In this chapter, results from four sets of specification tests and preliminary estimation are reported. The first section reports the results from tests of functional form specification, orthogonality, and the error term specification. These results motivate the use of a Cobb-Douglas production function, estimated by the method of maximum likelihood. The second section reports results from estimation of the stochastic frontier production function for each of the four data sets described in Chapter 3. Hypothesis tests of the parameters of the model are reported, and the estimates of the accepted frontier models are compared with the average ordinary least squares (OLS) production functions. Section three discusses the possibility of parameter instability across time, and Chow tests are performed to determine how the data should be partitioned for estimation. Section four reports the results from estimation of separate production functions for each data partition. Hypothesis tests are used to select the appropriate model for each time period, industry and sample. Frontier production functions are compared to the average OLS production functions. In the final section, the implications of the results for the distribution of the technical efficiency estimates are discussed.

Specification Test Results

Functional Form

Given the choice of the stochastic frontier methodology, a specific functional form must be chosen. Flexible forms were considered for the analysis. Flexible functional forms can be interpreted as second order numerical or differential approximations to the true function, whereas the traditional constant elasticity of substitution (CES) and Cobb-Douglas technologies are only first order approximations. A flexible forms is therefore less likely to lead to biased technical inefficiency estimates for industries with production functions that depart substantially from CES or Cobb-Douglas technology, which place severe limitations on the technology. Furthermore, estimates of flexible forms provide all of the economically relevant information about a technology: the level of production, the vector of marginal products, and the matrix of elasticities of substitution (Chambers 1988).

The transcendental logarithmic (translog) form has received a great deal of attention and application in empirical work. While it shares second-order approximation properties with other flexible forms, the translog has the fewest free parameters, and estimates of the parameters tend to converge more quickly than estimates from other forms (Nguyen & Reznek 1991). Furthermore, Guilkey, Lovell, and Sickles (1983) have compared the results of estimation of a known technology for the translog, the generalized Leontief, and the generalized Cobb-Douglas and have found the translog as reliable or more reliable than the other two forms. However, the translog form has special limitations. Second order approximation properties for the translog hold only locally. Furthermore, some researchers have raised theoretical objections to the translog because it need not be theoretically consistent; that is, it cannot represent globally convex isoquants (Chambers, 1988).

Testing Procedure

The choice between the Cobb-Douglas and translog forms was based on two criteria: the significance of the secondary coefficients, as revealed by the specification tests, and the impact of the change in functional form on the estimated residuals. The three factor (capital, labor, and materials) translog production function and its cost shares were estimated for each of the four data samples described in Chapter 3. Details of the derivation of the system are in Nguyen and Reznek (1991). The translog production function is

$$\begin{aligned} lnQ &= \alpha_o + \alpha_l lnL + \alpha_k lnK + \alpha_m lnM \\ &+ .5\alpha_{ll}(lnL)^2 + .5\alpha_{kk}(lnK)^2 + .5\alpha_{mm}(lnM)^2 \\ &+ \alpha_{lk}(lnL * lnK) + \alpha_{lm}(lnL * lnM) + \alpha_{km}(lnK * lnM). \end{aligned} \tag{5.1}$$

The cost shares are

$$
\begin{aligned}
S_l &= \frac{1}{\lambda}\left[\alpha_L + \alpha_{ll} lnL + \alpha_{lk} lnK + \alpha_{lm} lnM\right], \\
S_K &= \frac{1}{\lambda}\left[\alpha_k + \alpha_{kk} lnK + \alpha_{lk} lnL + \alpha_{km} lnM\right], \\
S_M &= \frac{1}{\lambda}\left[\alpha_m + \alpha_{mm} lnM + \alpha_{ml} lnL + \alpha_{mk} lnK\right].
\end{aligned}
\tag{5.2}
$$

Homogeneity of degree λ requires the following restrictions on both systems:

$$
\begin{aligned}
\alpha_k + \alpha_l + \alpha_m &= \lambda, \\
\alpha_{kk} + \alpha_{kl} + \alpha_{km} &= 0, \\
\alpha_{ll} + \alpha_{kl} + \alpha_{ml} &= 0, \\
\alpha_{mm} + \alpha_{ml} + \alpha_{mk} &= 0.
\end{aligned}
\tag{5.3}
$$

Rather than estimating the production function alone, the production function and share equations were estimated as a simultaneous system, in order to increase the degrees of freedom without adding to the number of free parameters (Berndt 1990). Because only two of the three cost share equations are linearly independent, one must be dropped from the estimation system. As explained in Chapter 3, the capital stock and capital cost measures are considered the least reliable components of the census data; hence, it is common practice when using these data to drop the capital cost-share equation (Nguyen and Reznek 1991).

Two tests were performed to consider the importance of the use of the flexible form. First, the translog was tested against the Cobb-Douglas for the significance of the second order terms as a group. The tests were based on the Gallant-Jorgenson analog of the likelihood ratio test (Gallant and Jorgenson 1979). The test statistic is

$$T^o = N * S(\alpha,V)_r - N * S(\alpha,V)_u \,, \tag{5.4}$$

where S_r and S_u are the minimum values of the objective functions of the restricted and unrestricted models, respectively, and N is the number of observations. T^o is distributed chi-square with degrees of freedom equal to the number of restrictions. The estimated disturbance covariance matrix from the unrestricted model was imposed in the restricted models, as required for the hypothesis tests.

Theoretical consistency was also tested for the translog production function. Monotonicity requires that the estimated marginal products of inputs be non-negative, and convexity of isoquants requires that the principle minors of the bordered Hessian alternate in sign. These conditions were tested at the means of the samples, and at each data point.

Finally, the residuals from the estimation of the two equations were tested for correlation. A high level of correlation between them indicates that the choice of functional form does not significantly affect the estimated residuals. Since the residuals, rather than the output elasticities and elasticities of substitution, are the focus of this study, practicality and parsimony would suggest that if these correlation are high, the simpler approach, a Cobb-Douglas form, should be adopted.

Test Results

Table 12 details the results of the likelihood ratio tests. In each case, the null

Table 12. Results of the likelihood ratio test to determine the functional form of the kernel of the stochastic frontier production function

Industry	Sample	$N^*S(\alpha,V)_R$	$N^*S(\alpha,V)_U$	To[a]	Pearson Corr.
3541	Census	9897	2597	7300	.9045
3541	ASM	18286	4551	13735	.9462
3542	Census	4541	1432	3109	.9603
3542	ASM	11794	3324	8470	.9464

[a] The test statistic (T^o) is compared to the critical value $\chi^2_6 = 12.6$.

hypothesis that all second order terms were equal to zero was strongly rejected. The implication is that the output elasticities are not constant and that the elasticities of substitution are not equal to 1. However, the Pearson correlations between the two functional forms are very high for all samples, implying that restricting the technology had little effect on the residuals.

Table 13 documents serious theoretical consistency problems with the estimated translog function. Although the monotonicity and convexity conditions held at the means for all samples, when tested at each observation, convexity was violated for 20 to 40 percent of the observations. The problem is most serious in the ASM samples. The implication of this result is that the translog form is allowing the data to reveal production relationships that are inconsistent with the theory of production. While some empirical researchers view this as an advantage to the translog form, others use nonconvexity as an example of the shortcomings of the translog form (Chambers 1988).

Table 13. Results of tests for theoretical consistency of the transcendental logarithmic production function

		Monotonicity		Convexity	
Industry	Sample	Violation at Means	Violations/ Total Obs.	Violation at Means	Violations/ Total Obs.
3541	Census	no	27/1150	no	352/1150
3541	ASM	no	71/2034	no	854/2034
3542	Census	no	9/642	no	133/642
3542	ASM	no	31/1367	no	567/1367

Considering the theoretical problems of applying the translog, the high level of correlation between the errors, and, most importantly, the considerable simplicity of the Cobb-Douglas form, the decision was made to use the Cobb-Douglas form.

Significance of the One Sided Error

Before the estimation of stochastic frontiers, evidence that technical efficiency exists was derived from the likelihood ratio test and the test for the skewness of the error. The results of these tests are shown in Table 14. The test statistic for the likelihood ratio test is distributed chi-square with 1 degree of freedom. The null hypothesis was that the variance of the half normal component of the error term was equal to zero. The null hypothesis was rejected for all samples except the metal-cutting census sample. This finding was confirmed by the chi-square test for skewness of the least squares error. These results suggest that technical inefficiency, as it is defined here, is present for each industry and sample.

Table 14. Results of specification tests for the stochastic frontier production function

Industry	Sample	Likelihood Ratio (λ)	Skewness (W)	Orthogonality (W)
3541	Census	2.657	4.206	8.034
3541	ASM	272.926	379.420	9.447
3542	Census	7.093	12.950	2.091
3542	ASM	177.049	306.127	12.369
Critical Value (α=.05)		7.810	5.990	3.840

Choice of Estimator

The fixed effects least squares dummy variable, feasible generalized least squares, and maximum likelihood estimators were estimated for each panel sample (i.e. the final samples with single time-period plants removed -- see Tables 3 and 4). Specification tests were performed on these samples to determine the appropriateness of the assumptions of each estimator. Recall that both maximum likelihood and feasible generalized least squares require the assumption that the regressors and errors are orthogonal. The results of Hausman's test of this assumption are shown in the last column of Table 14. For each of the samples, the orthogonality assumption is violated, except for the 3542 census sample. Griliches noted that correlation between inputs and errors might indicate that producers are aware of their efficiency levels, and that their input allocations may be influenced by this knowledge. If this is true, the estimates of the elasticities and the residuals may be biased (Griliches

1957). The fixed effects estimator is probably a more appropriate estimator than either the FGLS or MLE estimators.

For the purposes of this study, the influence of the estimation technique on the technical efficiency estimates and the plant rankings based on technical efficiency is the most important consideration. Technical efficiency estimates were output for the panel samples, and correlations between the MLE, FGLS, and fixed effects estimators were calculated, as shown in Table 15. Two sets of correlations are shown. The first three columns of Table 15 indicate the correlations between the technical efficiency estimates for the different estimators, and the second three columns contain correlations between the technical efficiency ranks resulting from each estimation.

The correlations show that the MLE and FGLS estimates of technical efficiency are closely correlated in most samples, indicating that the distribution assumptions imposed by the MLE have little effect on the estimates. This is particularly true of the ASM samples. Although the correlations for the census sample are lower, the rank correlations are so high that the order of plants is affected very little by imposing distribution assumptions.

Correlations between the LSDV estimator and the FGLS estimator reflect the impact of the orthogonality assumptions on the technical efficiency estimates. These correlations are very high for all samples, except for the metal cutting census sample. Although the Hausman test resulted in rejection of the orthogonality hypothesis, this restriction seems to have very little impact on the estimated results.

Table 15. Pearson correlation coefficients between technical efficiency scores and ranks from three estimators[a]

	Technical Efficiency			Rank		
Estimator	MLE	FGLS	LSDV	MLE	FGLS	LSDV
3541 Census						
MLE	1.000	0.904	0.806	1.000	0.988	0.881
FGLS	0.904	1.000	0.919	0.988	1.000	0.901
LSDV	0.806	0.919	1.000	0.881	0.901	1.000
3541 ASM						
MLE	1.000	0.981	0.953	1.000	0.994	0.957
FGLS	0.981	1.000	0.962	0.994	1.000	0.973
LSDV	0.953	0.962	1.000	0.957	0.973	1.000
3542 Census						
MLE	1.000	0.805	0.771	1.000	0.988	0.953
FGLS	0.805	1.000	0.971	0.988	1.000	0.957
LSDV	0.771	0.971	1.000	0.953	0.957	1.000
3542 ASM						
MLE	1.000	0.986	0.962	1.000	0.997	0.958
FGLS	0.986	1.000	0.960	0.997	1.000	0.958
LSDV	0.962	0.960	1.000	0.958	0.958	1.000

[a]Standard errors of the estimates are not provided because all estimates are significant at $\alpha = .01$.

For the sake of simplicity, one estimator was chosen for the entire analysis. Based on the orthogonality test, it appears that the fixed-effects estimator is the most appropriate. However, the fixed effects model has the important disadvantage of eliminating from the analysis plants that appear in only one year. Since the correlations are so high between the three estimators and especially between the ranks they produce, the maximum likelihood estimate will be used for the remainder of the analysis, and a time varying specification that allows for unbalanced panels will be applied.

Summary--Model Choices

The test results and discussion of the previous section led to the decision to estimate a stochastic frontier model with a Cobb-Douglas kernel by the method of maximum likelihood with parameters allowing for time variation. The model is

$$\begin{aligned} \ln(Q) &= \beta_O + \beta_L \ln(L) + \beta_M \ln(M) + \beta_K \ln(K) + v_{it} - u_{it} \\ u_{it} &= \eta_{it} u_i = (\exp[-\eta(t-T)]) u_i \\ v_{it} &\sim i.i.d.\ N(0,\sigma_v^2) \\ u_i &\sim i.i.d.\ |N(\mu,\sigma^2)| \\ t &\in \mathfrak{F}(i);\quad i = 1,2,\ldots,N, \end{aligned} \tag{5.5}$$

where Q, L, M, and K are the output, labor, materials, and capital as described in Chapter 3, η is an unknown scale parameter, and $\mathfrak{F}$ represents the set of T_i time periods for which observations for the ith firm are obtained. Note that since the u_i are distributed truncated normal, σ^2 is not the variance of u_i; rather, it is the variance of the normal distribution which is truncated at zero to obtain the distribution of the non-negative firm effects. The variance of u_i is given by

$$var(u_i) = \sigma^2\left[1 - \frac{\phi\left(-\frac{\mu}{\sigma}\right)}{1 - \Phi\left(-\frac{\mu}{\sigma}\right)}\left(\frac{\mu}{\sigma} + \frac{\phi\left(-\frac{\mu}{\sigma}\right)}{1 - \Phi\left(-\frac{\mu}{\sigma}\right)}\right)\right], \tag{5.6}$$

where $\phi(\cdot)$ and $\Phi(\cdot)$ represent the density function and the distribution function for the standard normal (Battese and Coelli 1991). The variance of u_i is smaller than σ^2, and the parameter γ is roughly proportional to the share of the total error variance attributable to the variance of the firm effects. As γ approaches 1, a larger share of the total variance of the error is explained by the variance of the one-sided distribution from which the u_i are taken.

The logarithm of the likelihood function for Equation 1, as derived by Battese and Coelli (1991), is

$$\begin{aligned} L^*(\theta;y) = {} & -\frac{1}{2}\left(\sum_{i=1}^{N} T_i\right)\{\ln(2\pi) + \ln(\sigma_s^2)\} \\ & -\frac{1}{2}\sum_{i=1}^{N} \ln(T_i - 1)\ln(1 - \gamma) - \frac{1}{2}\sum_{i=1}^{N} \ln[1 + (\eta_i'\eta_i - 1)\gamma] \\ & - N\ln[1 - \Phi(-z)] - \frac{1}{2}Nz^2 + \sum_{i=1}^{N}\ln[1 - \Phi(-z_i^*)] \\ & + \frac{1}{2}\sum_{i=1}^{N} z_i^{*2} - \frac{1}{2}\sum_{i=1}^{N}[\frac{(y_i - x_i\beta)'(y_i - x_i\beta)}{(1 - \gamma)\sigma_s^2}], \end{aligned} \tag{5.7}$$

where

$$\theta \equiv (\beta', \sigma^2, \gamma, \mu, \eta)', \quad z \equiv \mu/(\gamma\sigma_s^2)^{1/2},$$

$$z_i^* = \frac{\mu(1 - \gamma) - \gamma\eta_i(y_i - x_i\beta)}{(\gamma(1 - \gamma)\sigma_s^2[1 + (\eta_i'\eta_i - 1)\gamma])^{1/2}}. \tag{5.8}$$

The negative of the log likelihood function is minimized, using the program FRONTIER 2.0 (Coelli 1991).

A grid search routine is used to supply starting values to the iterative minimization process. In order to simplify the grid search, the model was reparameterized:

$$\sigma_v^2 + \sigma^2 = \sigma_S^2; \quad \gamma = \frac{\sigma^2}{\sigma_S^2}. \tag{5.9}$$

Since the parameter γ must lie between 0 and 1, it provides a convenient range over which the grid search can proceed.

The FRONTIER routine uses the Davidson-Fletcher-Powell quasi-Newton method of minimizing the negative of the log of the likelihood function. When the change in the log of the likelihood function and each of the parameters was less than .00001, the model was considered converged. For several models, a problem with convergence required reducing that criteria to .0001.

Model Results--Pooled Data

Equation 5.5 was estimated using four samples over the entire data period.

For each sample set, five models were estimated to facilitate parameter tests. Model 1 is the unrestricted time varying stochastic frontier model, as specified in equation 5.5. Model 2 is a special case of Model 1 in which the u_i have a half normal distribution; that is, μ is restricted to zero. Model 3 restricts η to 0, forcing the technical efficiency score to be the same for a given plant across years. Model 4 is the time invariant case with a half normal distribution, and Model 5 is the standard production function in which all plants are assumed to be fully technically efficient (i.e, the plant effects, u_{it} are absent from the model); these are the OLS estimates.

Estimation results for the five models are presented in Tables 16 and 17; standard errors are in parentheses. Hypotheses of the significance of the parameters of the distribution of the plant effects were tested with the generalized likelihood ratio statistic. Tables 18 and 19 contain the relevant test statistics for each of the hypothesis tests. For each test, the unrestricted model (Model 1) is assumed under the null hypothesis. The hypothesis that all parameters of the distribution of the plant effects (u_i) jointly are equal to zero is tested by comparing the log of the likelihood function for Model 1 and Model 5. For both industries, the null hypothesis is rejected and the existence of firm effects is indicated.

The joint null hypothesis that the plant effects are drawn from a half normal distribution and that efficiency does not vary over time is tested by comparing the log of the likelihood functions for Model 1 and Model 4. This joint hypothesis also is rejected for both industries.

To test the hypothesis that the u_i are distributed half normal, the log of the

Table 16. Maximum likelihood estimates for parameters of stochastic frontier production functions in the machine tool industry, metal-cutting type

	Census					ASM				
Parameter	Model 1	Model 2	Model 3	Model 4	Model 5	Model 1	Model 2	Model 3	Model 4	Model 5
β_o	1.180	1.294	1.361	1.372	1.226	2.012	1.840	2.963	2.040	1.598
	(0.035)	(0.063)	(0.053)	(0.065)	(0.051)	(0.089)	(0.063)	(16.45)	(0.071)	(0.045)
β_L	0.350	0.304	0.338	0.330	0.330	0.353	0.404	0.480	0.461	0.430
	(0.041)	(0.021)	(0.021)	(0.021)	(0.021)	(0.023)	(0.030)	(0.018)	(0.018)	(0.016)
β_M	0.434	0.440	0.428	0.431	0.436	0.551	0.538	0.529	0.526	0.544
	(0.008)	(0.015)	(0.014)	(0.015)	(0.014)	(0.014)	(0.012)	(0.013)	(0.012)	(0.010)
β_K	0.237	0.258	0.229	0.233	0.230	0.090	0.053	0.004	-0.002	0.024
	(0.028)	(0.028)	(0.018)	(0.018)	(0.018)	(0.016)	(0.023)	(0.013)	(0.014)	(0.012)
σ^2	0.098	0.145	0.490	0.120	0.102	0.131	0.249	0.116	0.208	0.106
	(0.016)	(0.010)	(0.119)	(0.010)		(0.009)	(0.010)	(0.005)	(0.017)	
γ	0.090	0.426	0.819	0.238	0	0.534	0.744	0.420	0.649	0
	(0.248)	(0.080)	(0.047)	(0.087)		(0.035)		(0.028)	(0.033)	
μ	0.323	0	-3.257	0	0	0.733	0	1.393	0	0
	(0.089)		(1.158)			(0.082)		(16.465)		
η	-0.236	-0.049	0	0	0	-0.035	-0.041	0	0	0
	(0.006)	(0.039)				(0.012)	(0.025)			
Ln(L)	-248.656	-280.871	-310.061	-312.100	-314.956	-326.536	-398.591	-407.588	-451.294	-597.764

Table 17. Maximum likelihood estimates for parameters of stochastic frontier production functions in the machine tools industry, metal-forming type

	Census					ASM				
Parameter	Model 1	Model 2	Model 3	Model 4	Model 5	Model 1	Model 2	Model 3	Model 4	Model 5
β_o	1.613	1.485	1.486	1.512	1.268	2.306	2.029	2.092	2.072	1.426
	(0.085)	(0.106)	(0.086)	(0.101)	(0.081)	(0.103)	(0.099)	(0.090)	(0.090)	(0.052)
β_L	0.380	0.414	0.436	0.427	0.413	0.457	0.487	0.472	0.475	0.491
	(0.034)	(0.408)	(0.032)	(0.032)	(0.031)	(0.038)	(0.049)	(0.022)	(0.021)	(0.019)
β_M	0.460	0.447	0.443	0.448	0.463	0.460	0.046	0.478	0.467	0.490
	(0.024)	(0.023)	(0.023)	(0.024)	(0.023)	(0.014)	(0.018)	(0.016)	(0.014)	(0.013)
β_K	0.150	0.147	0.128	0.132	0.136	0.037	0.028	0.033	0.030	0.042
	(0.023)	(0.025)	(0.023)	(0.023)	(0.023)	(0.030)	(0.039)	(0.017)	(0.016)	(0.014)
σ_2	0.164	0.192	0.502	0.161	0.126	0.151	0.214	0.130	0.227	0.097
	(0.023)	(0.014)	(0.144)	(0.017)		(0.016)	(0.019)	(0.025)	(0.023)	
γ	0.418	0.512	0.797	0.350	0	0.665	0.737	0.562	0.746	0
	(0.096)	(0.056)	(0.070)	(0.088)		(0.029)	(0.049)	(0.083)	(0.028)	
μ	0.408	0	-2.339	0	0	0.590	0	0.387	0	0
	(0.139)		(0.994)			(0.095)		(0.140)		
η	-0.060	-0.043	0	0	0	-0.037	-0.026	0	0	0
	(0.012)	(0.041)				(0.020)	(0.036)			
Ln(L)	-208.152	-218.737	-234.895	-237.004	-243.042	-137.053	-171.425	-186.194	-188.546	-340.163

Table 18. Tests of hypothesis for parameters of the distribution of plant effects, U_{it}, in the machine tool industry

Industry/ Assumptions	Null Hypothesis	$\chi^2_{0.95}$	Census χ^2 Stat.	Census Decision	ASM χ^2 Stat.	ASM Decision
Industry 3541						
Model 1	$\gamma = \mu = \eta = 0$	7.81	132.600	Reject	542.456	Reject
Model 1	$\mu = \eta = 0$	5.99	126.888	Reject	249.516	Reject
Model 1	$\mu = 0$	3.84	64.430	Reject	144.110	Reject
Model 1	$\eta = 0$	3.84	122.810	Reject	162.104	Reject
Industry 3542						
Model 1	$\gamma = \mu = \eta = 0$	7.81	69.780	Reject	406.220	Reject
Model 1	$\mu = \eta = 0$	5.99	57.704	Reject	102.986	Reject
Model 1	$\mu = 0$	3.84	21.170	Reject	68.744	Reject
Model 1	$\eta = 0$	3.84	53.486	Reject	98.292	Reject

likelihood function is compared for Model 1 and Model 2. Finally, the hypothesis that technical efficiency does not vary over time is tested by comparing the log likelihood for Model 1 with Model 3. As indicated in Table 18, the null hypotheses were rejected in each case; Model 1 was preferred over the more restricted models in each sample.

Frontier versus Average Production Functions

While Model 1 represents the frontier production function, Model 5, the OLS estimate, represents the "average" production function. The differences between Models 1 and 5 provide clues regarding the distinction between "best practice"

Table 19. Returns to scale, output elasticities, and cost shares for frontier versus average technology for both industries and samples

	Industry 3541				Industry 3542			
	Census		ASM		Census		ASM Sample	
	Frontier Model 1	Average Model 5	Frontier Model 1	Average Model 5	Frontier Model 1	Average Model 5	Frontier Model 1	Average Model 5
λ	1.021	.996	.994	.998	.990	1.012	.954	1.023
δ_L	.350	.330	.353	.430	.380	.413	.457	.491
δ_M	.430	.436	.551	.544	.460	.463	.460	.490
δ_K	.237	.230	.090	.024	.150	.136	.037	.042
S_L	.343	.331	.355	.431	.384	.408	.479	.480
S_M	.421	.438	.554	.545	.465	.458	.482	.479
S_K	.232	.231	.091	.024	.152	.134	.039	.041
S_K/S_L	.676	.698	.256	.056	.396	.328	.081	.085
S_L/S_M	.815	.756	.641	.791	.826	.891	.994	1.002

technology and "average practice" technology (Førsund and Jason, 1977). Table 19 provides a summary of the technology differences between Models 1 and 5 in each of the four samples. The parameter λ represents the sum of the output elasticities, or returns to scale. Since the function is homogeneous of degree λ, dividing the output elasticities for each input by λ provides that input's cost share.

The information in Table 19 is illustrated by plots of the frontier and average production technologies in Figures 6 through 9. The relationship between labor and materials is plotted for each technology, for the average value of output and the average capital stock for the given sample.

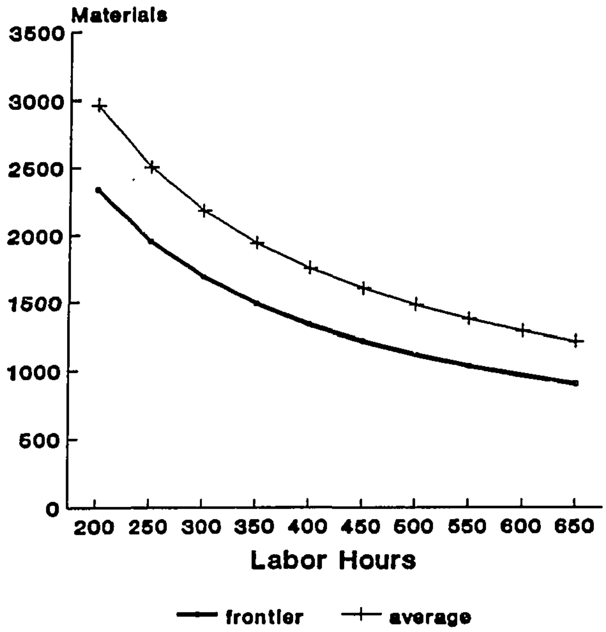

Figure 6. Frontier versus average technology for metal-cutting machine tools, census sample

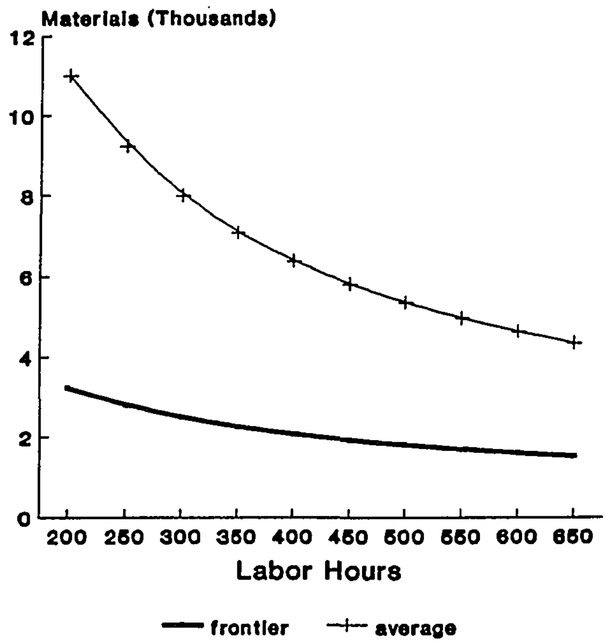

Figure 7. Frontier versus average technology for metal-cutting machine tools, ASM sample

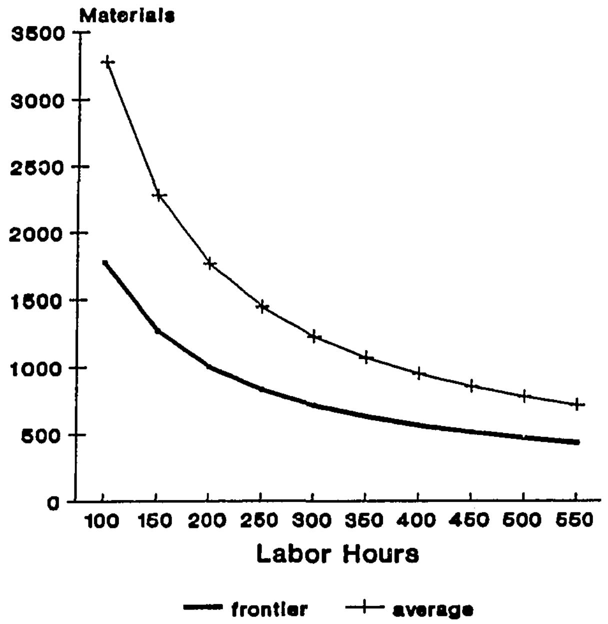

Figure 8. Frontier versus average technology for metal-forming machine tools, census sample

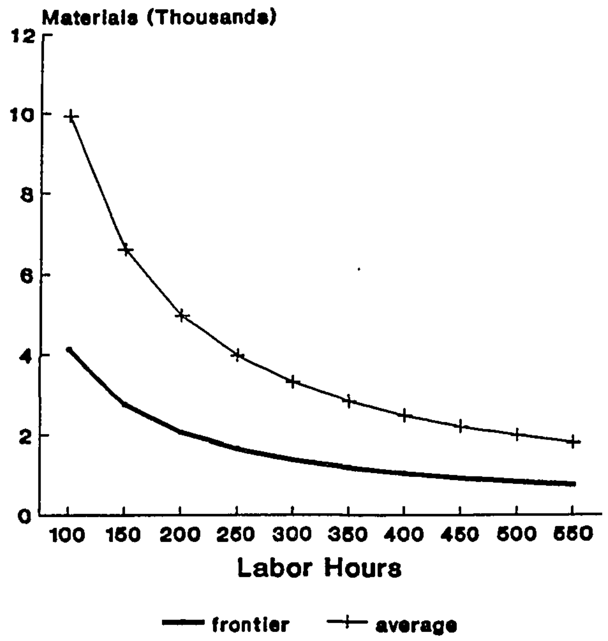

Figure 9. Frontier versus average technology for metal-forming machine tools, ASM sample

In both industries, the ASM data set exhibits greater differences between the average and frontier technologies. For example, for metal cutting tools, the census average and frontier technologies have very similar slope coefficients, and differ primarily by their intercept coefficients. For the ASM sample, however, the output elasticities of materials and capital are higher for the frontier technology, and the difference between the technologies, as shown in Figure 7, is more pronounced. This reflects the artificial homogeneity imposed by the imputation procedures of the census samples.

For metal forming tools, the ASM sample again displays a greater divergence between the frontier and average technologies. In both samples, the frontier technology is more labor intensive, but the difference is not great. There is no consistent pattern between samples regarding the intensity capital or materials.

Parameter Stability

The initial test results imply that technical efficiency varies over time in all samples. However, recall from Chapter 3 that capital-labor ratios, investment, output-labor ratios, and total factor productivity changed considerably across years within a sample. The implicit assumption of the models in Tables 16 and 17 is that the frontier technology is constant over time. Over a sixteen year period, it is likely that best practice technology has changed; evidence from Chapter 3 supports this position as well. It may be more appropriate to measure technical efficiency against a different production function in each period.

In order to investigate the significance of changes in the parameters of the best-practice production function over time, analysis of variance tests (Chow tests) for stability of the parameters of the production function were performed for Model 5, the model with no plant effects. Table 20 contains the results of three tests for each data set. The null hypothesis in each case was that the vector of parameters for the unrestricted model for period 1 data was equal to the vector of parameters for the unrestricted model for period 2 data.

For both census samples, parameter stability was tested between the subsample consisting of 1972-1977 data and that consisting of 1982-1987 data. If the null hypothesis was rejected, each of the two subsamples was tested further for stability between each census year.

The data span four ASM panels. Evidence from Tables 3 and 4 indicates that the makeup of the ASM panel changed substantially between these periods. The ASM data were therefore partitioned such that the ASM panel years were kept together. The first Chow test used the entire data period, 1972-1987, for the restricted model, and the unrestricted model used 1972-1978 and 1979-1987. If the hypothesis of stability of the parameter estimates between these two subsamples was rejected, the data sets were further partitioned into the four panel periods, and tests were performed for stability between each panel period.

For metal cutting tools, the results of the tests on the census data indicated that 1972 and 1977 should be pooled, but 1982 and 1987 should be modeled separately. Similarly, the ASM data should be pooled for 1972 through 1978, but the

Table 20. Chow tests for stability of parameter estimates over time

	Time Periods Tested			Sum of Squares				
Sample	Restricted	Unrestricted Period 1	Unrestricted Period 2	Restricted	Unrestricted Period 1	Unrestricted Period 2	F Statistic	Result
3541								
Census	1972-1987	1972-1977	1982-1987	116.442	52.561	45.130	54.706	Reject
	1972-1977	1972	1977	52.561	28.223	23.660	1.945	Fail to Reject
	1982-1987	1982	1987	45.130	25.260	17.418	7.701	Reject
ASM	1972-1987	1972-1978	1979-1987	214.884	90.786	106.782	44.391	Reject
	1972-1978	1972-1973	1974-1978	90.786	28.364	61.937	1.3409	Fail to Reject
	1979-1987	1979-1983	1984-1987	106.782	58.364	46.661	4.266	Reject
3542								
Census	1972-1987	1972-1977	1982-1987	80.146	33.688	34.930	26.630	Reject
	1972-1977	1972	1977	33.688	19.839	9.635	11.760	Reject
	1982-1987	1982	1987	34.930	16.826	16.801	2.877	Reject
ASM	1972-1987	1972-1978	1979-1987	131.654	55.999	58.847	49.723	Reject
	1972-1978	1972-1973	1974-1978	55.999	21.161	33.650	3.750	Reject
	1979-1987	1979-1983	1984-1987	58.847	40.641	16.559	4.744	Reject

Note: The F statistic is compared to the value of $F_{4,\infty} = 2.37$

samples for 1979-1983 and 1984-1987 should be modeled separately. In metal forming tools, all Chow tests resulted in a decision to reject the null hypothesis; hence production functions are estimated separately for each census year and for each set of years that compose an ASM panel period.

Model Results--Separated Data

Each of the models in Tables 16 and 17 was estimated with the partitioned data sets defined as a result of the Chow tests. The parameter estimates are shown in Tables 21 through 24, and the likelihood ratio tests dictating model choice are shown in Tables 25 and 26. Note that when only one year of data is used, the parameter η is irrelevant, and only Models 3, 4, and 5 are estimated.

Metal Cutting Tools

Estimates for metal-cutting tools from the census data provide no evidence of technical efficiency for years 1982 and 1987. The hypothesis that $\gamma = 0$ could not be rejected, indicating that variations from the estimated frontier were randomly distributed. For 1972 and 1977, evidence of technical efficiency was found, but the technical efficiency scores did not change from year to year. The hypothesis that the firm effects were insignificant was rejected, but the hypothesis that they are time-invariant cannot be rejected.

Estimates from the ASM data provide evidence of technical efficiency for each time period. The hypothesis that $\gamma = 0$ is always rejected, indicating the significance

Table 21. Maximum likelihood estimates for parameters of stochastic frontier production functions in the machine tools industry, metal cutting type, census sample

	1972-1977					1982			1987		
Parameter	Model 1	Model 2	Model 3	Model 4	Model 5	Model 3	Model 4	Model 5	Model 3	Model 4	Model 5
β_O	1.414	1.415	1.420	1.416	1.226	1.223	1.217	1.105	0.901	0.918	0.892
	(0.074)	(0.088)	(0.076)	(0.080)	(0.068)	(0.088)	(0.211)	(0.087)	(0.996)	(0.129)	(0.100)
β_L	0.307	0.290	0.321	0.290	0.279	0.225	0.231	0.232	0.246	0.246	0.246
	(0.028)	(0.029)	(0.026)	(0.028)	(0.028)	(0.037)	(0.038)	(0.038)	(0.897)	(0.039)	(0.038)
β_M	0.377	0.382	0.376	0.382	0.395	0.473	0.471	0.470	0.583	0.583	0.583
	(0.025)	(0.019)	(0.018)	(0.018)	(0.018)	(0.024)	(0.027)	(0.027)	(0.812)	(0.026)	(0.026)
β_K	0.307	0.317	0.296	0.317	0.315	0.275	0.276	0.272	0.178	0.178	0.178
	(0.025)	(0.026)	(0.026)	(0.026)	(0.026)	(0.028)	(0.032)	(0.032)	(0.741)	(0.029)	(0.028)
σ^2	0.508	0.119	0.658	0.120	0.088	0.636	0.097	0.086	0.075	0.072	0.072
	(0.033)	(0.014)	(0.173)	(0.014)		(0.495)	(0.045)		(0.997)	(0.008)	
γ	0.878	0.415	0.899	0.420	0.000	0.892	0.207	0.000	0.050	0.010	0.000
	(0.009)	(0.131)	(0.042)	(0.096)		(0.099)	(0.625)		(1.000)	(0.091)	
μ	-2.715	0.000	-3.875	0.000	0.000	-4.240	0.000	0.000	-0.373	0.000	0.000
	(0.240)		(1.241)			(4.007)			(1.000)		
η	0.008	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.030)	(0.003)									
Ln(L)	-111.008	-115.782	-110.110	-115.779	-119.678	-54.057	-54.809	-54.814	-23.778	-23.781	-23.777

Table 22. Maximum likelihood estimates for parameters of stochastic frontier production functions in the machine tools industry, metal cutting type, ASM sample

	1972-1978					1979-1983	
Parameter	Model 1	Model 2	Model 3	Model 4	Model 5	Model 1	Model 2
β_o	2.592	2.325	2.916	2.326	1.654	1.595	1.539
	(0.222)	(0.084)	(14.44)	(0.090)	(0.057)	(0.073)	(0.092)
β_L	0.387	0.336	0.387	0.338	0.351	0.351	0.372
	(0.026)	(0.026)	(0.025)	(0.026)	(0.023)	(0.061)	(0.031)
β_M	0.480	0.482	0.476	0.482	0.522	0.559	0.572
	(0.017)	(0.015)	(0.016)	(0.014)	(0.014)	(0.018)	(0.017)
β_K	0.113	0.109	0.114	0.107	0.103	0.098	0.072
	(0.021)	(0.021)	(0.019)	(0.021)	(0.017)	(0.050)	(0.026)
σ^2	0.103	0.285	0.097	0.240	0.090	0.146	0.307
	(0.009)	(0.028)	(0.064)	(0.026)		(0.071)	(0.027)
γ	0.597	0.840	0.572	0.814	0	0.644	0.832
	(0.025)	(0.019)	(0.031)	(0.024)		(0.189)	(0.018)
μ	0.968	0	1.231	0	0	0.427	0
	(0.199)		(14.44)			(0.098)	
η	-0.009	-0.026	0	0	0	-0.175	0.143
	(0.007)	(0.013)				(0.155)	(0.029)
Ln(L)	-39.452	-69.629	-42.087	-72.894	-216.148	- 63.214	-69.332

Table 22 (continued)

1979-1983			1984-1987				
Model 3	Model 4	Model 5	Model 1	Model 2	Model 3	Model 4	Model 5
1.705	1.618	1.320	1.478	1.554	1.455	1.554	1.342
(0.014)	(0.101)	(0.077)	(0.135)	(0.142)	(0.132)	(0.142)	(0.127)
0.423	0.417	0.416	0.283	0.297	0.290	0.303	0.340
(0.028)	(0.028)	(0.026)	(0.039)	(0.042)	(0.040)	(0.042)	(0.042)
0.581	0.577	0.556	0.617	0.611	0.614	0.608	0.608
(0.020)	(0.019)	(0.017)	(0.027)	(0.029)	(0.025)	(0.027)	(0.026)
0.024	0.024	0.049	0.085	0.079	0.085	0.077	0.044
(0.021)	(0.021)	(0.019)	(0.032)	(0.032)	(0.031)	(0.032)	(0.032)
0.096	0.160	0.090	2.085	0.239	1.544	0.211	0.126
(0.011)	(0.018)		(1.068)	(0.022)	(0.888)	(0.027)	
0.419	0.640	0	0.963	0.677	0.949	0.637	0
(0.066)	(0.048)		(0.021)	(0.040)	(0.033)	(0.057)	
0.394	0	0	-7.170	0	-6.186	0	
(0.138)			(4.225)		(4.020)		
0	0	0	-0.081	-0.044	0	0	0
			(0.035)	(0.043)			
-86.723	-90.163	-137.482	-113.296	-115.822	-114.480	-116.912	-141.593

Table 23. Maximum likelihood estimates for parameters of stochastic frontier production functions in the machine tools industry, metal-forming type, census sample

Parameter	1972 Model 3	1972 Model 4	1972 Model 5	1977 Model 3	1977 Model 4	1977 Model 5
β_o	1.913	2.185	1.889	1.309	1.330	1.026
	(0.105)	(0.168)	(0.149)	(0.109)	(0.135)	(0.120)
β_l	0.460	0.461	0.460	0.318	0.279	0.228
	(0.033)	(0.056)	(0.060)	(0.041)	(0.045)	(0.041)
β_m	0.370	0.365	0.370	0.512	0.533	0.569
	(0.024)	(0.038)	(0.040)	(0.033)	(0.036)	(0.037)
β_k	0.126	0.124	0.126	0.179	0.192	0.207
	(0.029)	(0.038)	(0.041)	(0.033)	(0.035)	(0.037)
σ^2	0.120	0.176	0.116	0.982	0.107	0.061
	(0.004)	(0.035)		(0.396)	(0.020)	
γ	0.049	0.567		0.970	0.712	0.000
	(0.002)	(0.156)		(0.016)	(0.111)	
μ	-0.608	0		-5.644	0	0.000
	(0.030)			(2.516)		
η	0	0				0.000
Ln(L)	-27.507	-56.440	-57.815	6.990	2.088	-1.268

Table 23 (continued).

1982			1987		
Model 3	Model 4	Model 5	Model 3	Model 4	Model 5
1.213	1.218	1.088	1.271	1.252	0.886
(0.127)	(0.180)	(0.131)	(0.194)	(0.208)	(0.196)
0.413	0.413	0.412	0.449	0.423	0.381
(0.054)	(0.056)	(0.057)	(0.065)	(0.074)	(0.076)
0.444	0.445	0.447	0.472	0.488	0.516
(0.039)	(0.040)	(0.041)	(0.049)	(0.051)	(0.053)
0.152	0.150	0.149	0.126	0.139	0.153
(0.036)	(0.037)	(0.038)	(0.047)	(0.052)	(0.054)
0.704	0.115	0.100	2.100	0.207	0.130
(0.261)	(0.037)		(0.839)	(0.042)	
0.889	0.237	0	0.970	0.628	0
(0.044)	(0.397)		(0.013)	(0.134)	
-4.428	0	0	-8.289	0	0
(1.979)			(3.635)		
0	0	0			0
-42.543	-44.106	-44.146	-45.962	-49.483	-51.135

Table 24. Maximum likelihood estimates for parameters of stochastic frontier production functions in the machine tools industry, metal-forming type, ASM sample

Parameter	1972-1973					1974-1978				
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 1	Model 2	Model 3	Model 4	Model 5
β_O	2.545	2.377	2.548	2.517	1.879	2.082	1.966	1.968	1.960	1.692
	(0.146)	(0.651)	(0.176)	(0.178)	(0.149)	(0.037)	(0.102)	(0.108)	(0.107)	(0.079)
β_L	0.434	0.446	0.488	0.485	0.452	0.461	0.459	0.460	0.457	0.493
	(0.044)	(0.082)	(0.052)	(0.053)	(0.054)	(.020)	(0.029)	(0.032)	(0.314)	(0.028)
β_M	0.389	0.406	0.398	0.405	0.430	0.432	0.429	0.433	0.431	0.446
	(0.021)	(0.068)	(0.029)	(0.029)	(0.033)	(0.042)	(0.018)	(0.191)	(0.019)	(0.018)
β_K	0.085	0.097	0.038	0.057	0.086	0.092	0.084	0.084	0.085	0.056
	(0.041)	(0.129)	(0.046)	(0.046)	(0.042)	(0.025)	(0.025)	(0.261)	(0.026)	(0.022)
σ^2	1.239	0.177	0.860	0.200	0.102	0.077	0.152	0.890	0.113	0.069
	(1.745)	(0.311)	(2.031)	(0.032)		(0.056)	(0.013)	(0.029)	(0.015)	
γ	0.973	0.810	0.949	0.786	0	0.412	0.692	0.461	0.572	0
	(0.384)	(0.356)	(0.119)	(0.048)		(0.511)	(0.034)	(0.178)	(0.065)	
μ	-5.225	0	-2.618	0	0	0.474	0	0.154	0	0
	(8.531)		(8.029)			(1.633)		(.198)		
η	0.435	0.152	0	0	0	-0.083	-0.103	0	0	0
	(0.089)	(0.128)				(0.075)	(0.055)			
Ln()	-18.254	-27.161	-32.916	-33.849	-56.778	-4.071	-6.569	-14.199	-14.363	-39.494

Table 24 (continued)

	1979-1983					1984-1987				
Parameter	Model 1	Model 2	Model 3	Model 4	Model 5	Model 1	Model 2	Model 3	Model 4	Model 5
β_o	1.642	1.497	2.451	1.524	1.158	1.680	1.822	1.712	1.813	1.439
	(0.118)	(0.087)	(10.290)	(0.098)	(0.071)	(0.219)	(0.293)	(0.023)	(0.252)	(0.196)
β_l	0.355	0.369	0.402	0.395	0.433	0.486	0.500	0.487	0.498	0.455
	(0.038)	(0.036)	(0.034)	(0.035)	(0.030)	(0.057)	(0.061)	(0.056)	(0.060)	(0.056)
β_m	0.554	0.557	0.590	0.576	0.570	0.434	0.419	0.435	0.424	0.477
	(0.024)	(0.025)	(0.025)	(0.024)	(0.023)	(0.039)	(0.042)	(0.038)	(0.040)	(0.037)
β_k	0.093	0.073	0.031	0.036	0.030	0.088	0.084	0.083	0.083	0.074
	(0.022)	(0.024)	(0.022)	(0.021)	(0.020)	(0.042)	(0.045)	(0.042)	(0.043)	(0.039)
σ^2	0.113	0.248	0.089	0.159	0.083	1.373	0.161	1.540	0.191	0.096
	(0.015)	(0.031)	(0.008)	(0.021)		(1.571)	(0.039)	(1.395)	(0.038)	
γ	0.593	0.798	0.494	0.693	0	0.964	0.718	0.968	0.752	0
	(0.039)	(0.146)	(0.051)	(0.485)		(0.043)	(0.082)	(0.034)	(0.065)	
μ	0.578	0	1.276	0	0	-5.778	0	-6.059	0	0
	(0.107)		(10.299)			(7.254)		(6.295)		
η	-0.105	-0.120	0	0	0.0	0.034	0.042	0	0	0
	(0.045)	(0.030)				(0.021)	(0.042)			
Ln(L)	-20.633	-25.553	-31.995	-36.880	-.84.996	-23.261	-24.344	-23.755	-24.797	-41.738

Table 25. Tests of hypothesis for parameters of the distribution of plant effects, U_{it}, in the machine tool industry, metal-cutting type

Sample/Year	Assumption	Null Hypothesis	$\chi^2_{0.95}$	χ^2 Stat.	Decision
Census 72-77	Model 1	$\gamma = \mu = \eta = 0$	7.81	17.340	Reject
	Model 1	$\mu = \eta = 0$	5.99	9.542	Reject
	Model 1	$\mu = 0$	3.84	9.548	Reject
	Model 1	$\eta = 0$	3.84	1.796	Fail to Reject
	Model 3	$\mu = 0$	3.84	11.338	Reject
Census 1982	Model 3	$\gamma = \mu = 0$	5.99	1.514	Fail to Reject
Census 1987	Model 3	$\gamma = \mu = 0$	5.99	-0.002*	Fail to Reject
ASM 1972 - 1978	Model 1	$\gamma = \mu = \eta = 0$	7.81	353.392	Reject
	Model 1	$\mu = \eta = 0$	5.99	66.884	Reject
	Model 1	$\mu = 0$	3.84	60.354	Reject
	Model 1	$\eta = 0$	3.84	5.270	Reject
ASM 1979 - 1983	Model 1	$\gamma = \mu = \eta = 0$	7.81	148.536	Reject
	Model 1	$\mu = \eta = 0$	5.99	53.898	Reject
	Model 1	$\mu = 0$	3.84	12.236	Reject
	Model 1	$\eta = 0$	3.84	47.018	Reject
ASM 1984 - 1987	Model 1	$\gamma = \mu = \eta = 0$	7.81	56.594	Reject
	Model 1	$\mu = \eta = 0$	5.99	7.232	Reject
	Model 1	$\mu = 0$	3.84	5.052	Reject
	Model 1	$\eta = 0$	3.84	2.368	Fail to Reject
	Model 3	$\mu = \gamma = 0$	5.99	54.226	Reject
	Model 3	$\mu = 0$	3.84	4.864	Reject

Note: Theoretically, it is impossible for this number to be negative, since the log of the likelihood function for the restricted model is always lower than that of the unrestricted model. However, after trying several different starting values and step sizes, it was determined that the iterative minimization process was functioning properly and approaching a saddle point. A feasible explanation for the negative statistic, given its size, is rounding error.

Table 26. Tests of hypothesis for parameters of the distribution of plant effects, U_{it}, in the machine tool industry, metal-forming type

Sample/Year	Assumption	Null Hypothesis	$\chi^2_{0.95}$	χ^2 Stat.	Decision
Census 1972	Model 3	$\gamma = \mu = 0$	5.99	60.616	Reject
	Model 3	$\mu = 0$	3.84	57.866	Reject
Census 1977	Model 3	$\gamma = \mu = 0$	5.99	16.516	Reject
	Model 3	$\mu = 0$	3.84	9.804	Reject
Census 1982	Model 3	$\gamma = \mu = 0$	5.99	3.206	Fail to Reject
Census 1987	Model 3	$\gamma = \mu = 0$	5.99	10.346	Reject
	Model 3	$\mu = 0$	3.84	7.042	Reject
ASM 1972-1973	Model 1	$\gamma = \mu = \eta = 0$	7.81	77.048	Reject
	Model 1	$\mu = \eta = 0$	5.99	31.190	Reject
	Model 1	$\mu = 0$	3.84	17.814	Reject
	Model 1	$\eta = 0$	3.84	29.324	Reject
ASM 1974-1978	Model 1	$\gamma = \mu = \eta = 0$	7.81	70.848	Reject
	Model 1	$\mu = \eta = 0$	5.99	20.584	Reject
	Model 1	$\mu = 0$	3.84	4.996	Reject
	Model 1	$\eta = 0$	3.84	20.256	Reject
ASM 1979-1983	Model 1	$\gamma = \mu = \eta = 0$	7.81	128.726	Reject
	Model 1	$\mu = \eta = 0$	5.99	32.494	Reject
	Model 1	$\mu = 0$	3.84	9.840	Reject
	Model 1	$\eta = 0$	3.84	22.724	Reject
ASM 1984-1987	Model 1	$\gamma = \mu = \eta = 0$	7.81	36.954	Reject
	Model 1	$\mu = \eta = 0$	5.99	3.072	Fail to Reject
	Model 3	$\mu = 0$	3.84	2.084	Fail to Reject
	Model 2	$\eta = 0$	3.84	0.906	Fail to Reject
	Model 3	$\gamma = 0$	3.84	33.882	Reject

of the variance of the one sided component of the error as a share of the variance of the total error. The full model is chosen as the appropriate model in all cases, except for 1984-1987. Technical efficiency does not vary over years for this period. The hypothesis that $\eta = 0$ cannot be rejected, indicating that Model 3 is appropriate.

Metal Forming Tools

For metal-forming machine tools, technical efficiency is indicated by the hypothesis tests on the census data in 1972, 1977, and 1987. For 1982, there is not sufficient evidence to reject the hypothesis that deviations from the frontier are due only to random variation. Model 3 is chosen for 1972, 1977 and 1987, but Model 5 is the appropriate model for 1982.

The model tests from the ASM sample lead to the choice of the full model for each time period, except for 1984-1987, in which the time invariant half normal model (Model 4) was chosen. This result parallels the results for metal-cutting machine tools. In both cases, technical efficiency is significant and changes over time, except for the 1984-1987 period.

Census/ASM Comparison

For both metal-cutting and metal-forming machine tools, the model choices dictated by the hypothesis tests are strongly influenced by which sample is used. The census data indicate no evidence of technical inefficiency in three out of seven models selected. This contrasts with the models chosen for the ASM data, which always include the parameters specifying the distribution of the one sided component of the error term. There are reasons to suspect that the inconsistent results are a function of the imputation procedures used by the Census Bureau. As explained in Chapter 3, census data are subject to a great deal more imputation, especially for capital stock data. Furthermore, the imputation procedure used for census data forces plants toward the industry averages. For this reason, it is believed that the homogeneity of the plant level data from the census is artificial.

While 1987 census data will be used for analysis in later chapters involving technology usage, the remainder of the analysis in this chapter and in Chapter 6 will focus on the ASM data.

Frontier versus Average Efficiency

Table 27 and Figures 10, 11, and 12 highlight the differences between the frontier and average production functions for metal cutting tools. The most interesting feature of these functions is the change in the divergence between the average and best practice frontiers over the years. From the first to the second time period, both the average and frontier technologies regressed, but the frontier technology regressed further; this is consistent with a higher average level of efficiency for the second time period. From the second to the third production function, the frontier regressed while average technology crept forward slightly. This would be consistent with higher efficiency scores as well, caused partially by movement of some plants to the southwest, and partially by a shift in the frontier.

Table 27. Comparison of frontier technology to average technologies for metal-cutting machine tools.

	1972-1978		1979-1983		1984-1987	
	Model 1	Model 5	Model 1	Model 5	Model 3	Model 5
λ	.98	.976	1.008	1.021	.989	.992
δ_L	.387	.351	.351	.416	.290	.340
δ_M	.48	.522	.559	.556	.614	.608
δ_K	.113	.103	.098	.049	.085	.044
δ_L	.395	.360	.348	.407	.293	.343
δ_M	.490	.535	.555	.545	.621	.613
S_K	.115	.106	.097	.048	.086	.044
S_K/S_L	.291	.294	.279	.118	.294	.128
S_L/S_M	.806	.673	.627	.747	.472	.560

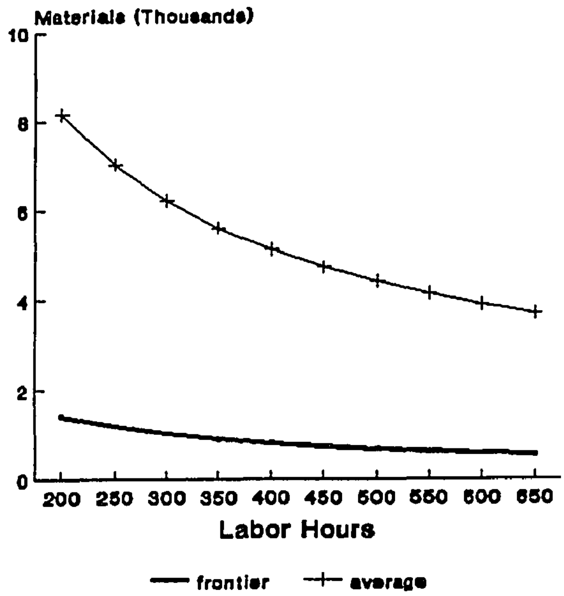

Figure 10. Frontier and average production functions for metal-cutting machine tools, 1972-1978

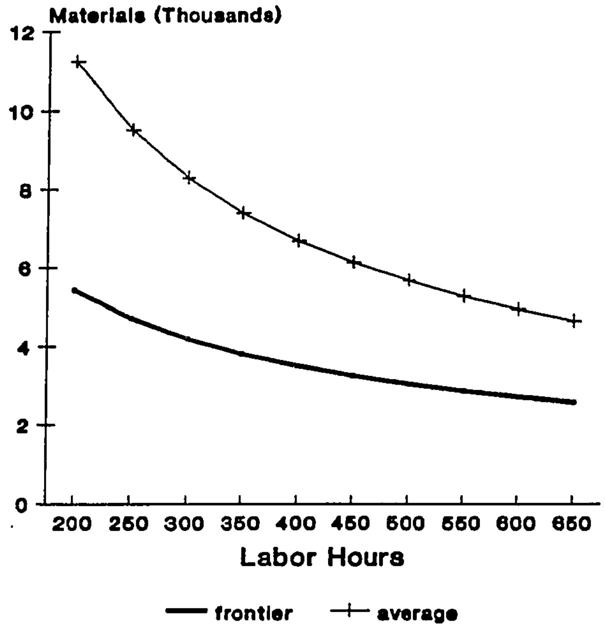

Figure 11. Frontier and average production functions for metal-cutting machine tools, 1979-1983

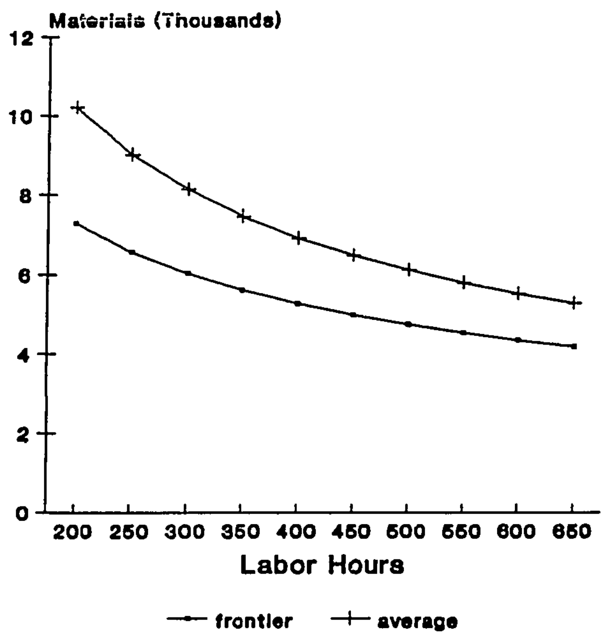

Figure 12. Frontier and average production functions for metal-cutting machine tools, 1984-1987

Over time, the frontier technology changed from being more to less labor intensive than the average technology. At the same time, materials began to command a larger cost share in the frontier technology. The frontier technology is consistently more capital intensive than the average.

Table 28 and Figures 13 through 16 highlight the differences between the frontier and average technologies for metal-forming tools. The frontier and average technologies are closer together at the beginning of the data period than they were for metal cutting tools. The gap widened in the second period, and it appears that this is partially due to movement of plants away from the frontier, as well as the shift of the frontier. By the final period, the gap between the average and frontier technologies had narrowed again, and average technology, overall, had regressed from its 1972-1973 placement.

The frontier technology is consistently less labor intensive than the average technology, except in the final period. Output elasticity for capital drops sharply for the average technology in the middle two periods.

Summary of Preliminary Estimation Results

A single stochastic frontier production function was estimated for each industry for the entire 16 year period. Chow tests of parameter stability suggested that these estimates were not stable over time, and subsets of the data appropriate for estimation of separate frontiers were identified. Parameter estimates of the stochastic frontiers for each subset of the data suggested the existence of technical

Table 28. Comparison of frontier technology to average technology for metal forming machine tools

	1972-1973		1974-1978		1979-1983		1984-1987	
	Model 1	Model 5	Model 1	Model 5	Model 1	Model 5	Model 4	Model 5
λ	.908	.968	.985	.995	1.002	1.033	1.005	1.006
θ_L	.434	.452	.461	.493	.355	.433	.498	.455
θ_M	.389	.430	.432	.446	.554	.570	.424	.477
θ_K	.085	.086	.092	.056	.093	.030	.083	.074
S_L	.478	.467	.468	.495	.354	.419	.496	.452
S_M	.428	.444	.439	.448	.553	.552	.422	.474
S_K	.094	.089	.093	.056	.093	.029	.083	.074
S_K/S_L	.197	.191	.199	.113	.263	.069	.167	.164
S_L/S_M	1.117	1.052	1.066	1.105	0.640	0.759	1.175	0.954

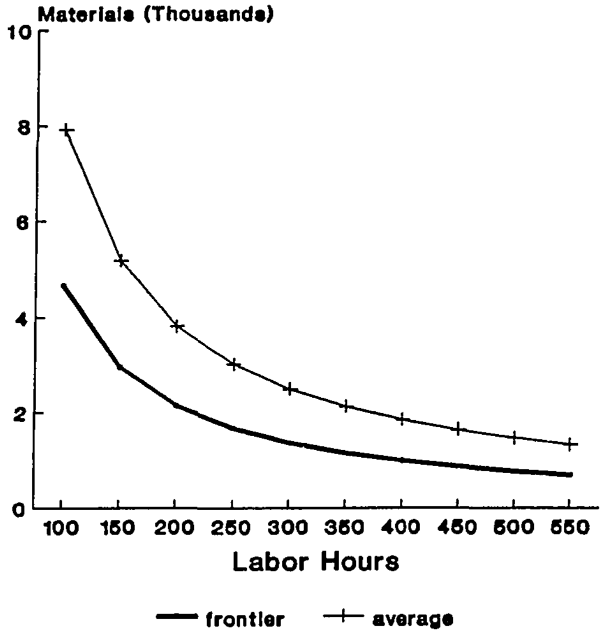

Figure 13. Frontier and average production functions for metal-forming machine tools, 1972-1973

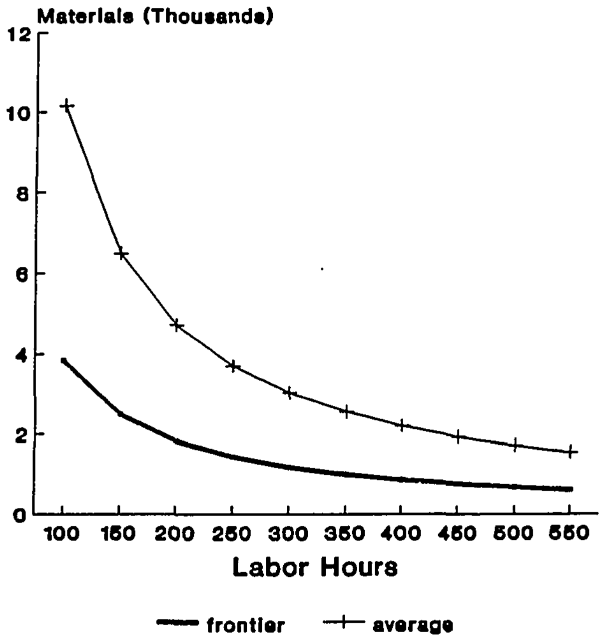

Figure 14. Frontier and average production functions for metal-forming machine tools, 1974-1978

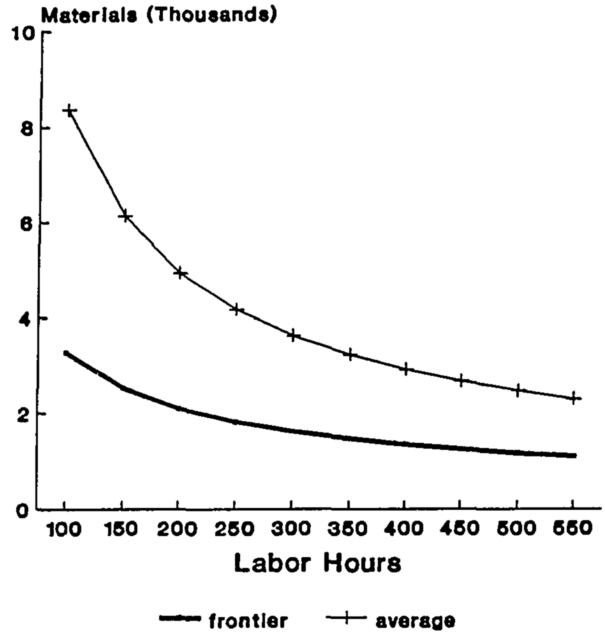

Figure 15. Frontier and average production functions for metal-forming machine tools, 1979-1983

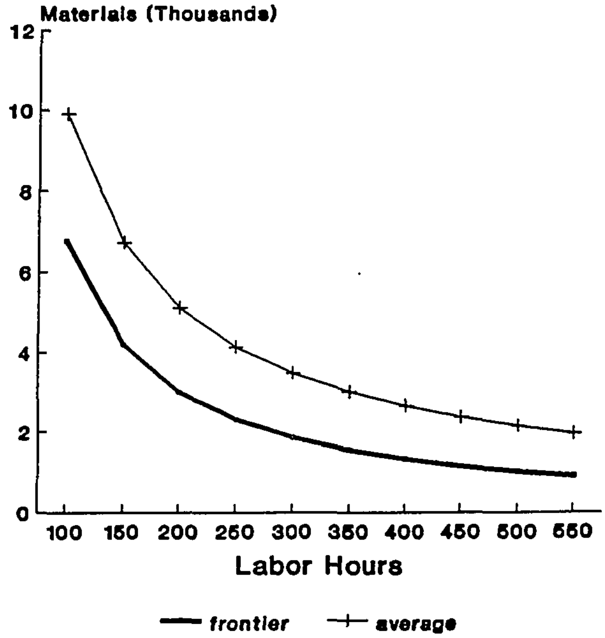

Figure 16. Frontier and average production functions for metal-forming machine tools, 1984-1987

efficiency in all but three subsets of the data, all of which taken from the census. Investigation into the effect of census imputation procedures on the heterogeneity of the sample led to a decision to accept the ASM efficiency estimates as more reliable. The remainder of the discussion in this chapter will refer only to the ASM data.

The Extent of Technical Efficiency

The predictor for technical efficiency, derived by Battese and Coelli (1991) is

$$E[\exp(-u_{it}|e_i] = \left[\frac{1 - \Phi[\eta_{it}\sigma_i^* - (\mu_i^*/\sigma_i^*)]}{1 - \Phi(-\mu_i^*/\sigma_i^*)}\right]\exp\left[-\eta_{it}\mu_i^* + \frac{1}{2}\eta_{it}^2\sigma_i^{*2}\right]$$

$$\mu_i^* = \frac{\mu\sigma_v^2 - \eta_i' e_i \sigma^2}{\sigma_v^2 + \eta_i'\eta_i\sigma^2} \qquad (5.10)$$

$$\sigma_i^{*2} = \frac{\sigma_v^2\sigma^2}{\sigma_v^2 + \eta_i'\eta_i\sigma^2}$$

where e_i represents the vector of e_{it} associated with the time periods observed for plant i and $e_{it} = v_{it} + u_{it}$. Technical efficiency averages for each industry and year are plotted in Figure 17. Note that the groups of observations estimated with the same production function all lie together, with discrete jumps at years in which a new production function is estimated. In 1984-1987, technical efficiency by plant does not vary, since the hypothesis that $\eta = 0$ could not be rejected. Differences in the averages for these years represent changes in the composition of the panel; i.e., plants exiting and entering the industry.

Figure 17. Average technical efficiency by year, metal-cutting and metal-forming machine tools

Examples of the relationship between the parameter estimates and the efficiency scores are shown in Figures 18 through 23. Each pair of figures refers to a separate industry/time period. The top plot in each figure is the normal distribution, drawn according to the parameter estimates of μ and σ^2. Two scales are given below the plot; the top scale is for the u_i and the bottom is the corresponding efficiency score ($\exp(-u_i)$). A vertical line is shown at $u_i = 0$, indicating the truncation point; the plant effects are drawn from the area to the right of this point. The tic marks that correspond to each reference point on the normal probability plot are included for reference to the histogram of the calculated efficiency scores that appears below the normal plot. Each bar in a histogram represents one half of a standard deviation, except in Figure 23, where each represents one quarter of a standard deviation.

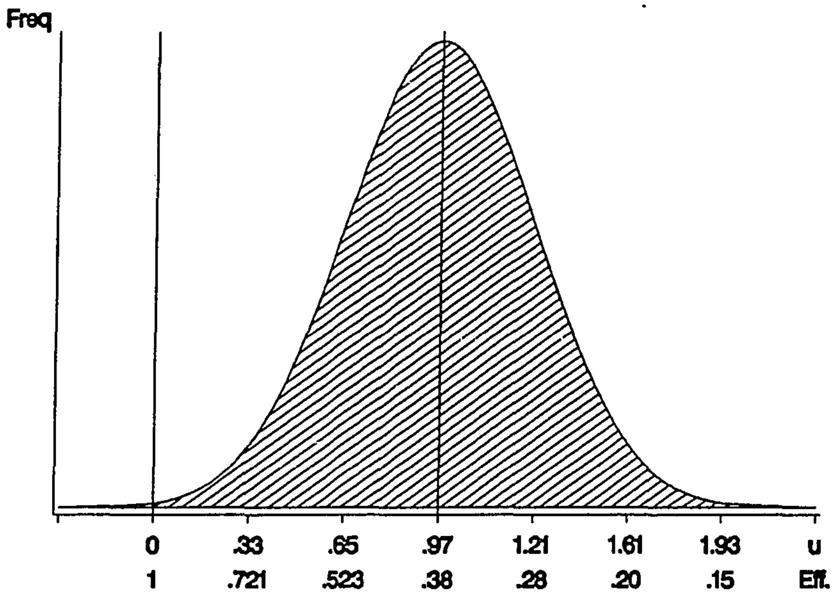

Figure 18. Theoretical distribution of plant effects for metal-cutting machine tools, 1978

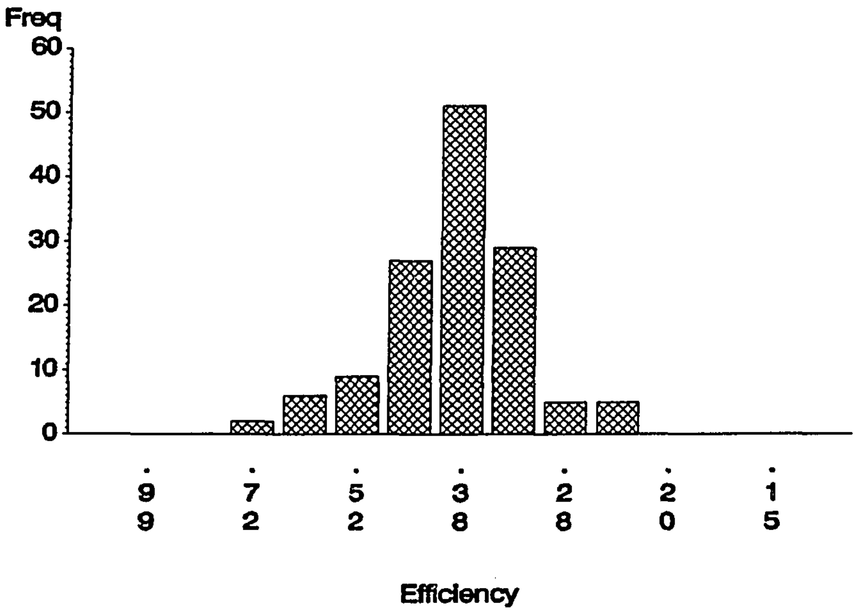

Figure 19. Histrogram of technical efficiency scores for metal-cutting machine tools, 1978

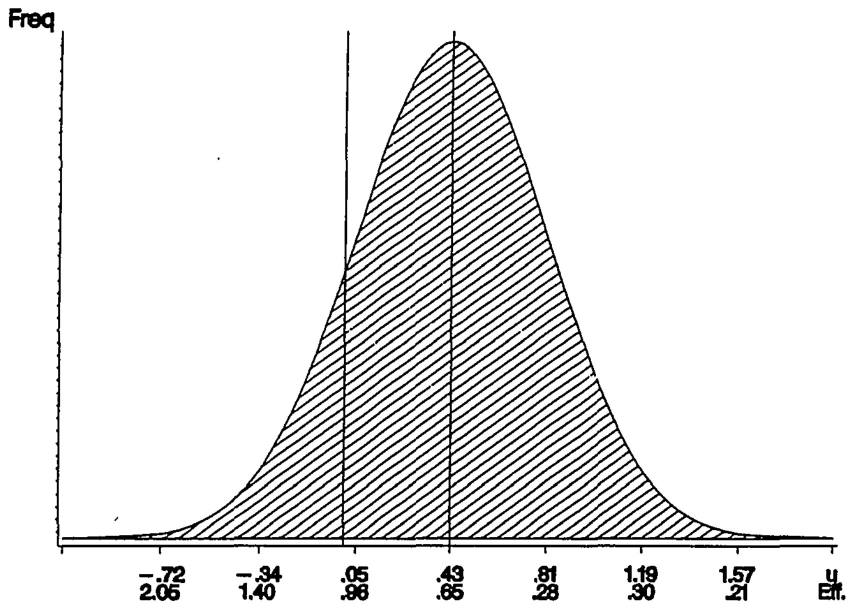

Figure 20. Theoretical distribution of plant effects for metal-cutting machine tools, 1983

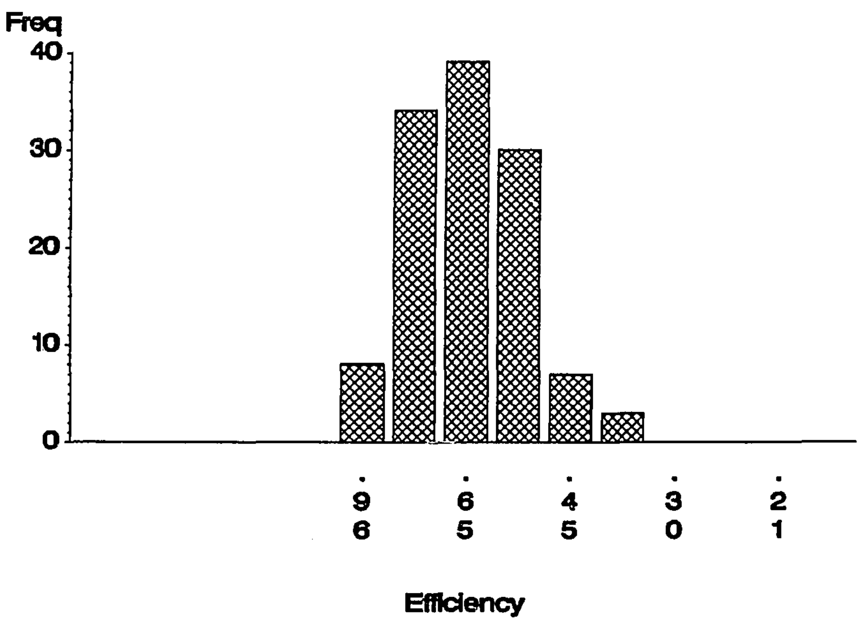

Figure 21. Histrogram of technical efficiency scores for metal-cutting machine tools, 1983

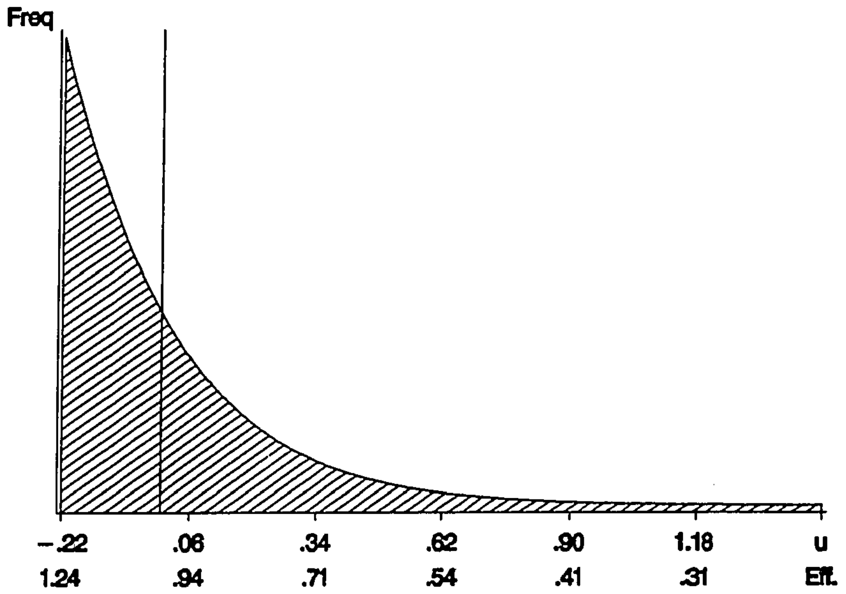

Figure 22. Theoretical distribution of plant effects for metal-forming tools, 1973

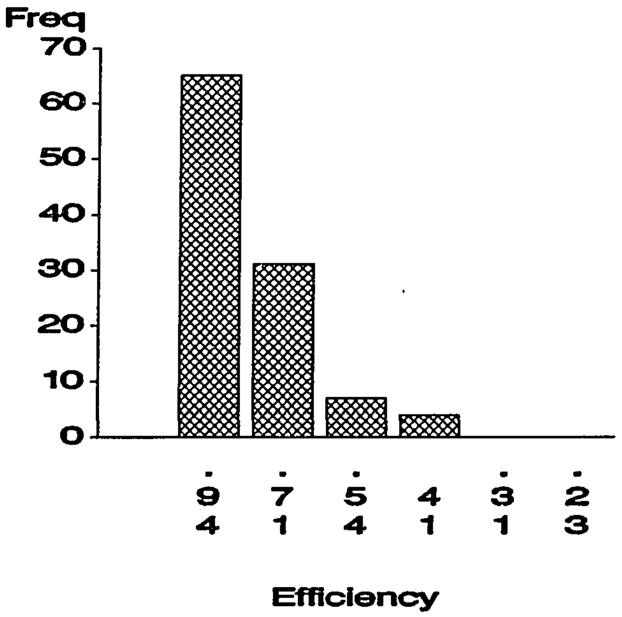

Figure 23. Histrogram of techical efficiency for metal-forming machine tools, 1973

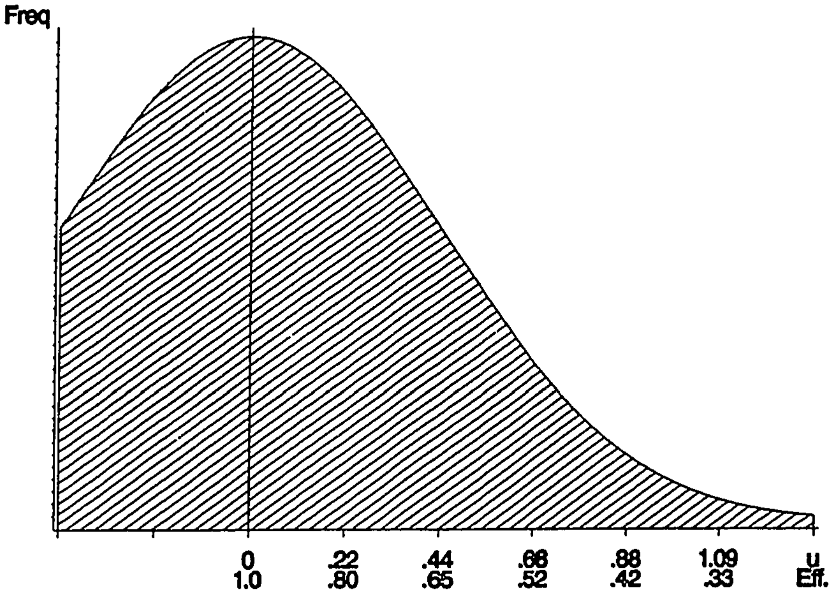

Figure 24. Theoretical distribution of plant effects for metal-forming machine tools 1987

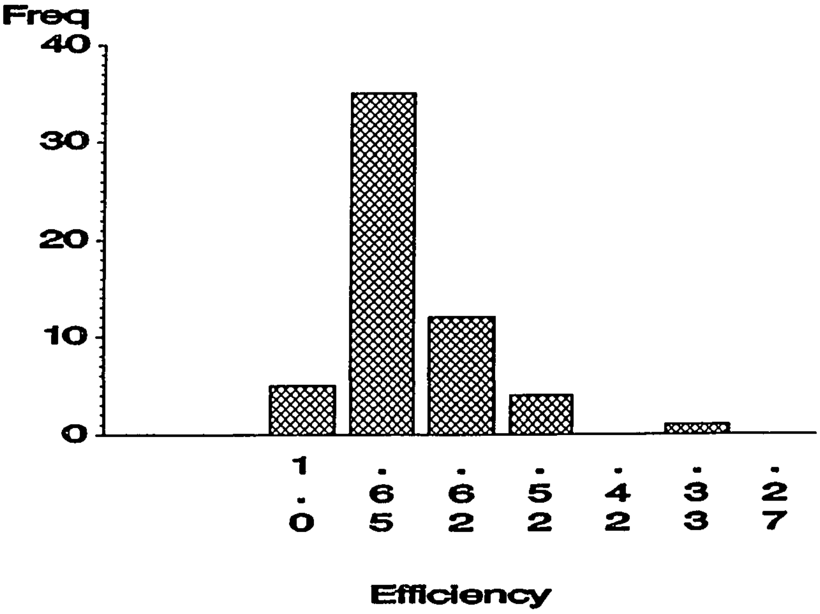

Figure 25. Distribution of technical efficiency for metal-forming machine tools, 1987

Metal-Cutting Tools

The model for years 1972-1978, as illustrated in Figure 18, has a mean of .968 and standard deviation of .321. The truncation point is 3.02 standard deviations to the left of the mean, and the plant effects for 1978 are drawn from a nearly normal distribution. The majority of the efficiency scores should lie between .524 and .275; the shape of the histogram in figure 19 approaches the expected distribution as defined by the model parameters. Since $\eta = -.009$, the u_i are smaller for earlier years of the sample (see the derivation in Equation 1), and technical efficiency falls over time. The histogram of efficiency scores for 1972-1977, if it was plotted, would be skewed farther to the left than the 1978 histogram.

Figure 20 shows the distribution of the plant effects for 1983 in metal cutting tools. It is similar to Figure 18 but, since the mean is smaller and the standard deviation larger, the truncation point is only 1.121 standard deviations to the left of the mean. Hence, the plant effects should be more skewed to the left, with the majority of the technical efficiency scores falling between 1 and .445. The histogram in Figure 20 shows that the average, maximum, and minimum efficiency scores all are higher for 1983 than for 1978. The value of η indicates that the histogram of efficiency scores for 1979-1982 would be skewed farther to the left.

The 1987 plant effects are not shown, but they are taken from the far right hand tail of the normal distribution. With a mean of -6.187 and standard deviation of 1.243, the truncation point occurs almost five standard deviations to the right of the mean. The distribution is similar to that of the 1973 distribution for metal-forming tools. Note that since $\eta = 0$ in this model, the efficiency scores for 1984 and 1985 are the same as the 1987 scores.

Metal-Forming Tools

The distribution of the firm effects for 1973 is shown in Figure 22. Like the 1987 distribution for metal-cutting tools, the firm effects are drawn from the extreme right hand tail of the normal distribution. The distribution from which the scores are taken hold most of its mass just after the truncation point. The truncation point lies 4.69 standard deviations to the right of the mean, and one standard deviation to the right of the truncation point represents an efficiency score of only .328. The histogram in Figure 23 shows that the actual distribution of the plant effects is fairly skewed to the left, with most of the observations lying between 1 and .6. The estimate of η is positive, so the scores are higher for 1973 than for 1972.

For 1978, the truncation point is 1.704 deviations to the left of the mean of .474. Theoretically, the efficiency scores should approach a nearly normal distribution, with the majority of the scores lying between .822 and .471. The estimate of η is negative; therefore, the distribution of efficiency scores decline over the period. For 1983, the picture is very similar. The truncation is 1.723 standard deviations to the left of the mean, which is .578. The negative value of η indicates that the scores decline over time.

For 1987, Model 4 was chosen as the appropriate model; the mean of the distribution is zero, as shown in Figure 23. The histogram of the efficiency scores in

Figure 24 resembles the half normal distribution.

Summary

Maximizing the likelihood function in Equation 5.7 produces estimates for the kernel production function, the mean and variance of the distribution of the two components of the error term, and the time variation parameter η. The expectation of the plant effects is calculated from these estimates (Equation 6), and technical efficiency scores are a simple transformation of the plant effects ($TE_{it} = \exp(-u_{it})$).

Technical efficiency for metal cutting tools declines over time within the time periods for which single frontiers are estimated. However, with each shift in the frontier production function, average efficiency improves compared to the efficiency scores for the previous period. This is probably due in part to regression of the frontier technology, and in part to improvements in efficiency.

For metal forming tools, efficiency grew from 1972 to 1973. For the following period, however, efficiency declines within the production function periods. Efficiency rises significantly for the period 1984-1987, approaching its 1973 level.

Visual inspection of the changes if the frontiers, given fixed output and capital reveals that some frontiers appear to shift backwards. Hence it is not always clear how much efficiency improvement is attributable to a plant moving toward the frontier and how much is due to the shift in the frontier. This issue will be examined in Chapter 7, in which Malmquist indexes of productivity change are decomposed into changes in efficiency and technical change.

CHAPTER 6. EMPIRICAL RESULTS II

Frontier technologies have been determined for metal-cutting machine tools and metal-forming machine tools for 1972 through 1987. Estimates of plant technical efficiency relative to the appropriate frontier exhibit variation across plants and years. In this chapter, the relationship between plant characteristics and efficiency is investigated. In the first section, the relationship between technical efficiency and plant size, plant age, average wages, ownership, location, and access to manufacturing extension is examined. In the second section, the determinants of plant survival are explored, and technical efficiency is evaluated as a predictor of the probability of survival. In the final section, the relationship between efficiency and growth is investigated.

Technical Efficiency and Plant Characteristics

Several plant and location specific variables were investigated for their association with technical efficiency. For the plant characteristics represented by continuous variables (size, average production worker wage, and investment), Pearson correlations were estimated between each variable and the plant's efficiency score as well as its rank (the plants are ranked separately for each year, in ascending order). The rank correlation is a better indicator of the association between the continuous variable and a plant's efficiency in a given year relative to other plants. That is, it controls for changes in the efficiency scores of all plants over time. For discreet variables, averages of technical efficiency are estimated by group, and tests of equality of the means are performed. A regression equation was then estimated to determine if any of these variables, controlling for the effect of the others, had strong predictive value for a plant's technical efficiency score.

Size

Two measures of size were correlated with efficiency and efficiency rank: total employment and total value of shipments. The correlations are displayed in Table 29. The total value of shipments is positively correlated with efficiency and efficiency rank in both industries.

The positive correlation between shipments and efficiency might be explained by returns to scale. However, the parameter estimates of the production function did not consistently indicate increasing returns, for either the frontier or the average technology. Even when increasing returns were indicated, they were very weak. A more likely explanation is that a high level of output is also associated with other plant characteristics that contribute to efficiency, particularly in a given year. An attempt to assess the impact of scale on efficiency while controlling for confounding factors is explored below with regression analysis.

The association between employment and efficiency is very weak. In metal-cutting machine tools, plants with relatively high employment also have relatively high efficiency ranks, but not higher efficiency scores. This seems inconsistent, but it may be due to systematic patterns over time. That is, while no correlation between

Table 29. Pearson correlation coefficients between efficiency and plant characteristics: size, average production worker wage, and investment[a]

	3541			3542		
Characteristic	Obs.	Efficiency	Efficiency Rank	Obs.	Efficiency	Efficiency Rank
Total Value of Shipments	2032	.1913 (.0001)	.0993 (.0001)	1367	.1050 (.0001)	.0933 (.0006)
Total Employment	2032	-.0024 (.9142)	.0500 (.0243)	1367	.0602 (.0260)	.0410 (.1299)
Average Prod. Worker Wage	2032	.6035 (.0001)	.0865 (.0001)	1367	.0661 (.0146)	-.0122 (.6523)
New Investment						
Year t	2032	.1435 (.0001)	.0087 (.6944)	1367	.0432 (.1106)	.0469 (.0828)
Year t-1	1486	.1756 (.0001)	-.0094 (.7170)	1030	-.0162 (.6044)	-.0192 (.5382)
Year t-2	1228	.1801 (.0001)	.0178 (.5338)	844	-.0422 (.2205)	-.0170 (.6226)
Year t-3	1024	.1810 (.0001)	.0073 (.8155)	679	-.0327 (.3948)	-.0609 (.1132)
Year t-4	828	.2042 (.0001)	.0160 (.6453)	540	-.0116 (.7876)	-.1229 (.0042)
Year t-5	671	.1877 (.0001)	.0076 (.8439)	422	-.0071 (.8847)	-.1664 (.0006)
Year t-6	597	.1459 (.0003)	-.0033 (.9357)	366	-.0313 (.5502)	-.1701 (.0011)
Year t-7	523	.0375 (.3928)	-.0311 (.4776)	309	-.0262 (.6460)	-.1664 (.0033)
Year t-8	450	.0660 (.1623)	-.0245 (.6042)	259	-.1305 (.0349)	-.2115 (.0006)

[a]Numbers in parentheses are probability that the value is observed under the null hypothesis that the correlation coefficient is equal to zero.

efficiency score and employment exists across years, within a year, plants with high employment also have relatively high scores.

The association between size and efficiency is clearly confounded by other factors. The relationship will be clarified in the regression analysis performed below.

Average Production Worker Wage

Average production worker wage is correlated with efficiency in both industries. This result confirms the preliminary information from Table 10 that showed a relationship between traditional efficiency measures and average wage. Plants with higher average production worker wages probably are paying for workers with better skills, which results in greater efficiency.

However, the correlation is weaker for metal-forming machine tools than for metal-cutting machine tools. This may be due simply to differences in the time trend of the two industries. Figure 17 showed that efficiency generally rose over time in metal-cutting machine tools, but fell slightly for metal-forming machine tools. The effects of time on the relationship between efficiency and wages can again be sorted out by the regression analysis below.

Investment

Correlation were calculated for efficiency and efficiency rank against investment in the concurrent year and in the fifteen previous years. Statistically significant correlations were found between efficiency score and lagged investment in both industries. In metal-cutting machine tools, the correlation was .143 in the concurrent year, rose slightly for each year backward, peaked at year t-4, then declined, and no statistically significant correlation was found after year t-6. No statistically significant correlations were found between investment and efficiency rank in this industry, indicating that investment and efficiency vary unsystematically over time.

In metal-forming machine tools, no statistically significant correlations were found between investment and efficiency score. Statistically significant correlations were found between lagged investment and efficiency rank; these correlations are negative and become significant at four year lag. This result seems counter-intuitive; plants making new investments should reap efficiency gains in the future. However, this negative association might reflect the capacity utilization problem. Plants that increased capacity during the boon of the early 70s might have suffered especially severe capacity utilization problems in later years. However, there is little reason to believe that this would be true for metal-forming tools, but not for metal-cutting tools. Perhaps it is not simply the level of investment that is important, but the type of investment. In Chapter 7, the relationship between efficiency and specific technologies will be investigated using plants responding to the 1988 Survey of Manufacturing Technology.

Ownership

A plant owned by a multi-unit firm is likely to have higher efficiency for two reasons: first, because it is likely to benefit from the specialization of manufacturing functions, and second, because the administrative functions of the plant are likely to be provided by corporate headquarters. In metal-cutting machine tools, 56 percent of the 380 separate plants are owned by firms that also own other plants. This 56 percent of the plants represents about 73 percent of the observations, because the plants owned by multi-unit firms tend to be present in the sample over a longer period of time. In metal-forming machine tools, 55 percent of the plants are owned by multi-unit firms, and these account for about 69 percent of the observations.

Averages of technical efficiency by year and ownership class are shown in Table 30. Tests of significance of the difference of the means resulted in acceptance of the null hypothesis that the means were equal in all years, except for 1983 in metal-forming machine tools. There is no evidence from these tests to support the hypothesis that plants owned by multi-unit firms are more efficient than their single unit counterparts.

Age

Measurement of plant age with the LRD is limited by the truncation of the data. Longitudinal linkage of plants across census years is available as early as 1963; however, if a plant is operating in 1963, the first year of operation is unknown. About 54 percent of the plants in metal-cutting machine tools and 47.4 percent of the plants in metal-forming machine tools were operating in 1963. Furthermore, plants

Table 30. Average efficiency scores for plants owned by single and multi unit firms

	3541		3542	
Year	Single-Unit	Multi-Unit	Single-Unit	Multi-Unit
1972	.409	.421	.747	.749
1973	.411	.415	.811	.826
1974	.405	.412	.711	.725
1975	.400	.407	.689	.707
1976	.387	.406	.671	.682
1977	.401	.409	.638	.656
1978	.394	.404	.671	.633
1979	.797	.809	.659	.709
1980	.761	.774	.659	.682
1981	.723	.735	.631	.651
1982	.695	.699	.594	.627
1983	.652	.668	.545*	.606*
1984	.841	.810	.716	.768
1985	.837	.806	.716	.771
1987	.825	.828	.730	.773

*Difference between means is significant at $\alpha = .05$.

that began operating between 1964 and 1967 were first observed in 1967; plants beginning operations between 1968 and 1972 were first observed in 1972; and plants beginning operations between Census years sometimes are not added to the ASM sample until after the following Census. Therefore, it was decided to treat age as a discrete, rather than a continuous variable. The plants were partitioned into five groups according to the year in which they were first observed on the LRD. Age group 1 was first observed in 1963; age group 2 was first observed in 1967; age group 3 was first observed in 1972; age group 4 was first observed in 1973 through 1977; age group 5 was first observed in 1978 through 1982; age group 6 was first observed from 1983 through 1987.

Average efficiency scores and the number of observations by year for each group are provided in Tables 31 and 32. Results of tests of significance of the differences between mean efficiencies of each group are in the final column. In metal-cutting machine tools, the youngest plants are often the least productive, and in years 1973-1976, 1979, and 1983, these differences are statistically significant. For years 1984-1987, the least productive plants are those in age group 2. The group with the highest average efficiency score was always neither the youngest nor the oldest, except in 1984. From 1983 to 1984, the plants in group 6 changed from being the least to the most productive as a group. It is interesting to note that between these two years, there was complete turnover in this group; i.e., none of the plants in 1983 was also present in the sample in 1984. This is probably at least partially due to the

Table 31. Average efficiency scores and number of plants by year and age group, metal-cutting tools

Year	Group 1 to 63	Group 2 64 - 67	Group 3 68 - 72	Group 4 73 - 77	Group 5 78 - 82	Group 6 83 - 87	Signif. Diff.
1972	.412 124	.444 15	.426 25	--[a]	--	--	None
1973	.409 129	.452 16	.426 22	.329 3	--	--	1,2,3 with 4
1974	.402 101	.459 12	.437 20	.344 4	--	--	1,2,3 with 4
1975	.395 101	.457 11	.452 16	.362 8	--	--	2 with 4
1976	.392 98	.448 12	.449 18	.352 9	--	--	2,3 with 4
1977	.401 85	.447 12	.434 16	.386 14	--	--	None
1978	.395 88	.417 12	.435 15	.379 18	(D)[b]	--	None
1979	.804 95	.837 9	.796 11	.826 5	.787 8	--	2 with 5
1980	.771 95	.792 9	.761 12	.797 5	.734 10	--	None
1981	.734 100	.758 9	.724 12	.764 5	.697 15	--	None
1982	.701 97	.724 6	.691 12	.699 6	.663 12	--	None
1983	.670 82	.679 7	.651 11	.657 5	.649 11	.596 5	1,2 with 6
1984	.815 78	.763 8	.845 24	.833 7	.814 13	.880 5	1,2 with 6 2 with 3
1985	.812 77	.763 8	.843 23	.831 6	.810 12	.827 7	2 with 3
1987	.830 65	.757 7	.856 13	.789 7	.851 9	.811 4	2 with 3

[a]-- = no observations for this cell.
[b](D) = data are suppressed to prevent disclosure.

Table 32. Average efficiency scores by year and age group, metal-forming tools.

Year	Group 1 to 63	Group 2 64 - 67	Group 3 68 - 72	Group 4 73 - 77	Group 5 78 - 82	Group 6 83 - 87	Signif. Diff.
1972	.762	.835	.598	--[b]	--	--	1 with 2,3
	72	16	16				2 with 3
1973	.835	.883	.727	.773	--	--	1 with 2,3
	72	14	18	3			2 with 3,4
1974	.718	.731	.713	.754	--	--	None
	61	21	17	5			
1975	.700	.714	.695	.698	--	--	None
	58	20	17	6			
1976	.682	.690	.678	.637	--	--	None
	57	23	16	10			
1977	.656	.663	.638	.636	--	--	None
	52	15	9	12			
1978	.637	.636	.603	.615	(D)[d]	--	None
	48	16	10	15			
1979	.707	.679	.700	.699	.736	--	None
	56	13	13	22	6		
1980	.675	.652	.678	.661	.712	--	None
	58	13	11	21	6		
1981	.650	.623	.647	.641	.630	--	None
	53	13	10	18	8		
1982	.625	.616	.610	.600	.587	--	None
	50	8	10	11	8		
1983	.591	.576	.579	.553	.551	.636	None
	46	7	11	11	5	3	
1984	.766	.830	.797	.746	.718	.706	1 with 2
	34	4	3	6	7	5	2,3 with 6
1985	.761	.833	.822	.797	.718	.706	2,3 with 6
	36	3	4	5	7	5	
1987	.750	.785	.829	.764	.818	.752	None
	35	3	3	8	4	4	

[a]-- = no observations for this cell.
[b](D) = data are suppressed to prevent disclosure.

changes in the ASM panels between years. Issues of survival are investigated further in the next section.

In metal-forming machine tools, age appears far less important in determining efficiency. Sometimes the most productive plants are the oldest, sometimes the youngest. There are very few statistically significant differences between age groups. The association between age and efficiency may be weaker in this industry because of a slower pace technological change. That is, if new plants embody new production technology, and if the pace of technological change is slower in metal-forming machine tools, then new plants may not be technologically different from older plants.

The pattern of correlation between age and efficiency in metal-cutting machine tools suggests a process of "learning by doing" (Arrow 1962). New plants amy be less productive because the workers and managers do not have much experience with the new plant and equipment. However, the oldest plants are not the most efficient, so the advantage of experience may wane as the vintage of the capital increases.

Plant age does not necessarily reflect the vintage of the machinery, as old plants may be retooled. The capital vintage question was addressed indirectly by the correlations between investment and efficiency. However, in order to separate the effects of learning by doing and capital vintage, more precise data on the vintage of capital as well as the turnover of employees is required than are available for this study.

Location

Theories of industrial location suggest that relative productivity might be affected by the physical location of the plant. Several factors typically are cited by managers as important to location choice: the condition of local infrastructure, such as access to adequate supplies of water, energy, and transportation services; environmental regulations, such as solid waste disposal regulations and water and air pollution regulations; and market criteria such as proximity to customers, suppliers, competitors, and other offices of the company (Anderson et al. 1990). It is reasonable to assume that these locations are preferred because they either lower costs or improve demand.

Some of these conditions might be expected to vary between metropolitan and nonmetropolitan areas. Rural areas sometimes are deficient in essential infrastructure, and may not be close enough to population centers to provide an adequate labor force. Rural areas might also lack essential business services, which may be especially important to plants that are to small to support in-house services. Plants located in rural areas might be too far from their competitors and customers to benefit from the agglomeration economies that might increase efficiency for plants in metropolitan areas.

Other factors raise efficiency for a plant with a rural location: the availability and price of land, tax rates, and less congestion. One recent studies of productivity differences between rural and urban locations showed that the advantage of rural or urban location is likely to depend on the specific resource requirements of the industry (Martin et al. 1992).

Most machine tool manufacturers are located within Standard Metropolitan Statistical Areas. Only 12.6 percent of the plants in metal-cutting machine tools and 16.3 percent of plants in metal-forming machine tools are located outside SMSAs. Table 33 shows average efficiency scores for plants located in metropolitan and nonmetropolitan locations. It appears that efficiency in the machine tool industry is not sensitive to metropolitan or nonmetropolitan location; no significant differences were found, except for 1984 and 1985 in metal-forming machine tools. In this case, metropolitan plants, on the average, were about 10 percent more efficient than nonmetropolitan plants.

The lack of metropolitan efficiency effects might reflect the failure of location to proxy for the supposed advantages or disadvantages it provides. In order to study more directly the possible impact of location and agglomeration, a measure of the siting of plants relative to their customers and suppliers should be constructed. This variable might more accurately reflect agglomeration, and the efficiency variations might be stronger. While construction of such a variable is possible with data from the LRD, this task is left to later work.

Access to Manufacturing Extension

In 1972, manufacturing extension programs were operating in five states (Georgia, Iowa, North Carolina, Pennsylvania, and Tennessee). These states contain few machine tool manufacturers, and only about 5 percent of the machine tool

Table 33. Average efficiency scores for plants in metropolitan and nonmetropolitan locations, by year.

	3541		3542	
Year	Metropolitan	Nonmetropolitan	Metropolitan	Nonmetropolitan
1972	.420	.396	.753	.718
1973	.417	.392	.824	.805
1974	.412	.402	.717	.749
1975	.407	.396	.699	.721
1976	.403	.400	.679	.678
1977	.406	.413	.653	.652
1978	.401	.407	.628	.633
1979	.804	.813	.709	.676
1980	.767	.788	.679	.642
1981	.728	.756	.653	.604
1982	.691	.740	.621	.592
1983	.660	.685	.584	.575
1984	.819	.828	.773*	.678*
1985	.814	.828	.777*	.678*
1987	.827	.821	.770	.717

*Difference between means is significant at $\alpha = .05$

manufacturers in the U.S. had access to industrial extension services (the assumption that all manufacturing extension programs are accessible to all manufacturers is feasible; while there are a few instances in which only small plants are targeted, most programs service any manufacturing plant located in the state (Clarke and Dobson 1991)). Not until the inception of the Ohio Technology Transfer Organization (OTTO) program in 1979 did a significant share of the machine tool industry have access to these services. With the addition of Ohio in 1979, machine tool manufacturers in states with operating programs represented about 20 percent of the entire machine tool industry. The inception of the Michigan Manufacturing Institute in 1981 brought that percentage to about 50 percent; by 1987, about 75 percent of the machine tool manufacturers in the sample had access to industrial extension services.

Table 34 shows that access to manufacturing extension is not associated with higher relative extension offices. In metal-cutting machine tools, while plants with access to manufacturing extension services had a higher average efficiency than other plants in ten of the fifteen years, this difference was statistically significant only for years 1977 and 1982. In metal-forming machine tools, the extension plants were on the average more efficient in only six of the fifteen years; none of the differences was statistically significant. Access to services, of course, does not imply that direct assistance was provided. However, it does imply public efforts to improve the flow of information to manufacturing regarding new technologies and manufacturing management. Failure to find significant correlation might be due to confounding effects that are associated with low efficiency. In fact, it may be that the low

Table 34. Average efficiency scores for plants located in states with active manufacturing extension program, versus those not located in any of those states[a]

Year	States Operating Programs	Percent of Plants 3541	Percent of Plants 3542	Average Efficiency 3541 With Access	Average Efficiency 3541 Without Access	Average Efficiency 3542 With Access	Average Efficiency 3542 Without Access
1972	5	3.66	10.58	.462	.416	.728	.751
1973	5	4.71	10.28	.428	.413	.809	.823
1974	5	6.57	7.69	.486	.405	.767	.718
1975	5	5.15	8.91	.512	.399	.731	.699
1976	5	5.84	10.38	.483	.397	.700	.676
1977	5	7.87	9.09	.512*	.399*	.654	.652
1978	5	7.46	8.89	.472	.396	.631	.629
1979	6	19.53	19.09	.785	.810	.675	.710
1980	7	20.61	19.27	.750	.775	.647	.678
1981	8	51.06	33.33	.744	.720	.636	.647
1982	8	48.12	34.48	.721*	.677*	.614	.616
1983	8	47.93	33.73	.681	.647	.598	.574
1984	15	57.04	45.76	.809	.836	.739	.776
1985	17	66.92	68.33	.806	.836	.758	.771
1987	25	73.33	77.19	.820	.843	.758	.781

[a]Source: Start years for industrial extension programs in most states are taken from Clarke and Dobson, 1991. Some start dates were obtained by the author by phoning the industrial extension services.

efficiency of manufacturing in a given state is a catalyst for the development of aprogram. The regression analysis performed below analyzes the effect of extension with other variables held constant. In Chapter 7, data on actual assistance provided to plants by manufacturing programs is merged with the LRD data to determine the impact of actual participation, rather than access, on efficiency.

Summary: What Plant Characteristics Contribute to Efficiency?

A significant and strong association with efficiency was found for size (measured in total value of shipments) and the average production worker wage. A somewhat weaker relationship with efficiency was found for investment and age; almost no relationship with efficiency was found for multiple versus single unit firm ownership, metropolitan versus nonmetropolitan location, and access to manufacturing extension. However, the correlations and hypothesis tests reported above did not control for the effects of other variables. In order to glean more information from the data about the relationship between plant specific variables and efficiency, a simple linear regression model explaining the log of the efficiency score was estimated for each industry. The results of the estimation are reported in table 35, with standard errors in parentheses. Abbreviations for independent variables are listed in Table 36.

The log of the total value of shipments could not be included in the regression because of the obvious problem with correlation between total value of shipments and efficiency, since efficiency is equal to output minus a function of the inputs.

Table 35. Results from estimation of a linear regression model of plant characteristics on technical efficiency

Independent Variable	Parameter Estimate / Standard Error	
	3541	3542
Intercept	-1.462*	-0.919*
	(0.049)	(0.048)
t	0.041*	-0.018*
	(0.002)	(0.002)
Multi	-0.063*	-0.009
	(0.013)	(0.011)
Metro	-0.036	0.045*
	(0.015)	(0.013)
AGE2	0.077*	0.033*
	(0.021)	(0.016)
AGE3	0.061*	0.004
	(0.017)	(0.016)
AGE4	-0.083*	0.027
	(0.025)	(0.017)
AGE5	0.098*	0.031
	(0.027)	(0.026)
AGE6	-0.015	0.105*
	(0.053)	(0.044)
Ext	0.048*	0.025*
	(0.014)	(0.013)
Invest[a]	7.40 E-6	-1.79 E-5*
	(4.02 E-6)	(0.67 E-5)
Log of Avg TVS	0.017*	0.048*
	(0.005)	(0.006)
log of AVGPW	0.214*	0.111*
	(0.021)	(0.019)
Adj. R^2	.599	.148

[a]This variable could not be logged because of zeros in the data.

*coefficient is statistically different from zero.

Table 36. Abbreviations for key variables

Variable Name	Description
Q	Real output
M	Real value of materials
VQ	Nominal output
TVS	Total value of shipments
endFGI	Finished goods inventory, end of year
begFGI	Finished goods inventory, beginning of year
endWIPI	Work-in-process inventory, end of year
begWIPI	Work-in-process inventory, beginning of year
APWW	Average production worker wage
PWW	Total production worker wages
PWH	Total production worker hours
NPWW	Total Non-production worker wages
L	Labor (production worker equivalent hours)
K	Capital stock (net, in constant dollars)
GBV	Gross book value of the capital stock
NSTKCON	Net industry capital stock (2 digit), constant dollars
GSTKHIS	Gross industry capital stock (2 digit), historical dollars
BR	Building rent
BRR	Building rental rate (2 digit industry)
MR	Machinery rental
MRR	Machinery rental rate (2 digit industry)

[a]all dollar denominated variables are reported as thousands of dollars. Labor is reported as thousands of hours.

Therefore, size was measured by taking an average of the total value of shipmentsover all years the plant was in the sample.

Metal-Cutting Machine Tools

Of all the variables considered, average production worker wage has the strongest influence on efficiency. The coefficient is both statistically and quantitatively significant. Since both variables are logged, the coefficient can be interpreted as an elasticity. For every percentage change in the average production worker wage rate, a .214 percent change in technical efficiency occurs. Of course, this does not imply causation. Simply raising wages will not increase efficiency, but the evidence supports the contention that plants that pay higher production worker wages are higher efficiency plants.

The size of the plant, as measured by the average value of the total value of shipments, does influence efficiency, but the coefficient is very small. This indicates that the strong correlations found in the previous section were probably due to the factors confounding the relationship between size and efficiency. For example, larger plants generally pay higher wages (Dunne and Schmitz 1992).

Plants that are part of multi unit firms are relatively less efficient. This is counter intuitive, given the ability of multi-unit firms to concentrate administrative activities in home offices, and allow plants to specialize in production. However, there may be other factors to consider. The MIT Commission on Industrial Productivity (March 1989) noted the increasing conglomerate ownership of machine tool builders as a factor contributing to the decline of the industry, primarily through lack of reinvestment. Conglomerates used the profitable machine tool companies to support corporate overhead and less profitable divisions, rather than returning profits to the machine tool divisions for investment. Failure to invest in new equipment did not significantly effect the machine tool builders for a number of years, because life cycles of machine tools are long (March 1989). The implication is that the plants being operated by multi-unit firms were not being operated to maximize the future profits of the machine tool plant, but the profits of the firm.

Age classes entered the model as dummy variables, as listed in table 36. AGE1 was left out of the model so the coefficients of the other age variables should be interpreted relative to AGE1 plants. The pattern of coefficients for the age variables confirms the findings from the correlations.Relative to the oldest plants, ages 2,3, and 5 always are more efficient. Plants in AGE5 have highest efficiency and plants in AGE6 were not different from AGE1 plants.

Access to manufacturing extension has a positive influence on efficiency. The coefficient is small, but is well within statistical significance. The implication is that the information circulated by the extension services aid in improving the flow of technological knowledge to manufacturers. While the results are weak, this was expected, given the blunt measure of access used here. In Chapter 7, an analysis of the effect of direct intervention on efficiency is performed.

Variation of the efficiency scores is fairly well explained by the independent variables; the adjusted r-square statistic is .602. A hypothesis test on the distribution of the residuals of the model show that the errors are normally distributed.

Metal-Forming Machine Tools

For industry 3542, wage and size both influence the efficiency score. The wage coefficient is smaller than it is for metal-cutting machine tools, but the coefficient for size is larger. Investment has a very small but statistically significant negative coefficient. This is opposite of what we would intuitively expect, but may be due to problems of capacity utilization for plants that overexpanded prior to the 1982-83 recession.

Ownership has no significant effect on efficiency. Age seems to be a less important factor in this industry than for metal-cutting machine tools, and, just as was found for the tests of mean differences, there is no district pattern of efficiency over age. AGE2 and AGE6 plants both are more efficient than the oldest plants.

Metropolitan location has a positive influence on efficiency for metal-forming tools. No such effect was found for metal-cutting machine tools, and this may be due to the relative concentration of the customers of the metal-forming tool industry. Their primary customers are the auto manufacturing industry. During the 1970s and early 1980s, before many of the foreign owned auto manufactures began operating in the U.S., the auto industry was concentrated around Detroit. Almost twenty percent of the metal-forming tools manufacturers in the U.S are located in Michigan. Perhaps proximity to these customers provided an efficiency advantage for those located in the Detroit metropolitan area.

The availability of manufacturing extension has a positive influence on efficiency. This coefficient should be interpreted with caution, in light of the findings regarding location. If agglomeration economies do exist in this industry, but are not all captured by the metro variable, then some of these effects might be included in the extension variable. For the plant located in Michigan, it is impossible to separate the impact of the extension activities of the Michigan Industrial Technology Institute from agglomeration economies that might not be captured by the metro variable. This issue is explored further in Chapter 7.

The fit of the model for industry 3542 was very poor. The adjusted r-square statistic is very small, and the model does not produce normally distributed residuals. Perhaps the assumptions of the OLS regression model are not valid for efficiency and plant characteristics in this industry. Considering these results together with those of the correlations and hypothesis tests, few of the plant characteristics examined can sufficiently explain why some plants in industry 3542 are more efficient than others.

Efficiency, Growth, and Survival

Plants with higher efficiency are expected to grow more quickly and will survive longer than plants with lower efficiency. Efficient plants are able to produce at lower cost, or higher quality products. In a competitive market, they will therefore capture an infinitely large share of the market and should be able to live longer.

In this section, two issues are addressed. First, do plants with higher efficiency scores experience a greater probability of survival, and second, do plants with higher efficiency scores experience a higher growth rate in subsequent years? Survival is analyzed by applying a probit model, and growth is analyzed by correlating efficiency ranks and growth rate rankings.

Efficiency and Survival

The association between plant survival and efficiency was investigated by estimating the probability of plant survival as a function of technical efficiency and other plant specific characteristics. In order to develop a model, several decisions about the dependent variable had to be made. First, the year of plant death had to be established. Second, the time period over which death probability is defined had to be decided, and finally, the unit of observation had to be selected.

Year of Death

Data for all plants that were ever in the ASM sample were examined across time from 1963 to 1988 to determine the final year that the plant was observed operating in any manufacturing industry. The last year in which the plant appeared in either the ASM or census data in any industry was recorded as the plant's last death year. The data examined to determine the death year was not affected by changes in the ASM sample, since death is only recorded if a plant is never observed again, in either the census or the ASM samples, in any manufacturing industry. For plants present in the 1987 data, a death was recorded only if the plant was not operating in 1988 and was part of the ASM sample for 1984-1988. If the plant was not part of the ASM sample for that year, there was no way to determine if the plant had survived past 1987.

Time Horizon

Choosing the time horizon over which to define the death probability posed several problems. The most logical choice was to measure the probability that death occurs in the following year as a function of the current year variables such as efficiency, size, wage, etc. The death counts calculated with this approach are shown in Table 37 under Definition 1. One flaw in this approach is that the last year of each ASM panel period, 1973, 1978, 1983, had to be removed from the analysis because the death rate would be overestimated in those years. For example, if a plant was in the ASM sample in 1978, but was not in the ASM panel that started in 1979, and it did not appear in the 1982 census, then the death was associated with the observation for 1978, even if the plant continued to operate until 1981.

This approach to defining death produced a very small number of death observations, especially when the ASM transition years were removed. This was primarily an artifact of turnover in the ASM sample. There were many more deaths than 56 for metal-cutting machine tools and many more than 41 for metal forming machine tools over the period. But many plants are not observed the year before their deaths because they had been dropped from the sample, either because they had switched out of the industry or because they were no longer ASM plants. With such a small amount of variation in the dependent variable, results from the probit

Table 37. Number of plant deaths for two alternative definitions of death

Year	3541 Total Plants	3541 Deaths Def. 1[a]	3541 Deaths Def. 2[b]	3542 Total Plants	3542 Deaths Def. 1	3542 Deaths Def. 2
1972	164	0	74	104	0	36
1973	170	3	76	107	1	33
1974	137	0	60	104	0	32
1975	136	3	55	101	1	34
1976	137	2	53	106	4	21
1977	127	1	47	88	1	21
1978	134	8	46	90	4	21
1979	128	1	33	110	0	26
1980	131	2	34	109	2	27
1981	141	5	37	102	3	22
1982	133	3	35	87	5	20
1983	121	14	27	83	13	17
1984	135	2	27	59	2	7
1985	133	10	24	60	4	5
1987	105	2	2	57	1	1
Total	2032	56	143	1367	41	81

[a]Number of plants not observed again in manufacturing.

[b]Number of plants not observed operating at the end of the period.

analysis of survival became suspect. Furthermore, year dummy variables could not be included in the model because some years had no deaths. A dummy variable indicating which ASM panel the time period represented (Pan2, Pan3, Pan4) was included instead.

A second approach defined death in the broadest sense possible: death anytime within the observed sample period. It is possible that plant failure is a function not only of the conditions and efficiency of the plant in the year previous to the closure, but also of its efficiency and conditions in previous years. The logit model for this approach estimates the probability that the plant survives throughout the sample period.

Unit of Observation

Provided the that the time horizon for estimation of survival probabilities was the entire sample period, the unit of observation had to be determined. Two methods were considered. In the first, the plant was the unit of observation. For metal-cutting machine tools, 143 of the 380 separate plants observed died before the end of the sample period. In metal-forming machine tools, 81 of the 251 separate plants died.

Independent variables for this model ideally would be efficiency and plant characteristics for each year of plant operation. However, these variables are highly serially correlated; including each as independent variables would lead to unstable estimates of the parameters. Furthermore, since many plants are included in the industry ASM sample for only a few years, the probit model could not include the lags of the plant characteristics as independent variables because there would be many missing values in the data. Therefore, the independent variables for the probit were the averages of the plant characteristics and efficiencies.

Some adjustment of the efficiency averages to account for systematic variation of efficiency scores over time was desired. Without this adjustment, a plant that was in the sample early in metal-cutting machine tools, for example, and then dropped out would automatically have a lower average of efficiency scores. Average rank was considered, but the range of this measure would vary with the number of plants in the sample. The average relative rank of the plant was used instead. Average relative rank was constructed by dividing the plant's rank for the year by the number of plants in the sample in that year. This index has the same theoretical range--between zero and one--of the efficiency score itself. These relative ranks were averaged across time, and this is used as the independent variable representing efficiency.

Dummy variables indicating the presence of the plant in the ASM sample in each year were included to control for the systematic variation of the independent variables over time. These are not mutually exclusive variables; a plant could have a value of 1 for each of them; hence although all are included in the model, it is fully identified.

The third probit model estimated the probability that a plant observed in a given year would survive through the sample period, as a function of efficiency and plant characteristics for that year only. The number of deaths for each year is given in Table 37 under Definition 2. The table tells, for example, that 74 of the 164 plants observed in metal-cutting machine tools in 1972 died before the end of the sample period. Year dummy variables were added to the model to account for the truncation of the data that does not allow observation of the death of plants after the end of the sample period. In addition, all observations for 1987 were eliminated, because the opportunity to observe their death was so limited.

The three models described above were estimated with probit analysis as described in Maddala (1983). Tables 38 through 40 provide results for the first, second, and third death definitions, respectively. Each table shows the actual parameter estimates and the multiplication factors for calculating marginal probabilities. This factor was calculated from the averages of the variables and the parameter estimates. In particular, the marginal probabilities are

$$\frac{\partial P_i}{\partial x_{ij}} = \varphi(X_{ij}\beta_i)\,\beta_i,$$

where φ is the p.d.f. of the standard normal . The factors listed in the tables are the value the p.d.f. at the average of $X\beta$, as suggested by Greene (1990). The numbers in parentheses under the parameter estimates are the chi-square statistics from Wald tests based on the observed information matrix and the parameter estimates. They are distributed chi-square with 1 degree of freedom. Hence the critical value at α = .05 is 3.84. For each model, a comparable logit analysis was estimated, and the results were almost identical to the probit, with respect to both the log of the likelihood function and the marginal probabilities.

Fit of the models was measured in two ways. The proportion of observations for which the model forecasted correctly was calculated as follows. If the predicted probability was greater than .5, it was counted as a predicted survival. Otherwise, it was counted as a predicted death. The proportion of observations for which this prediction was correct is listed in the table and is titled "Prop. Correct." This statistic doesn't have much meaning for the first set of estimations; there are so few deaths that if the model predicted survival universally, it would be right most of the time. McFadden r-square statistic is simply 1 - [log L_{UR}/log L_R] where L_{UR} is the likelihood function from estimation of the model with no regressors (intercept only), and L_R is the likelihood function for the given model (Maddala 1988).

Results

The most generally applicable result across each of the models is that the independent variables are not very good predictors of the survival of plants, especially for metal-forming machine tools. The plant level analysis of survival over the entire period (Model 2) does the best job of fitting a model to the data. Even in this case, however, the highest value for the McFadden r-square is .402.

Plant-year short term analysis. This analysis modeled the probability of a plant surviving to the next year, as a function of the plant characteristics of that year. The results from this analysis are shown in Table 38. The fit of the models is very

Table 38. Coefficients chi-square statistics and fit statistics from probit analysis of the probability of survival to the next year, panel analysis

	3541		3542	
Variable	Model 1	Model 2	Model 1	Model 2
Factor[a]	.023	.022	0.032	0.024
Intercept	0.458 (0.389)	1.801* (29.185)	1.681* (9.562)	2.829* (71.923)
Efficiency	0.796 (1.040)	1.438 (3.575)	0.419 (0.299)	
Average Wage	-0.021 (1.865)	-0.026 (3.150)		-0.111* (13.938)
Log of TVS	0.271* (10.607)			
Employment		1.015e-3* (5.382)	2.458 R-3* (4.572)	2.336 E-3 (3.228)
Multi	-0.479* (4.606)			
Metro	-0.135 (0.201)			
AGE2	0.184 (0.194)	0.197 (0.243)		-0.262 (0.769)
AGE3	0.247 (0.599)	0.124 (0.171)		-0.042 (0.015)
AGE4	-0.358 (1.327)	-0.421 (2.029)		-0.474 (2.692)
AGE5	-0.540* (4.070)	-0.598* (5.436)		-0.734* (4.189)
AGE6	-2.328* (36.720)	-2.261* (35.767)		-1.476* (9.941)
Pan2	-0.519 (2.138)	-0.657* (3.853)	0.252 (1.399)	0.140 (0.293)
Pan3	-0.385 (0.852)	-0.603 (2.462)	-0.554* (5.088)	0.544 (2.076)
Log Likelihood	-116.743	-120.798	-104.067	-91.910
Prop. Correct	70.0	70.1	75.7	75.8
McFadden R^2	.237	0.211	0.066	0.175
Observations	1607	1607	1087	1087

[a]Multiplication factor for marginal probabilities at the means of the independent variables.
*significantly different from zero at $\alpha = .05$

poor, especially for metal-forming machine tools. There is little evidence that any of the independent variables has much influence over the probability of survival to the next year.

Efficiency approaches significance only in metal-cutting machine tools, and only when size is measured by the total value of shipments. The change in the coefficient from Model 1 to Model 2 is probably due to the strong correlation between shipments and efficiency found earlier.

The average wage carries a negative coefficient that is not statistically significant for metal-forming machine tools. The effect of adding wage to the model is that employment becomes insignificant. This could be caused systematic changes in employment and wages over time that have not been accounted for by the panel dummies. Dummy variables could not be included for every year because some years had zero deaths, so the time effects could not be completely accounted for.

Longitudinal analysis. This analysis predicts the survival probability of a plant as a function of the averages of plant characteristics over time. The results of the model appear in Table 39. As indicated by the McFadden r-square statistics, the fit for these models is much improved over the models in Tables 38. However, the fit for metal-forming machine tools is still very poor.

Average efficiency over the life of the plant contributes to its chances for survival in metal-cutting machine tools, regardless of the efficiency measure used. No model produced coefficients for efficiency in metal-forming machine tools that approached statistical significance. It appears that efficiency is not an important

Table 39. Coefficients, chi-square statistics and fit statistics from probit analysis of the probability of survival to end of period, cross section analysis

Variable	3541		3542	
	Model 1	Model 2	Model 1	Model 2
Factor[a]	.316	.314	.280	.289
Intercept	-.333 (.205)	-1.083 (1.823)	0.821* (5.631)	0.195 (0.825)
Average Rel. Rank	.718* (4.541)			
Average Efficiency		2.116* (5.617)		
Log of Average Shipments	.229* (4.561)	0.249* (5.400)		0.090 (0.551)
Average Employment			2.159E-3 (2.955)	
Average Wage	-.078* (3.965)	-0.109* (5.913)	-0.075 (3.571)	-0.072 (3.263)
Multi	-.674* (9.875)	-.665* (9.480)	-0.847* (14.857)	-.802* (13.293)
AGE2	-.191 (0.429)	-0.151 (0.269)		
AGE3	-.572* (4.551)	-0.610* (5.072)		
AGE4	-.453 (1.609)	-0.402 (1.260)		
AGE5	-1.207* (9.793)	-1.390* (11.925)		
AGE6	-2.478* (19.685)	-2.870* (23.683)		
In72	-.735* (7.003)	-.642* (5.195)	-0.357 (0.672)	-0.275 (0.428)
In73	-.273 (0.943)	-.190 (0.454)	0.072 (0.027)	0.068 (0.025)
In74	-.741 (3.262)	-.659 (2.636)	0.303 (0.395)	0.363 (0.564)
In75	-.390 (0.606)	-.383 (0.588)	-0.309 (0.303)	-0.213 (0.146)

Table 39 (continued)

Variable	3541 Model 1	3541 Model 2	3542 Model 1	3542 Model 2
In76	.645 (2.289)	.649 (2.330)	-0.081 (0.044)	-0.226 (0.364)
In77	-1.188* (4.248)	-1.073 (3.771)	0.109 (0.055)	0.199 (0.188)
In78	.957 (2.850)	.998 (3.376)	0.359 (0.658)	0.342 (0.600)
In79	0.017 (0.001)	-.143 (0.048)	0.744 (0.161)	0.794 (1.881)
In80	-.335 (0.253)	-.409 (0.344)	-1.410* (4.211)	-1.293 (3.696)
In81	.438 (0.986)	.372 (0.703)	1.099* (5.063)	0.948* (4.080)
In82	-.283 (0.921)	-.377 (1.628)	-0.416 (1.085)	-0.367 (0.859)
In83	.508 (2.647)	.597 (3.495)	0.456 (1.378)	0.421 (1.199)
In84	-.980 (3.240)	-1.106* (4.098)	-0.980 (1.396)	-1.030 (1.866)
In85	1.170* (5.019)	1.094* (4.306)	1.606 (3.394)	1.706* (4.652)
Log Likelihood	-50.928	-150.366	-117.299	-118.688
Prop. Correct	80.5	80.8	76.9	74.5
McFadden R^2	.400	.402	.257	.248
Observations	380	380	251	251

Table 40. Coefficients, chi-square statistics and fit statistics from probit analysis of the probability of survival to end of period, plant-year long term analysis

	3541		3542	
	Model 1	Model 2	Model 1	Model 2
Factor	.344	.330	.286	.275
Intercept	-.991* (10.587)	0.583* (8.481)	-1.584* (13.172)	0.134 (0.172)
Average Wage	-.060* (4.428)	-0.019 (2.282)	-0.108* (28.367)	-0.104* (26.028)
Log of TVS	.267* (60.031)		0.332* (40.697)	
Total Empl.		1.455 E-3* (100.008)		0.002* (36.380)
Efficiency	.353 (1.126)	.655* (3.957)	0.451 (1.244)	1.112* (8.024)
Investment	1.219 E-4* (8.629)	-	4.762 E-4* (8.199)	3.536 E-4* (3.864)
Multi	-.889* (106.606)	-.816* (102.114)	-0.799* (61.927)	-0.761* (60.221)
Metro	-.512* (21.390)	-.426* (17.198)		
Ext.	.159 (2.805)	0.179 (3.474)	0.515* (16.550)	0.546* (18.691)
AGE2	.084 (0.438)	0.136 (1.154)	-0.122 (1.015)	-0.074 (0.373)
AGE3	-.418* (16.981)	-.386* (14.606)	-0.074 (0.311)	0.028 (0.048)
AGE4	.060 (0.140)	-.004 (0.001)	-0.308* (4.823)	-0.323* (5.375)
AGE5	-.536* (10.956)	-.459* (7.827)	0.072 (0.083)	0.055 (0.049)
AGE6	-2.909* (34.079)	-3.086* (35.369)	-1.474* (14.337)	-1.421* (13.516)
t73	-0.052 (0.127)	-.023 (0.025)	-0.075 (0.152)	-0.082 (0.194)
t74	0.105 (0.464)	-.038 (0.058)	0.060 (0.096)	0.014 (0.541)

Table 40 (continued)

	3541		3542	
	Model 1	Model 2	Model 1	Model 2
t75	-.030 (0.036)	0.057 (0.131)	0.102 (0.267)	0.237 (1.436)
t76	0.081 (0.264)	0.188 (1.412)	0.254 (1.634)	0.429* (4.652)
t77	0.152 (0.867)	0.272 (2.744)	0.487* (4.967)	0.713* (10.767)
t78	0.161 (0.964)	0.324* (3.926)	0.478* (4.555)	0.764* (11.817)
t79	0.113 (0.296)	0.214 (1.063)	0.334 (2.520)	0.557* (7.013)
t80	0.150 (0.542)	0.283 (1.942)	0.391 (3.289)	0.636* (8.722)
t81	0.188 (0.866)	0.351 (3.082)	0.529 (0.230)	0.844* (13.346)
t82	0.310 (2.381)	0.458* (5.358)	0.632 (0.251)	0.978* (14.870)
t83	0.668* (9.892)	0.801* (14.782)	0.992* (13.450)	1.342* (24.155)
t84	0.686* (8.897)	0.796* (12.439)	1.340* (16.695)	1.695* (26.280)
t85	0.863* (13.056)	0.976* (17.306)	1.504* (16.695)	1.886* (26.301)
Log Likelihood	-1008.981	-989.156	-626.843	-623.047
Prop. Correct	73.1	73.1	78.4	78.0
McFadden R^2	.171	.187	.161	.166

[a]Multiplication factor for marginal probabilities, taken at the means of the vector of independent variables.

*Significant at α = .05.

factor in the survival of a plant producing metal-forming tools. This might be explained by industry structure that tolerates inefficiency through industrial relationships.

The size effect is strong in metal-cutting machine tools, but not significant in metal-forming machine tools. This might be interpreted as evidence that small plants are more likely to survive in the metal-forming tool industry that the metal-cutting tool industry. The fact that the average metal-forming tool plant is smaller than the average metal-cutting plant lends support to this observation.

Average wage is negative and significant in metal-cutting machine tools, and the effect approaches significance in metal-forming machine tools. When efficiency effects are controlled for, plants with higher wages are less likely to survive.

Plant-year analysis. This analysis differs from the previous two analyses because, although there is an observation for every plant year, as in the panel analysis, a death is recorded if the plant dies by 1987, as in the longitudinal analysis. Thus, several observations on a single plant can be associated with a death, and only cross sectional differences, not time series differences, are captured by the model.

These results are similar to those of the first analysis. For both industries, efficiency is only significant when the size is measured by employment rather than output. High wages detract from efficiency probability, confirming this result from both of the previous analyses. The significance of the investment coefficient can be interpreted either as showing that investment increases the probability of survival, or that plants managers anticipating a short time horizon have no incentive to invest.

Summary: Efficiency and Survival

Several observations are common to each analysis of plant survival. The probability of survival is most consistently predicted by size, wage, and ownership. These observations are robust with respect to the model specification, but not the industry. While metal-cutting machine tools showed average shipments, average wage, multi-versus single unit ownership, and efficiency and age to be important variables in determining survival, only singed versus multi unit ownership had a consistent impact on survival in metal-forming machine tools. The longitudinal analysis explained the greatest amount of variation in the dependent variable for both industries. The longitudinal analysis also provided the strongest evidence that efficiency contributes to plant survival.

Some evidence was found to support the hypothesis that access to industrial extension increases the probability of survival for metal-forming machine tools. This result is not robust with respect to model specification.

Efficiency and Growth

We suspect that a plant with higher efficiency will be able to capture a larger market share, since its relative efficiency implies either that it can produce products of comparable quality at lower cost than other plants, or that it is able to produce a higher quality output with a given vector of inputs. In order to investigate the impact of efficiency on the output growth of a plant, the one year growth rate in the total value of shipments was ranked by year for each plant. This ranking was correlated

Table 41. Pearson correlations coefficients between the rank of the growth rate of the total value of shipments and efficiency rank

Efficiency Rank Lag	3541	3542
year t	0.1100* (.0001) 1573	0.1417* (.0001) 1075
year t-1	0.0601* (.0214) 1465	0.0581* (.0631) 1024
year t-2	0.0904* (.0019) 1176	0.0957* (.0065) 807
year t-3	0.0688* (.0304) 990	.1333* (.0006) 661
year t-4	0.0471 (.2137) 699	.2089* (.0001) 444
year t-5	0.0676 (.0860) 647	0.1845* (.0002) 406
year t-6	0.0321 (.4869) 471	.1838* (.0018) 286
year t-7	0.0474 (.3007) 478	.1314* (.0261) 287
year t-8	0.0561 (0.2459) 429	.1779* (.0052) 245
year t-9	0.0698 (.1847) 363	.1733* (.0141) 200

with the plant's efficiency ranking for year t, t-1,... t-9. The results of this correlation are shown in Table 41. The numbers in parentheses are the probability of observing the estimated value of the correlation coefficient under the hypothesis that the correlation is equal to zero. The bottom figures indicate the number of observations on which the correlations are based. Since the growth rate calculation requires that a plant be present in the sample for two consecutive years, the number of observations for the concurrent rank correlations is smaller than the total number of observations.

The rank of output growth is positively related to present and lagged values of efficiency growth for both industries. In metal-cutting machine tools, the significance of the correlations only lasts for four years. After four years, the advantage of higher efficiency wears off if it is not maintained. For metal-forming machine tools, the correlations are significant and positive for the concurrent efficiency rank, and for all efficiency ranks lagged for nine years.

Apparently, the advantage of higher efficiency lingers for a longer period of time in metal-forming machine tools. This may be due to longer life cycles for the products of this industry. In 1983, 37 percent of the metal-forming machine tool in use by manufacturers in the U.S. were at least 20 years old. By contrast, the percentage of metal-cutting tools that was 20 years or older was 32 percent (March 1989). The distribution of the age of tools is generally skewed toward longer lives for metal-cutting tools. Manufacturers tend to replace metal-cutting tools less frequently, so they have an opportunity to change their perception of the machine tool builder less often. With no new experience on which to base an opinion, customers might return to the same tool builder that was efficient eight or ten years ago.

Expansion of market share through efficiency improvement is a long term strategy that requires investment in process and product development. The failure of American manufacturers to consider a long term perspective is often cited as a cause of slipping American industrial competitiveness (Dertouzos 1989). The MIT Commission on Industrial Productivity discovered a number of practices common to German and Japanese machine tool builders that reflect a long term perspective, such as taking low profit jobs to take advantage of "learning by doing." It is clear that efficiency pays off in the long run with larger market share. Encouraging American machine tool builders to consider the long term might be important to assuring the survival of the industry.

Summary

In this chapter, three features of the relationship between efficiency and plant characteristics were investigated. In the first section, it was established that plant size, age, and average production worker wage are important determinants of technical efficiency. Metropolitan location is an important (positive) influence on efficiency for metal-forming machine tools, and ownership by a multi-unit firm is an important (negative) influence in on efficiency metal-cutting machine tools. The existence of a manufacturing extension program also positively influences efficiency in both industries.

In the second section, it was discovered that large plants, plants with relatively low wages, plants owned by firms owning only 1 plant are more likely to survive. Efficiency contributed to survival for metal-cutting machine tools, but this result was not robust with respect to model specification. Industrial extension improves the probability of survival by one definition of death, but only for metal-forming machine tools. This result was not robust with respect to the definition of death that was employed.

Finally, among surviving plants, those with relatively high efficiency scores had higher output growth rates than those with lower relative efficiency scores. Efficiency increases future market share.

These results suggest policy actions for improving efficiency and survival in the machine tool industry:

1. Improving market share and encouraging cooperation among builders in order to capture size advantages;
2. Enrich worker skills to improve efficiency, and encouraging young more engineers to focus on the problems of manufacturing;
3. Encourage communication between customers and suppliers in order to create agglomeration economies even for remotely located plants;
4. Promote a more direct relationship between ownership and management so that the-long term interests machine tool business are not removed from the decisionmaking of the firm;
5. Advocate manufacturing extension programs to the industry as a vehicle

for improving plant efficiency, especially when builders are considering investment in new plant and machinery, to shorten the time of adjustment to new technologies.

CHAPTER 7. EMPIRICAL RESULTS III

Several empirical questions regarding the relationship between plant characteristics and technical efficiency have been raised but only marginally addressed. Technical efficiency scores that were developed and discussed in Chapters 5 and 6 measure the efficiency of a plant relative to the estimated best practice frontier. Plots of the frontiers showed that over time, the frontiers did not always shift inward, indicating technical advance; in fact, it appeared that technological regression occurred over time. The first section of this chapter takes a more precise approach to measurement of shifts in the frontier technology. Malmquist indexes of productivity change are constructed, and decomposed into technical change (shift is the frontier) and efficiency improvement (movement toward the frontier).

The analyses presented in Chapter 6 shed light on the factors that advance efficiency. One of the theoretically most important factors contributing to technical efficiency is the adoption of new technology. While variables such as investment, age, and wage rates suggested the role of new technology in efficiency determination, no direct measure of technology adoption was available on the LRD dataset to test the relationship. In the second section of this chapter, data from the 1988 Survey of Manufacturing technology are merged with the LRD data to examine the impact of technology adoption on technical efficiency.

The availability of industrial extension services in the state in which a plant is located is associated with improved efficiency. However, this variable was a poor proxy for actual intervention of the program in the manufacturing activities of plants. In the final section of this chapter, data on clients of the manufacturing extension services of Iowa, Michigan, and North Carolina are examined to develop more information about the relationship between extension service and efficiency.

Technical Efficiency and Technological Change

Technical efficiency scores indicate the efficiency of a plant relative to the relevant best practice frontier. These scores give no indication of the placement of the frontier, and changes in technical efficiency could be the result of a combination of shifts in the frontier (when it is allowed to do so) and efficiency improvement in a real, rather than relative sense. An application of the Malmquist index of productivity change, first developed by Caves, Christensen and Diewert (1982) decomposes changes in the technical efficiency score for a group of plants across years into shifts in the best practice production function and improvements in the real efficiency of plants. In this section, the methodology for constructing Malmquist indexes from Farrell efficiency measured is reviewed, and an application to stochastic frontiers is developed. The methodology is applied to the machine tool industry, and explanations for the results are perused.

Malmquist Indexes of Productivity

Following the notation introduced in Chapter 2, the Farrell measure of technical efficiency is

$$F_i(u,x) = \min\{\lambda : \lambda x \in L(u)\}. \tag{7.1}$$

Färe, Grosskopf, Lindgren and Roos (1992) have defined a Malmquist input based productivity measurement using the Farrell efficiency concept. Consider two input correspondences, $L^t(u^t)$ and $L^{t+1}(u^{t+1})$. Then define:

$$F_i^t(u^t,x^t) = \min\{\lambda : \lambda x^t \in L^t(u^t)\}, \tag{7.2}$$

$$F_i^t(u^{t+1},x^{t+1}) = \min\{\lambda : \lambda x^{t+1} \in L^t(u^{t+1})\}, \tag{7.3}$$

$$F_i^{t+1}(u^t,x^t) = \min\{\lambda : \lambda x^t \in L^{t+1}(u^t)\}, \tag{7.4}$$

$$F_i^{t+1}(u^{t+1},x^{t+1}) = \min\{\lambda : \lambda x^{t+1} \in L^{t+1}(u^{t+1})\}. \tag{7.5}$$

In Figure 26, (which assumes $u^t = u^{t+1}$), equation 7.2 is represented by oe/od; equation 7.3 is oc/ob; equation 7.4 is of/od and equation 7.5 is to oa/ob. Equation 7.2 and 7.5 are the traditional Farrell efficiency measures for periods t and t+1, respectively. Equation 7.3 compares period t technology to the input and output vector used in period t+1; Equation 7.4 compares period t+1 technology to the input and output vectors used in period t.

Färe, et al. (1992) define the Malmquist input based productivity measure as:

$$M_i^{t+1}(u^{t+1},x^{t+1},u^t,x^t) = \left[\frac{Fi^t(u^t,x^t)}{F_i^t(u^{t+1},x^{t+1})} \times \frac{F_i^{t+1}(u^t,x^t)}{F_i^{t+1}(u^{t+1},x^{t+1})}\right]^{\frac{1}{2}}. \tag{7.6}$$

The index can be decomposed into changes in efficiency and movements of the frontier:

$$M_i^{t+1}(u^{t+1},x^{t+1},u^t,x^t) = \frac{F_i^t(u^t,x^t)}{F_i^{t+1}(u^{t+1},x^{t+1})} \times \left[\frac{F_i^{t+1}(u^{t+1},x^{t+1})}{F_i^t(u^{t+1},x^{t+1})} \times \frac{F^{t+1}(u^t,x^t)}{F^t(u^t,x^t)}\right]^{\frac{1}{2}}. \quad (7.7)$$

The first term in equation 7.7 is the ratio of efficiency in year t to efficiency in year t+1; the term in brackets is a measure of technical change composed by taking the geometric average of the ratio of the shifts in the frontier at u^{t+1} and u^t. Improvements in productivity occur when M^{t+1} is less than one. The individual components have a similar interpretation: if a ratio is less than unity its change is a source of productivity improvement.

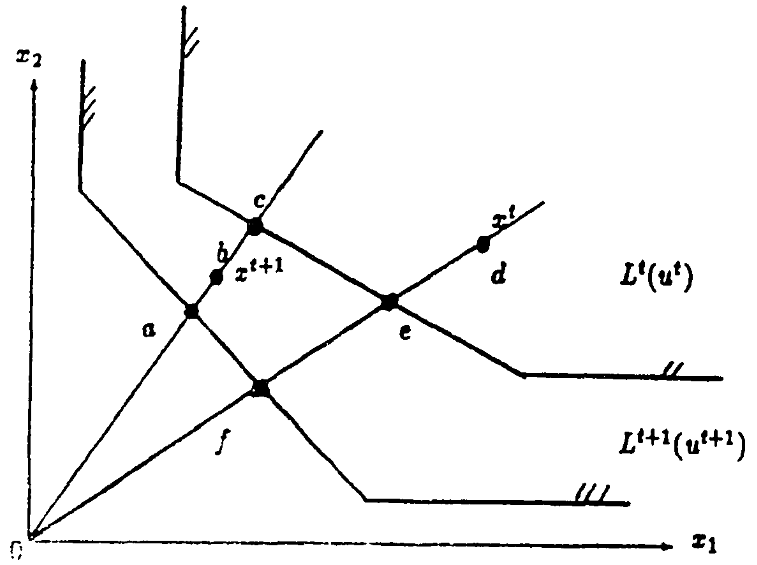

Figure 26. The Malmquist input based productivity index

To apply the Malmquist input based productivity index to stochastic frontiers, consider a simple stochastic frontier model with Cobb Douglas technology:

$$lny_{it} = \alpha_t + \sum_{j=1}^{N} \beta_{jt} lnX_{ijt} + v_{it} - u_{it} \tag{7.8}$$

where i indexes the plant, t indexes time, and N represents the number of inputs in the production function, v is a normally distributed disturbance with mean 0 and variance σ_v^2, and u is distributed truncated normal with mean μ and variance σ^2. The Farrell efficiency term is the exponential of -u. Therefore, it can be expressed as

$$F_i^t(q^t, x^t) = \frac{y_{it}}{A_t \prod_{j=1}^{N} X_{ijt}^{\beta_{jt}} V_{it}} \tag{7.9}$$

where A is the exponential of α and V is the exponential of v. Similarly, for period t+1,

$$F_i^{t+1}(q^{t+1}, x^{t+1}) = \frac{y_{i,t+1}}{A_{t+1} \prod_{j=1}^{N} X_{i,j,t+1}^{\beta_{j,t+1}} V_{i,t+1}}. \tag{7.10}$$

Application of the Malmquist index is straightforward, except for the presence of V. The Färe, et. al. application involved no error term, i.e. the frontier was deterministic. The problem specific to this application is which error term to associate with each of the four derivations of the efficiency term that compose the Malmquist index. In equation 7.8, the disturbance from period t clearly goes along with the efficiency score from period t. The same is true for the efficiency score for period t+1. However, which error term to include in the denominator is less clear for equations 7.3 and 7.4. Should equation 7.3 include the random disturbance from t, which is the period over which the technology is defined, or from period t+1, which is the period from which inputs and outputs are taken?

Assume that the disturbance term represents random events in a given time period that affect productivity, i.e. weather, strikes, machinery breakdown, etc. Then it seems logical to assign the disturbance term to the same time period as the vector of inputs and outputs. For case 2 the appropriate question is, "given the inputs, outputs, and random events occurring in period t+1, how does production compare to the frontier from period t?" Similarly, for case 3, the question is "given the inputs, outputs, and random events occurring in period t, how does production compare to the frontier from period t+1?" This approach assumes that with no random variation in the factors of production, technology is essentially a deterministic engineering relationship. If all factors of production could be measured perfectly, then a given vector of inputs would always produce the predicted value of output.

The alternative approach is to associate the error term with the technology itself, rather than the input vector. The assumption in this case is that the production function is not deterministic, but a stochastic relationship due to uncertainty about the technology, rather than the inputs.

For this application, assumption one is adopted. Equations 7.3 and 7.4 are calculated as follows:

$$F_i^t(q^{t+1},x^{t+1}) = \frac{y_{i,t+1}}{A_t \prod_{j=1}^{N} X_{i,j,t+1}^{\beta_{j,t}} V_{i,t+1}} \tag{7.11}$$

and

$$F_i^{t+1}(q^t,x^t) = \frac{y_{i,t}}{A_{t+1} \prod_{j=1}^{N} X_{i,j,t}^{\beta_{j,t+1}} V_{i,t}} \tag{7.12}$$

The Malmquist index can be calculated directly from each component in equations 7.2 through 7.5, and technical change can be backed out using equation 7.6.

Results

The Malmquist index, efficiency ratio, and technical change were calculated for each plant, using the last year of each time period for which a production function was calculated as reference years. For industry 3541, the Malmquist decomposition was performed for 1978 compared to 1983 and 1983 compared to 1987. For industry 3542, the Malmquist decomposition was calculated for 1973 compared to 1978, 1978 compared to 1983 and 1983 compared to 1987. Averages weighted by the average of the total value of shipments were calculated to provide an industry average that weights plants with a larger value of output more heavily in the development of the index. Note that the index can only be calculated for plants that were observed in both of the reference years. The results are presented in Table 42.

For metal-cutting machine tools, the Malmquist index indicates a total factor productivity decline from the first to the second production function, but a slight improvement in productivity from the second to the final period. A similar trend is observed for metal-forming machine tools: productivity decline until 1983, and then a slight improvement for the final period. These results partially agree with the simple total factor productivity calculations made with the LRD data and presented in Tables 8 and 9. The only discrepancy is that the TFP in Table 8 does not improve in the final period for industry 3541.

The decomposition of the Malmquist index into its components reveals two interesting results. First, the frontier technology appears to have regressed over the entire period for industry 3541 and from 1978 to 1987 for industry 3542. This result confirms the casual observations regarding production function shifts gleaned from plots of the frontier technology in Figures 10 through 16.

The second interesting result from Table 42 is that while both industries have suffered declines in productivity over the sample period, the decomposition into technical change and efficiency improvement is quite different. Metalcutting machinetool builders have made greater gains in efficiency over time relative to their best practice frontier than have the metal-forming tool manufacturers. This was illustrated in Figures 9 through 11 by the decreasing space between the frontier and average practice technologies. For metal-forming machine tools, the decomposition is more evenly divided between technological change and efficiency improvement (or deterioration).

Table 42. Decomposition of the Malmquist index for the machine tool industry, averages weighted by the average of the total value of shipments

	3541				3542			
Year	Malmquist TFP	Efficiency Ratio	Tech. Change	N	Malmquist TFP	Efficiency Ratio	Tech. Change	N
Indexes calculated using the last year of the production period								
1973/ 1978					1.182	1.376	0.862	59
1978/ 1983	1.267	0.624	2.037	61	1.269	1.092	1.165	40
1983/ 1987	0.969	0.804	1.205	58	0.892	0.838	1.064	29
Indexes calculated using the first year of the panel sample								
1972/ 1974					0.961	1.107	0.870	77
1974/ 1979	1.045	0.528	1.982	63	1.129	1.019	1.109	46
1979/ 1984	1.275	1.073	1.189	62	1.054	0.975	1.079	29
Unweighted indexes								
1973/ 1978					1.225	1.336	0.920	59
1978/ 1983	1.296	.624	2.080	61	1.269	1.092	1.165	40
1983/ 1987	.986	.828	1.191	58	0.862	0.808	1.067	29

The decomposition is important to the understanding of the forces underlying changes in total factor productivity. Despite the appearance of efficiency improvement in industry 3541, this is not due to movement of plants toward the frontier, but of shifts in the technology toward the plants. In industry 3542 from 1973 to 1978, the efficiency worsened, but this was due partly to the shift backward of the best practice technology. The plants were chasing a moving target.

The observed regression in the frontier technologies seems implausible: certainly, the state of knowledge in the industry, which is what the frontier theoretically represents, cannot get worse. While this is not an unprecedented result-- Färe et al (1992) also find technological regress for Swedish pharmacies between 1980 and 1981, 1982 and 1983, and 1983 and 1984--it is disturbing because of it is counterintuitive.

There are two categories of possible explanations for what is observed about technical change. The first is statistical. That is, what we observe may be an artifact of the base years, the weighing scheme, or how inputs are measured. The second category is a set of real forces that might be observed in the machine tool industry. For example, plants defining the frontier in earlier years are either losing productivity or are leaving the industry.

Reference Years

The most immediate possibility for explaining the strange result with respect to the frontier is that it is an artifact of the reference years chosen. In order to check for robustness with respect to which years were chosen, the indexes were recalculated using different reference years. The first year in a panel sample was chosen for the reference year. The results, listed in Table 42, show that although there are some fairly substantial changes with respect to the relative efficiency scores and TFP measures, the technical change component is fairly constant. Furthermore, the variance of the technical change measure is fairly small; an examination of individual observations revealed only small variations about the mean.

Weighting

The Malmquist indexes were checked for robustness with respect to the weights chosen for the averages. The indexes were recalculated without weighting them, so that each plant contributed equally to the index. The results still indicate a regression of the frontier. Thus, the index decomposition did not differ drastically for small and large plants.

Finally, the Malmquist productivity indexes were checked against a published and widely used industry level total factor productivity measure developed by Wayne Gray (1989). The Gray industry level TFP, listed in Table 43, coincides roughly with the Malmquist TFP averages in Table 42. In industry 3541, increases and declines in TFP were small until 1982 and 1983. Declines in TFP of 13 and 21 percent in those two years dispel any concerns that technological regression in the machine tool industry might be an artifact of the estimation method or the data.

Table 43. Industry changes in total factor productivity by year

Year	3541	3542
1973	0.040	0.048
1974	0.021	-0.018
1975	-0.138	-0.076
1976	-0.173	-0.011
1977	-0.019	-0.044
1978	0.021	-0.017
1979	-0.009	-0.024
1980	-0.015	-0.057
1981	0.014	-0.076
1982	-0.131	-0.060
1983	-0.210	-0.046
1984	0.019	0.047
1985	-0.025	-0.008
1986	0.009	-0.013
1987		

Source: Gray, 1989.

Capital Input Definition

A common assumption in productivity measurement is that the flow of capital services is proportional to the capital stock. This assumption underlies the study conducted by Färe, Grosskopf, Lindgren, and Roos (1992) for Swedish Pharmacies, as well as the Gray total factor productivity indexes. When the actual machine hours or capacity utilization of the capital stock is not taken into account in the capital input measurement, productivity will fall in periods in which the utilization rate is low. If this occurs for all plants in the industry, including those defining the frontier, then the frontier shifts backward. In this case, it is not the best practice *knowledge* that has regressed, but the best practice *practice*. The fixed nature of the capital stock is driving the backward shift in the frontier.

Investigating this possibility, consider the serious slump that occurred in machine tool production from 1981 to 1984. During this time, output fell dramatically, while the capital stock continued to rise, as plants received previously ordered equipment. Decline in the capital stock caught up with declines in output only as older equipment was retired and new equipment was not ordered to replace it. The result was a drastic decline in the output per unit of capital ratio, as shown in Tables 8 and 9. The most dramatic regression of the frontier for both industries was between 1978 and 1983. Table 44 shows that capacity utilization in the machine tool industry reached a trough in 1982 and 1983 in both the metal-forming and metal-cutting industries.

One other possible reason for regression of the best practice technology for machine tool manufacturers is that the plants defining the frontier in early samples exited the industry before the new frontier was constructed. In Chapter 5 it was established that high efficiency plants are not more likely to close down than low efficiency plants, but the possibility of exit to other industries has not been explored. In order to check this possibility, plants that shift industries would be identified, and their efficiency scores compared to plants that remain in the industry. If plants that define the frontier leave the industry, then the next-most-efficient plant defines the

Table 44. Capacity utilization rates in the machine tool industry, fourth quarters

Year	3541		3542	
	Preferred Rate[a]	Practical Rate[b]	Preferred Rate	Practical Rate
1973	(S)[c]	(S)	(S)	(S)
1974	66	65	83	66
1975	75	72	82	74
1976	72	66	80	71
1977	71	67	84	72
1978	78	70	83	75
1979	77	70	77	72
1980	76	70	90	75
1981	70	66	78	66
1982	44	41	51	45
1983	49	46	45	38
1984	48	43	79	71
1985	53	46	84	69
1986	46	42	73	61
1987	54	50	90	90

[a]Preferred rate is ratio of actual operations to preferred level of operations.

[b]Practical rate is ratio of actual operations to practical capacity.

[c](s) indicates that the estimate has been withheld because it did not meet publication standards.

Source: U.S. Department of Commerce, Bureau of the Census, *Survey of Plant Capacity*, 1978, 1982, 1988.

frontier, causing technology regression.

Summary

In Chapter 5, examination of plots of the frontier technology showed visually that the best practice frontier had regressed over time in both industries. In this section, this issue was investigated more precisely with Malmquist indexes of productivity change. Results show that the frontier technology for industry 3541 shifted out, away from the origin, and that improvements in efficiency were mainly technological regression, but the Malmquist decomposition was much more evenly weighted between efficiency changes and shifts of the frontier in industry 3542. It is likely that regression in the frontier is caused mainly by problems of capacity utilization.

Technology Adoption and Technical Efficiency

The results presented in Chapter 6 indicated that efficiency in the machine tool industry was associated with a number of plant characteristics. However, the differences in efficiency have not been completely explained, particularly for industry 3542. Furthermore, unobserved differences in technology have been cited as a possible reason for the dissimilarities between the metal-cutting tool industry and the metal-forming tool industry. In this section, data from the 1988 Survey of Manufacturing Technology (SMT) are merged with the LRD to address these issues. Information from the SMT regarding the type of technologies used in machine tool industries are presented. Farrell efficiency measures are estimated for this much smaller data set using linear programming techniques, and the resulting efficiency scores are correlated with a simple measure of the level of technology in the plant.

Survey of Manufacturing Technology

The 1988 Survey of Manufacturing Technology contains information on the extent of advanced-technology usage at a large number of U.S. manufacturing plants. The sampling frame for the SMT was manufacturing plants with 20 or more employees and in two-digit manufacturing industries 34 through 38. The industries covered in the sample are Fabricated Metal Products (34), Nonelectrical Machinery (35), Electric and Electronic Equipment (36), Transportation Equipment (37) and Instruments and Related Products (38). The survey consisted of questions about the plant's usage of seventeen advanced technologies, from five major technology groups during the year 1987, as well as a few other variables identifying plant characteristics. The seventeen technologies are listed and described in Table 45. These technologies represent relatively new innovations that have general use across a wide range of industries. A more detailed description of the SMT data is provided by Dunne (1991).

The SMT collected technology data for 9,682 establishments, from a total census universe of 39,556. The universe frame was stratified on the basis of three digit SIC code and size of total employment, with the three size classes being 20 to 99, 100 to 499 and greater than 500 employees. Simple random sampling was

Table 45. Description of technologies covered by the survey of Manufacturing Technology

Technology	Description
Computer Aided Design Engineering	Use of computers for drawing and designing parts or products and for analysis and testing of designed parts or products
CAD controlled machines	Use of CAD output for controlling machines used to manufacture the part or product
Digital CAD	Use of digital representation of CAD output for controlling machines used to manufacture the part or product
Flexible Manufacturing Systems/Cell	Two or more machines with automated material handling capabilities controlled by computers or programmable controllers, capable of single path acceptance of raw materials and delivery of finished product.
Numerically/Computer Controlled Machines	NC machines are controlled by numerical commands punched on paper or plastic mylar tape while CNC Machines are controlled throughout an internal computer
Materials Working Lasers	Laser technology used for welding, cutting, treating, scribing, and marking.
Robot	A reprogrammable, multifunctioned manipulator designed to move materials, parts, tools, or specialized devices through variable programmed motions.
Pick/Place Robot	A simple robot with 1-3 degrees of freedom, which transfers items from place to place.
Automatic Storage Retrieval Systems	Computer controlled equipment providing for automatic handling and storage of materials, parts, and finished products.

Table 45 (continued)

Technology	Description
Automatic Guided Vehicle Systems	Vehicles equipped with automatic guidance devices programmed to follow a path that interfaces with work stations for automated or manual loading of materials, parts, tools, or products.
Technical Data Network	Use of Local Area Network (LAN) technology to exchange technical data within design and engineering departments.
Factory Network	Use of LAN technology to exchange information between different points on the factory floor.
Programmable Controller	A solid state industrial control device that has programmable memory for storage of instructions, which performs functions equivalent to a relay panel or wired sold state logic control system.
Computers Used for Control on the Factory Floor	Excludes computers imbedded in machines, or computers used solely for data acquisitions and monitoring. Include computers that may be dedicated to control, but which are capable of being reprogrammed for other functions.
Automatic Sensors used on inputs	Automated equipment used to perform tests and inspections on incoming or in process materials
Automatic Sensors used on Final Products	Automated equioment used to perform tests and inspections on Final Products

Source: U.S. Department of Commerce, Bureau of the Census, Current Industrial Reports, *Manufacturing Technology 1988.*

performed with each strata, and weights were assigned to each plant; the weights were the inverse of the sampling fractions for the strata. The purpose of the weighting scheme was to estimate cell counts within each size and industry class (U.S. Department of Commerce 1989).

For each of the seventeen technologies, plants indicated whether or not that technology was in use in the plant. No information was collected regarding the degree to which a technology was used in the plant. The lack of usage intensity data is a weakness that places plants using the technologies throughout their operations insame category as plants using the technology in a very limited sense. Nonetheless, the SMT is a valuable survey because it provides direct measures of technology use at a highly desegregated level and for a very large number of manufacturing plants.

Table 46 provides information on the usage of each advanced technology in each of the five major industry groups, and for the machine tool industry (industries 3541 and 3542). The percentages are weighted using the SMT weights. The most commonly used technologies include computer aided design, numerically controlled/computer numerically controlled (NC/CNC) machines, and computerized communications and control. Relative to other industries, machine tool plants are heavy users of computers on the factory floor. Computer aided design and manufacturing, computers used for communication and control, and NC/CNC machine tools is also fairly common among them. However, they make little use of other flexible machining or assembling technologies or automated materials handling, and make only modest use of automated sensor based inspection.

Table 46. Percent of establishments using technology

Technology	34	35	36	37	38	Machine Tools
Design & Engineering						
Computer Aided Design	26.8	43.2	48.5	39.9	48.9	4.01
CAD Controlled Machines	13.1	21.6	16.0	16.6	14.6	17.0
Digital CAD	6.5	11.0	12.8	10.0	12.5	28.1
Flexible Machining and Assembly						
Flexible Mfg Systems	9.0	11.0	11.9	12.6	10.8	5.5
NC/CNC Machines	32.2	56.7	34.9	37.3	33.6	35.1
Lasers	2.9	3.6	7.5	6.0	4.3	4.8
Pick/Place Robots	5.7	5.8	13.1	10.4	8.6	9.5
Other Robots	4.4	5.2	6.9	10.5	4.4	0.6
Automated Material Handling						
Automatic Storage /Retrieval Systems	1.0	3.6	4.9	4.7	4.2	4.2
Guided Vehicle Systems	0.8	1.7	1.8	3.3	1.3	0
Automated Sensor Based Inspection						
Materials Sensors	6.7	8.5	16.2	12.7	12.2	8.2
Output Sensors	8.3	9.9	22.2	14.4	15.4	12.6
Communication and Control						
LAN for tech data	13.4	18.5	24.9	22.0	25.8	21.9
Factory LAN	11.6	16.3	21.1	18.7	21.3	21.9
Intercompany Computer Network	14.9	12.4	16.2	21.7	13.8	4.8
Programmable Controllers	26.8	33.9	38.0	32.0	32.7	24.7
Computers Used on Factory Floor	21.1	28.1	34.5	27.4	32.3	36.2
Number of Establishments (weighted)	12,746	13,176	7,293	3,425	2,916	305

Source: U.S. Department of Commerce, Bureau of the Census, Current Industrial Reports, *Manufacturing Technology 1988*, and author's calculations.

Following Dunne and Schmitz (1991) a measure of advanced technology usage is constructed from the responses to the seventeen questions on the SMT on individual technology use. The number of technologies used in a plant is summed, and a plant using a greater number of technologies is considered more advanced-technology intensive. In Table 47, the plants are partitioned into four groups: those using none of the advanced technologies; those using 1 or 2 of the advanced technologies; those using three to five of the advanced technologies; and those using six or more. The presented percentages are weighted using the SMT weights.

Both of the machine tool industries have a larger percentage of plants with two or fewer technologies in use than the average for all industries surveyed. Metal-cutting machine tool plants apply a larger number of advanced technologies than metal-forming machine tool plants. This could explain some of the results found earlier regarding the importance of wages and plant age for efficiency. Within both industries, there is a great deal of variation among plants with respect to the number of technologies employed. We might find that this variation explains in part differences in efficiency between plants.

Efficiency and Technology Use

Only 43 plants (215 weighted) from industries 3541 and 19 plants (90 weighted) from industry 3542 were included in the Survey of Manufacturing technology. Since this subset of the data was so small and covered only one year, it was decided to reestimate technical efficiency measures for this group of plants alone.

Table 47. Percentage of plants using a given number of technologies

No. of Technologies	3541	3542	Total Sample
0	24.1	38.7	25.8
1-2	42.2	40.0	29.0
3-5	15.6	8.7	27.2
6 or more	18.1	12.5	18.0

Source: U.S. Department of Commerce, Bureau of the Census, Current Industrial Reports, *Manufacturing Technology 1988*, and author's calculations.

Because the samples were so small, linear programming methods were employed to estimate Farrell efficiency measures separately for each industry (the stochastic frontiers were attempted, but the likelihood functions were poorly behaved because of the few number of observations).

The Farrell efficiency measures were calculated with the linear program routine run on the SAS statistical package. The linear program constructs a piecewise linear representation of the technology that envelops the sample data, and then computes the Farrell measure for each plant by solving the program:

$$F(x,u) = \min\{\lambda: \lambda x \in L(u)\}. \tag{7.14}$$

Details of the linear programming problem can be found in Lovell and Schmidt (1988).

The Farrell efficiency scores were correlated with the number of technologies used by the plant. These correlations, both weighted according to their SMT weights, and unweighted, are presented in Table 48. The correlations for the number of technologies with both efficiency and wage are statistically different from zero for industry 3541 only when the weights are applied. Although these weighted correlations provide evidence that technical efficiency is promoted by the adoption of advanced technologies, this result hinges on the suitibilty of these weights for this purpose.

The assumption behind the weighting scheme is that plants in a given three digit SIC code and a given size class have similar patterns of technology adoption. Using these weights for the correlation with efficiency also requires the assumption that the similarity extends to technical efficiency as well. At best, the evidence associating the number of technologies used with efficiency and wage is weak.

While the evidence linking technology to wage and efficiency is inconclusive, several facts were gathered from this analysis. First, machine tool builders lag a number of other industries in the use of advanced manufacturing technologies. Second, plants in industry 3542 are less technology intensive that metal-cutting machine tool builders. This seems to support the contention made earlier that the pace of technological change may be slower in the metal-forming tool industry, which makes plant age and wages less important determinants of technical efficiency.

Of particular note is the virtual nonexistence of flexible manufacturing systems in the plants of machine tool builders. This is interesting because FMS is the most recently developed and flexible machining technology, and several American machine tool builders began selling then in the early 1980s, but not one installed them for use or experimentation in their own operations until years later. By contrast, virtually all

Table 48. Pearson correlation coefficients between the number of technologies and the efficiency score

	3541		3542	
	Weighted	Unweighted	Weighted	Unweighted
Efficiency	.4499 (.0025)	0.0932 (0.4165)	-.5044 (.0277)	-.0493 (.7887)
Wage	.3254 (.0332)	0.0892 (0.4356)	-.1629 (.5051)	0.1396 (0.4447)

of Japan's significant builders had one or more FMS systems in house by the early 1980s, and one had begun using them as early as 1972. One of the ways that the Japanese have broken into the high end market for machine tools is by experimenting with the newest technologies in their own plants (March 1989). It appears that the American builders have not adopted this strategy.

Manufacturing Extension and Technical Efficiency

Evidence was found in Chapter 6 that plants located in states with active industrial extension programs were more efficient. This variable was an admittedly poor proxy for actual intervention, but did reflect some benefits of manufacturing extension that might not require direct intervention. In this section, the affect of intervention by manufacturing extension is examined with the help of data from industrial extension programs in Michigan, North Carolina, and Iowa. The data are quite limited, and interpretation of statistical results is suspect. However, some information can be derived from a casual examination of the data.

The names, addresses, and, in some cases intervention dates were obtained for machine tool manufacturers that were clients of the Michigan Industrial Technology Institute, the Center for Industrial Research and Service at Iowa State University, and the Industrial Extension Service at North Carolina State University. The names and addresses were used to search for the plant identification number on the LRD, using the name and address file that is derived from survey mailings. The matching process is imperfect, and not all of the clients of the industrial extension services that were provided could be matched with the LRD. This is partially due to differences in the SIC codes assigned to the plant by the Census Bureau and the industrial extension services. The final sample included 305 plant-years in industry 3541 in Michigan, North Carolina, and Iowa. Of these, 39 observations were for client plants. In industry 3542, there were 106 total observations and 17 of these were client observations. The major drawback of this data was that dates of participation could not be determined for all of the clients. An intervention analysis is not possible. The analysis should not be interpreted as analyzing the effect of extension, because it is not always certain at what time the intervention occurred. Essentially, what can be accomplished is a cross section study between plants that at some time have been clients of the extension agency and those that have not.

Only census data were included for the analysis because many of the plants identified as extension clients were not part of the ASM. Because so few observations were available for each industry, Farrell efficiency measures were calculated using the linear programming procedure employed for the analysis of technology usage.

Results

Table 49 shows the results of a test for differences of the means of client and nonclient plants. In both industries, the efficiency score for the client plants is significantly lower than the average score for the nonclient plants. Because an intervention analysis is not possible, there are two feasible explanations for this result. The most likely scenario is that the least efficient plants are more likely to seek out or attract assistance. This idea is confirmed by a study by the National Governors' Association that found that field agents for industrial extension services often target failing firms for industrial extension (Clarke and Dobson 1992).

Several instances of intervention in the middle of a series of observations on a single plant was observed. In each of the three cases in which efficiency was observed before and after an intervention with a known date, the efficiency of the plant improved. However, this does not imply causality because the efficiency scores were estimated over four census years (1972, 1977, 1982, and 1987) and the general trend was an improvement in efficiency over time.

Few conclusions can be derived from this analysis. The only concrete result is that industrial extension clients are generally less efficient that other plants in their states. A more thorough analysis of the impact of direct extension intervention will not be possible until more reliable data are collected and made available by the many industrial extension services that have started since the middle 1980s. Given

Table 49. Average efficiency for plants receiving direct assistance from manufacturing extension versus those that never have.

	3541		3542	
	N	Avg. Eff[a].	N	Avg. Eff.
Clients	39	0.159 (0.032)	17	0.185 (0.058)
Non Clients	266	0.272 (0.017)	29	0.326 (0.032)

[a]Numbers in parentheses are the standard errors of the mean.

the importance of policy evaluation in an era of tight state budgets, simple but complete and reliable data systems should be developed for tracking the services provided to extension clients, and for tracking their progress in achieving the objectives for which the extension service was employed.

CHAPTER 8. SUMMARY AND CONCLUSIONS

The perceived problem of declining industrial competitiveness in the United States has been approached by many researchers using a wide variety of data sources, estimation methods, and procedures. The machine tool industry and its declining competitiveness has been studied with industry aggregate data by Baily and Chakrabarti (1988), and with case study data by the MIT Commission on Industrial Productivity (March 1989). This study has employed a unique and rich plant level database and a promising econometric technique to generate plant level estimates of technical efficiency. These estimates were used to make comparisons and to draw tentative conclusions about the possible sources of efficiency differences among machine tool manufacturers. The results of the study are outlined below, and policies that may improve efficiency in the machine tool industry are suggested. Several methodological and empirical issues that arise in empirical analyses of efficiency and competitiveness that have not been addressed in this analysis are considered for future research.

Summary of Empirical Results

It was expected that the examination of efficiency in the machine tool industry would uncover significant evidence of technical inefficiency. The industry's decline over the last twenty years has raised a number of questions about the causes of this decline, and inefficiency has been one of the widely discussed sources. Furthermore, studies of plant level total factor productivity have revealed heterogeneity among plants in a wide range of industries (e.g. Baily et al 1992). Since technical efficiency is a relative measure, industrial heterogeneity with respect to productivity and efficiency is associated with it.

Ample evidence was found to verify that many machine tool plants were technically inefficient. The first manifestations of technical inefficiency in both industries were the significance of the composed error term and the skewness of the ordinary least squares residuals. Further evidence was provided by the estimated stochastic frontiers. The hypothesis that the variance of the portion of the error term representing technical efficiency was equal to zero was strongly rejected for both industries. Visual evidence was provided by comparing the best practice with average production functions for each industry and finding significant divergence. These comparisons also provided evidence of the relative average efficiencies of the two industries. Metal-cutting machine tools exhibited more inefficiency, implying greater heterogeneity among metal-cutting machine tool plants.

The parameters of the frontier production function were unstable over time, indicating that best practice technology in the machine tool industry had shifted. Once the data were partitioned appropriately and separate frontiers estimated for each time period, the reason for this instability became apparent. Best practice technology had actually regressed over time, particularly in the metal-cutting machine tool industry. Although plots of the average efficiency scores by year and industry showed substantial progress for plants in the metal-cutting machine tool industry, evidence from plots of the production function aroused suspicion that this was at least partially a result of the frontier shifting toward the plants, rather than the plants moving toward the frontier.

A number of procedures were performed to determine the association between plant characteristics and technical efficiency. These results showed that efficiency is associated with large plants, plants that pay high wages, and plants that reside in states with industrial extension programs. The advantage of size is not surprising, since larger plants are often are able to specialize production and non-production activities, hire workers with specialized skills, and cover the fixed costs of product and process development over a larger scale of output. Wage probably acted as a proxy for worker skill, but the effect of wage was not significant in metal-forming machine tools. This may be due to less intense use of advanced technology in this industry, which was one of the observations from the Survey of Manufacturing Technology. The positive result for industrial extension was interpreted with the proviso that the variable used to indicate access to extension was a poor proxy for actual intervention. However, the access variable does reflect improvements in the information available to machine tool manufacturers, even when direct intervention does not occur.

Estimates of the probability of survival in the machine tool industry showed that efficiency contributed to survival probability, as did size and lower wages. The models' ability to predict survival was especially poor for metal forming machine tools. A number of variables that are not present on the LRD were conjectured to affect the survival of plants. These variables include worker and manager skills and access to capital. While wages probably reflect worker skill to some extent, this relationship is imperfect and a more direct measure of skill would probably improve the model's ability to predict survival.

Decomposition of the Malmquist indexes confirmed the casual observation that frontiers had shifted backward. The most plausible explanation for this result is that all plants, even the most efficient plants in the industry, suffered from low capacity utilization rates. In fact, failure to employ resources to their full capacity is most likely driving many of the results of the analysis. For example, large plants are probably better able to shift capital and labor to alternative uses when a particular segment of their business is slow. While capacity utilization was low for both industries, regression of the stochastic frontier was not nearly as severe in the metal forming machine tool industry as it was in the metal cutting machine tool industry. This result is driven by the homogeneity of plants in the metal forming machine tool industry. Changes in the efficiency of plants defining the frontier did not drastically alter the placement of the frontier.

There was only weak evidence that plants employing a greater number of technologies were more efficient. However, patterns of technology use in the machine tool industry did reveal that this industry generally lagged a number of other industries in the adoption of advanced technologies. This is especially relevant to the issue of international competitiveness, since Japanese and German machine tool makers are competing successfully with U.S. manufacturers for markets for sophisticated manufacturing technologies, including flexible manufacturing systems and machining centers. One strategy international machine tool manufacturers have used to develop this market is to experiment with these technologies on the floors of their own plants.

No conclusions could be drawn about the impact of intervention by industrial extension on the efficiency of plants in the machine tool industry. The main result of this analysis was that low efficiency plants either seek the advice of the extension services or are targeted by the service providers. A more complete analysis of the effect of intervention requires substantial effort for gathering data from individual clients of extension services. Since many of these services have only recently become operational, a well conceived plan for systematically collecting this data would contribute a great deal to future evaluation efforts.

Policy Recommendations

By far, the most pressing problem facing the machine tool manufacturers in the Untied States is that their capital stock is not being fully employed. The only way to solve this problem is to recapture markets lost to the foreign machine tool manufacturers and to develop new international markets. International markets are especially important for smoothing the cyclicality of the industry without accumulating backlogs that force customers to other suppliers for prompt service.

One way to build markets is to communicate more closely with potential customers. Users of machine tools in the U.S. have expressed dissatisfaction with the quality of the tools available from domestic producers. Results from this study suggest that manufacturing extension might be an effective vehicle through which effective communication might be developed between users and suppliers. These strategies might include encouraging interaction between users and suppliers with technology workshops, maintaining directories of manufacturers and referral services, and dissemination of information regarding new product technology which might encourage customers to replace existing machine tools.

In order for market strategies involving market failure to succeed, U.S. machine tool manufacturers must be willing to listen closely and invest in "relationship specific capital," developing the manufacturing technology that will meet the specific needs of a particular user or industry. This is a strategy that entails long term risk, which U.S. manufacturers have often been accused of not being willing to face. This strategy has been used successfully by the Japanese, but their machine tool manufacturers were backed by the significant resources of the Ministry of International Trade and Industry (MITI). MITI's investment in the development of the Japanese machine tool industry has been substantial (March 1989). In order to encourage U.S. machine tool manufacturers to invest in new capital and develop new products, similar risk sharing arrangements might be needed.

Aside from expansion of market share, improvement of efficiency in the machine tool industry might require substantial industrial restructuring. The recession of 1982 and 1983 and subsequent failure of the industry to recover has already cleared many plants from the industry. However, many small inefficient machine tool plants still exist and are not likely to survive among larger more efficient plants. Those small plants with aggressive strategies for keeping abreast of new technology, developing ties with customers and other manufacturers, and pursuing new markets are most likely to survive.

For the plants that continue to operate, improving worker skills is important to efficiency improvement strategies. Workers capable of recognizing sources of inefficiency in production and able to adjust the manufacturing process to correct it are likely to contribute a great deal to plant efficiency. This strategy must be combined with investments in new equipment to replace the aging industrial capital stock. Product development, including close cooperation with major customers, should be a priority. Policy to encourage these measures include tax credits for worker training and investment and training programs, often available through manufacturing extensions.

Finally, the machine tool industry must find ways to improve performance for its existing customers. However, having the capacity to deliver orders quickly during busy times could require a capital buildup that can drag down efficiency. Achieving the flexibility to manufacture alternative products, such as machine tool accessories and parts, might be the key to this strategy. Perhaps the machine tool manufacturers should consider a stronger adoption of the most flexible manufacturing technologies from their own industry.

Issues for Further Research

A number of methodological decisions taken in the analysis may have affected the results and suggestions for policy intervention. Tests for robustness with respect to approach (parametric or nonparametric) functional form, the estimator used, and the data sample could be performed to confirm the results of the study.

Capital stock data for 1986 could be constructed by interpolating between the data for 1985 and data for 1987. This would fill out the time series, but would restrict the data set to plants existing in both of these years. Filling in the missing data points in the time series would provide an additional reference for observing trends and calculating indexes.

The analysis could be repeated for a select group of plants that are in the sample for the entire data period. Using a "balanced panel" may provide more information about the dynamics of efficiency changes within a plant over time. Some exploratory analysis of balanced panels for the ASM samples for 1974-1978 and 1979-1983 were performed, and the preliminary results were similar to the original results. Comparing balanced and unbalanced panel results might provide a vehicle for comparing the efficiency of plants that stay in the industry with those who exit. More importantly, changes in technical efficiency in a balanced panel will reflect changes in efficiency for individual plants, rather than reflecting changes in the structure of the industry.

The impact of policy intervention has been addressed only marginally. A worthwhile project for future research would be to set up a database system at an industrial extension service that would be simple to maintain and would collect the data relevant to the analysis of efficiency at the plant level. While there would be a lag between the data was set up and the time analysis could begin, the development of the data system itself would contribute a great deal to prospects for future research.

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