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Assessing the Resource Base of Japanese and U.S. Auto Producers: A Stochastic Frontier Production Function Approach

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The "resource-based view of the firm" has become an important conceptual framework in strategic management but has been widely criticized for lack of an empirical base. To address this deficit, we utilize a new method for identifying interfirm differences in efficiency within the context of stochastic frontier production functions. Using data on Japanese and U.S. automobile manufacturers, we develop measures of resources and capabilities and test for linkages with firm performance. The results show the influence of manufacturing proficiency and scale economies at the firm and plant level. We apply the parameter estimates to account for Toyota's superior efficiency relative to other producers.

Key words: resource-based view; stochastic frontier; production function; automotive
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1. Introduction

In recent years strategic management scholars have expressed enormous interest in the resource-based view (RBV) of the firm. This perspective regards the firm as a heterogeneous bundle of resources—some superior and others perhaps inferior—plus organizational capabilities that may enable the firm to deploy resources more efficiently than rivals. Variation in the quality of resources and capabilities leads to the generation of economic rents, which may appear as differences in profitability. Such performance differentials can persist for long periods when imitation is impeded.

Despite its appeal as a conceptual framework, the RBV has often been criticized for lack of an empirical base. Few researchers have been able to develop measures of resources and capabilities, identify their importance in a specific industry context, and link firms' resource positions to dimensions of performance. In this paper we attempt such an investigation, using historical data on Japanese and U.S. automobile companies. Our aim is to better understand competitive heterogeneity in the global automotive industry.

To implement our study, we utilize a new methodology from the econometrics literature. Recent work by Battese and Coelli (1995) on the estimation of stochastic frontier production functions (SFPF) provides a framework for identifying the sources of interfirm differences in efficiency. We develop dynamic measures of resources and capabilities and assess their impact on automotive company performance using the Battese and Coelli model. We demonstrate the potential of this model for adding empirical content to the RBV. More generally, our analysis links the perspective of the RBV with the methods of production economics.

Our findings show long-lived operational differences among the auto producers in our sample. Arguably, such differences in efficiency are equivalent to sustained competitive advantage (Porter 1996). Toyota has been the most efficient producer in the auto industry in recent decades, and many prior studies have addressed the sources of Toyota's superior performance (e.g., Fujimoto 1999a, b). Using Toyota as an example, we show how the SFPF methodology can be used to quantify a firm's advantage over rivals.

Our discussion is organized as follows. First, we introduce the concept of a frontier production function, developing its connection to the RBV in the specific context of the automotive industry. We then describe the Battese and Coelli (1995) model and the specification used in our study. This is followed by estimation results for the 11 firms in our sample over a three-decade period from the 1960s to 1997. Drawing from these estimates, we make interfirm comparisons. A final section summarizes the findings and concludes.

2. The RBV Within a Production Function Model of Firm Performance

Frontier Production Function Models

Where the RBV views the firm as a bundle of resources and capabilities, neoclassical economics considers the firm as a vessel in which labor and capital (and other potential inputs, such as materials and energy) are combined to form productive outputs. This notion is captured by the concept of a "production function," e.g.,

$$Y = F(K, L), \tag{1}$$

where Y denotes the firm's output, and K and L are its capital and labor inputs. Given data on a sample of firms in an industry, standard econometric methods can be used to estimate the industry production function. The estimated parameters show the trade-offs between inputs as well as potential economies of scale. If time-series data are available, the rate of technical progress (and possible input-saving biases) can also be estimated. A vast literature applies such methods to firm- or plant-level data on a range of industries. Although it is recognized that individual firms can deviate from the industry production function, such deviations are normally taken as random error.

One problem with this traditional approach is that conceptually, the production function embodies the trade-offs faced by an efficient firm that utilizes best-practice methods for its industry. However, most firms are not fully efficient in their use of inputs, and thus they fall below the industry frontier. Econometric advances by Aigner et al. (1977) and Meeusen and van der Broeck (1977) led to the development of SFPF models that can be estimated to identify the production frontier and the relative positions of firms.[1] Such SFPF models explicitly recognize firm heterogeneity, whereas more traditional economic approaches assume it away.

Figure 1 **Firms Relative to Industry Production Frontier**

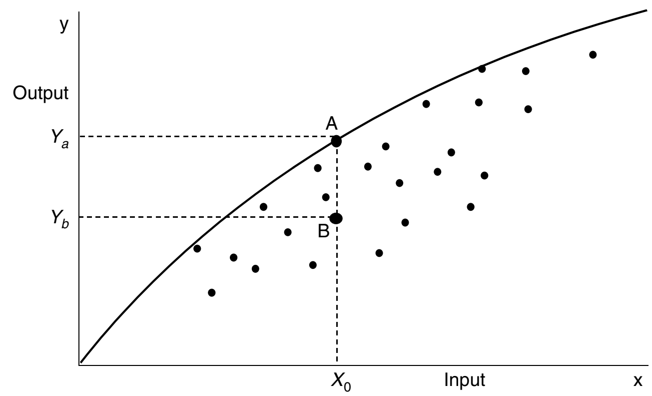


Figure 1 illustrates the concept of an industry production frontier, where the maximum feasible output, Y^*, from any quantity of input is given by the function, $Y^* = F(X)$, where X corresponds to the inputs of Equation (1). In Figure 1, firm A lies on this efficient frontier, whereas firm B falls below. Both firms consume the same quantity of input, but B has lower output. The technical efficiency (TE) of firm B is defined as the ratio of B's output to that of fully efficient firm A. Thus, technical efficiency can be thought of as the firm's scaling factor relative to the frontier in the range: $0 < \text{TE} \leq 1$. The output of any firm i can be written as, $Y_i = F(X_i)\text{TE}_i$, or in the case of a two-input production function, $F(K_i, L_i)\text{TE}_i$.

Early forms of the SFPF model made it possible to estimate the industry production function and the technical efficiency of firms using cross-section data. Researchers interested in the determinants of technical efficiency have often pursued a second stage of analysis where the TE_i estimates are regressed on a set of explanatory factors (e.g., Caves and Barton 1990, Caves 1992, Knott and Posen 2005). Although this two-stage procedure suffers from conceptual problems (Kumbhakar and Lovell 2000, pp. 262–266), it provides a method for assessing efficiency differences at a specific point in time. Given that data are needed on many individual units, studies of this type have focused on industry-level factors rather than the performance of specific firms.

In recent years, panel-data models have been developed for SFPF. This paper utilizes the panel-data approach of Battese and Coelli (1995), which allows technical efficiency to be estimated as a function of firm-specific, time-varying factors. Consider a production frontier model of the form,

$$Y_{it} = F(K_{it}, L_{it})\text{TE}(Z_{it}), \tag{2}$$

where Y_{it} denotes the output of firm i in period t, and K_{it} and L_{it} are the firm's capital and labor

[1] Kumbhakar and Lovell (2000) survey the historical development of SFPF models, and Greene (1997) provides a good technical overview. In addition to SFPF, the econometrics literature offers three techniques for the analysis of productive efficiency: total factor productivity (TFP) indices, data envelopment analysis (DEA), and least-squares econometric production models. DEA has advantages for analysis of multioutput production but does not provide statistical inference for estimated parameters. The SFPF and least-squares methodologies allow for such inference, and the SFPF approach has the further advantage that it incorporates a model of the inefficiency effects, so that interfirm differences can be examined. For an overview and comparison of these methodologies, see Coelli et al. (1998).

inputs.[2] Output is determined by the product of $F(\cdot)$ and $\mathrm{TE}(\cdot)$. The first term, $F(K_{it}, L_{it})$, corresponds to the industry's "best-practice" production function in period t. A firm that fully employs best-practice methods (given its current levels of K_{it} and L_{it}) and executes perfectly in period t would lie on the frontier represented by $F(\cdot)$. The TE term represents the firm's technical efficiency, which is parameterized as a function of firm-specific factors, denoted by the vector, Z_{it}. Given panel data on firms in a given industry, the Battese and Coelli (1995) approach can be used to estimate the parameters of such a production function and efficiency model. The approach offers advantages over prior methods by estimating both the production function and the determinants of firm efficiency in a single stage, and by doing so in a way that allows parameters and efficiencies to vary over time. The approach also yields an estimate of the technical efficiency of each firm in each year, which allows the dynamic performance of firms to be directly compared.

Resource-Based View of the Firm

In parallel with economists' development of frontier production functions, business strategy researchers have elaborated the "resource-based view of the firm" as a conceptual framework for assessing interfirm differences in performance (e.g., Barney 1986, Rumelt 1987, Dierickx and Cool 1989, Peteraf 1993). The RBV must be regarded as a perspective rather than a theory, as debate continues over its essential constructs (Hoopes et al. 2003). The central idea—that sustained differences in performance can be traced back to underlying differences in firms' resources and capabilities—seems incontrovertible. Indeed, some have argued that the RBV is essentially a tautology (Priem and Butler 2001). Researchers have given structure to the RBV by proposing definitions of resources and capabilities and the conditions under which they contribute to competitive advantage. Even so, the RBV has lacked the clarity required for empirical specification, and it has proved difficult to operationalize the RBV in a consistent manner across firms and industries. Empirical work on the RBV has been largely ad hoc, lacking common approaches to modeling, measures, and hypothesis testing.

RBV researchers have sought to identify conditions under which resource endowments support superior profitability. Focusing on imperfections in markets for input factors, Barney (1991) proposed that resources contribute to sustained competitive advantage when they are "valuable," "rare," "difficult to imitate," and "difficult to substitute." Building upon coalitional game theory, MacDonald and Ryall (2004) have outlined a more precise set of conditions under which a firm can be shown to both create and appropriate economic value. Such studies provide only limited guidance, however, on ways to implement empirical tests of the RBV, or even to calibrate the importance of resources and capabilities in a given industry environment.

Reasonable consensus has emerged on how firm-specific factors should be classified under the RBV. Some of the clearest distinctions are provided by Makadok (2001), who defines "resources" as observable assets that can be individually valued and traded; "capabilities," on the other hand, are organizationally embedded and thus can be transferred only through sale of the firm (or major subunits). Such definitions are useful but incomplete, as they ignore categories of producer advantage like those derived from economies of scale, which are important in auto manufacturing and other industries. (Ironically, scale differentials are one of the few dimensions of firm heterogeneity recognized by conventional economists, yet they are barely considered in the literature on the RBV.) Hoopes et al. (2003) suggest that scale advantages are neither resources nor capabilities, but fall in a separate category of "cost drivers."

In this paper we do not attempt to resolve the conceptual debate with regard to the RBV. Rather, we propose that SFPF models can help give structure to empirical work in this area of research. Other studies in the strategic management field have begun to provide the RBV with greater empirical content. For example, Henderson and Cockburn (1994) documented firm-specific influences on the patenting behavior of pharmaceutical companies, and Helfat (1997) found that the ability of energy companies to diversify into synthetic fuels was largely determined by the nature of their resource base. Quantitative field studies, such as Clark and Fujimoto's (1991) work on product development in the automotive industry, provide evidence on the magnitude of differences in firms' capabilities and their performance implications.

In the marketing literature, Dutta et al. (1999) introduced a two-stage approach for operationalizing the RBV: SFPF methods are used in the first stage to obtain estimates of firms' capabilities relative to the industry frontier; these capability estimates are then regressed on measures of firms' financial performance. While such multistage procedures may be necessary to incorporate financial measures of performance within an SFPF framework, in the present study we propose a more direct approach based on the single-equation production frontier model (Equation (2)). This model incorporates resources that are essential to production, notably capital and labor,

[2] Ideally, the list of inputs should include raw materials, but such data are unavailable for the automotive firms in our study. Therefore, we measure output net of materials inputs (i.e., value added).

within the production function; all other influences are included in the Z_{it} vector of the technical efficiency term. If we consider capital and labor as the firm's basic resources, and Z_{it} as its vector of capabilities, the model formalizes some common notions of the RBV. For example, Amit and Shoemaker (1993, p. 35) state that resources are "stocks of available factors that are owned or controlled by the firm ... property, plant and equipment, human capital, etc. Capabilities, in contrast, refer to a firm's capacity to deploy resources ... they can abstractly be thought of 'intermediate goods' generated by the firm to provide enhanced productivity of its resources." Such conceptions of the RBV resemble the logic of the frontier production function model.

Despite a common focus on firm heterogeneity, the RBV and SFPF literatures have emphasized different performance metrics. SFPF models provide a framework for assessing efficiency, whereas the RBV has traditionally been invoked to account for variation in profitability. Nevertheless, we propose that efficiency may represent a superior metric for empirical studies of the RBV. Indeed, Peteraf and Barney (2003) argue that the RBV is "an efficiency-based explanation of performance differences" that excludes other determinants of profitability, such as market power and collusion.

Our model emphasizes differences in efficiency but also conveys a broader conception of firm performance than might be immediately apparent. We estimate a transformation of Equation (2) that allows technical efficiency, scale economies, and capital investment to be evaluated in terms of their impact on labor productivity, a comprehensive measure of performance that is particularly meaningful in manufacturing industries. Productivity gains flow not only to the firm's shareholders (as increased profits), but also to employees (wage increases) and consumers (price reductions). Thus, from the standpoint of economic welfare, productivity represents a more fundamental performance metric than profitability. Furthermore, profits can be a misleading indicator of performance when comparisons are drawn across countries where competitive conditions differ. Among auto makers, for example, Toyota is commonly regarded as a superior competitor, yet Toyota's profit rates over the period of our sample fell below those of General Motors (GM), whose performance in recent decades has often been described as poor.[3]

Our methods, applied at the firm level, are complementary to the "insider econometrics" approach using plant or production-line data to test hypotheses on the nature of organizational capabilities (e.g., Ichniowski and Shaw 1999, 2003). We use publicly accessible data and draw heavily on others' accounts of the industry phenomena to give structure to our empirical model. Our methods offer insights into the sources of efficiency differences but do not yield the fine-grained understanding that is possible in more microlevel studies.

3. Drivers of Productive Efficiency in the Automotive Industry

A firm's resources and capabilities have value only in context. One can easily identify generic categories of capabilities (for manufacturing businesses, such categories would include product design, production, supplier relations, marketing, etc.), but the specifics depend on the industry environment. For example, product design skills in the automotive industry are clearly distinct from the capabilities that support drug discovery and development in the pharmaceutical industry. Hence, any empirical study of the RBV must consider resources and capabilities in the industry context where they potentially hold value.

Prior studies of the automotive industry offer guidance on the types of resources and capabilities likely to be important in that sector. In a widely cited book on the automotive industry, Womack et al. (1990) suggest that best practice has shifted in recent decades from a paradigm of "mass production" to one of "lean production." While aspects of mass production still matter, innovations by leading Japanese producers have led to important changes in factory management, product design, and coordination with suppliers. Many recent studies on the automotive industry have explored these trends and their implications (e.g., Dyer 1996; Dyer and Nobeoka 2000; Fujimoto 1999a, b; Helper and Sako 1995; Novak and Eppinger 2001).

In the following, we adopt the "mass production/lean production" distinction to organize discussion of key resources and capabilities held by automotive assemblers. To be as specific as possible, we show how the empirical measures used in our study have evolved for our sample of eight Japanese and three U.S. auto makers from the mid-1960s through 1997.[4] Our data are entirely from public

[3] Over the 1983–1997 period, the ratio of operating income to sales was slightly higher, on average, for GM (6.0%) than for Toyota (4.9%). Toyota has, nevertheless, been enormously profitable by Japanese standards: In each year since 1983, Toyota's operating income has exceeded that of all other Japanese auto makers combined.

[4] The sample includes all of the major firms that produced passenger cars under their own name in Japan and the United States with the exception of Mitsubishi. For Honda, we omit observations prior to 1975, when the firm's output consisted primarily of motorcycles. The starting year for other Japanese producers varies slightly, depending on data availability.

sources (company annual reports on business segments relating to motor vehicle production, unless otherwise indicated).[5] Given data limitations, some of our measures serve only as weak proxies for types of capabilities that are highlighted in the literature on the automotive industry. We include these imperfect measures in our analysis, as our objective is to develop a set of dynamic indicators that are comprehensive enough, at least in principle, to capture the main dimensions of heterogeneity considered important in the auto industry. At the end of the paper we discuss various biases that may stem from deficiencies in our measures, among other limitations.

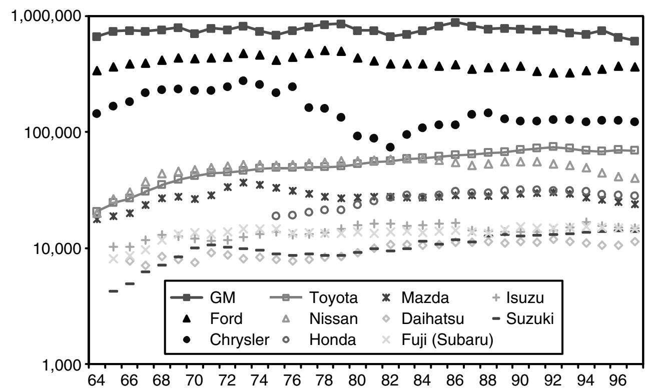
Scale Economies

One mass production concept that has always been important in the automotive industry is economies of scale. Producers incur substantial model-specific fixed costs at many points in the automotive value chain. Such fixed (and mostly sunk) investments are required for product design and development, production dies and tooling, and in some cases, advertising. To be competitive in the mass market, high volumes (per model life cycle or per year, depending on the cost element) are required to spread the fixed costs over many units. Given continual improvements in technology and uncertainty regarding model sales, the firm must be large enough to sustain the frequent development of new vehicles.

Our measure of a firm's overall scale is its total employment. Figure 2 plots the count of employees for the automotive companies by firm and year. (A logarithmic axis is used to capture the range among firms in our sample.) Daihatsu, Fuji, Isuzu, and Suzuki have remained very small; their (Japanese) employment has always been less than 20,000. By comparison, GM's (worldwide) employment has exceeded 600,000 for decades. These size differentials have been remarkably persistent. While small auto makers can sometimes substitute for internal scale by striking alliances with other producers (e.g., to share components, such as engines), such arrangements are imperfect.

In addition to unit-cost savings that may arise with increases in the overall size of the firm, it is meaningful to consider scale economies at sublevels of the firm. For example, savings from the spread of product design and tooling costs may depend on the annual or lifetime volume of specific vehicle models (or of product families that share components). We have chosen not to incorporate vehicle-specific measures of scale in this study, as they are hard to assess and only partially under the control of the firm. Moreover, the ability to achieve these scale economies may be related to firm size, which is already incorporated in our analysis.

Figure 2 Number of Employees



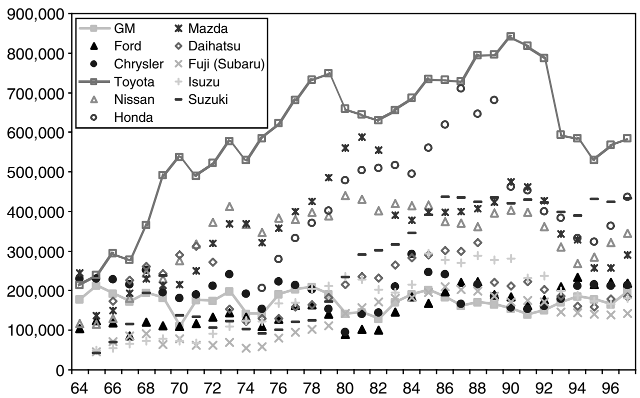
A related dimension of scale that is both meaningful and observable is the average size of the firm's final assembly plants. Early engineering studies (e.g., Pratten 1971) suggested that most plant-level scale economies in the auto industry are achieved at a volume threshold of about 200,000 annual vehicles per assembly plant. In the 1960s, however, the Japanese began to modify the configuration of automotive assembly plants by combining on-site stamping with two or more vehicle assembly lines to create a much higher volume per plant. If this new organization is more cost-effective, we should find gains in efficiency as plant size increases to 400,000 units or more. To incorporate these potential plant-level economies of scale in our model, we include each firm's annual average output per assembly plant in Z_{it}.

Figure 3 plots the average annual output per domestic assembly plant for the firms in our sample.[6] It shows that Toyota has maintained the largest plant scale, with annual output in the range of 400,000 to 800,000 vehicles per plant. The three U.S. producers fall well below this range, reflecting their historical policy of limiting plant capacities to about 200,000 units annually. Figure 3 gives clear evidence that Toyota and other major Japanese

[5] Financial and employment data for Japanese companies are from annual issues of the Daiwa *Analyst's Guide*, with supplementary detail for the 1965–1976 period obtained directly from Daiwa Securities Corporation. The Japanese data are limited to motor vehicle production within Japan; all transplant operations outside of Japan are excluded. The U.S. data are from the companies' annual financial reports and Compustat. Nonautomotive operations (such as financing subsidiaries) have been mostly excluded. For U.S. firms, the data on value added, employment, and capital investment include international operations, as sufficient detail was not reported on automotive units in the United States.

[6] For each firm these values were obtained by dividing total domestic production of vehicles by the number of domestic assembly plants. The annual production and plant data are from company annual reports, *Wards Automotive Reports*, and the Japanese Automobile Manufacturers Association.

Figure 3 Average Vehicle Output per Plant



producers maintained much higher plant scale than their American rivals since the early 1980s.[7]

American producers have operated smaller assembly plants for several reasons. One is a belief that dispersed plants reduce the likelihood of strikes and other disruptions. A second reason is historical: many U.S. plants date back to a period when all facilities were built to contain a single assembly line. Once investment is in place, it is uneconomic to replace such plants unless their deficiencies become substantial. A third reason is skill based: the Big Three have been slow to develop capabilities for mixed-model assembly that are required to efficiently operate a higher volume plant. Annual output per model has been much higher in the United States than in Japan; this has allowed the American auto makers to dedicate each of their plants to assembly of a specific model. Such an approach simplifies operations and minimizes the need for flexibility on the production line. In the long run, though, the problem-solving skills gained by the Japanese in running mixed-model assembly may have provided greater cost savings (Schonberger 1982, pp. 119–121).

This difference in plant operation between U.S. and Japanese producers suggests the interaction between an organizational capability and economies of scale. Firms that operate larger-scale assembly plants are also likely to have skills in mixed-model assembly. A significant effect for plant size in our SFPF analysis would denote the potential influence of both factors.

Capital Investment

Another resource input in the "mass production" category is aggregate capital investment. Economists have long emphasized the role of investment in raising output per worker. Moreover, econometric studies in the 1980s identified higher rates of investment in plant and equipment as the primary factor responsible for Japan's rise relative to the United States in manufacturing industries (e.g., Norsworthy and Malmquist 1983, Jorgenson and Kuroda 1992). By comparison, the RBV assigns little if any role to differences in fixed investment. Stocks of plant and equipment are easy to imitate; an automotive firm cannot gain competitive advantage by merely increasing investment. Thus, the firm's stock of fixed capital cannot be considered a strategic resource from the standpoint of the RBV. In our study we therefore take the firm's stock of fixed capital as a control variable, but we make calculations to compare its impact with that of other, potentially more strategic factors.

Over the three decades of our sample, the auto companies substantially upgraded their plant and equipment as automated machinery replaced human effort in many areas of vehicle assembly. In Japan, real capital stock per employee (K/L) rose steadily, roughly tripling from the mid-1960s through the late 1980s.[8] Toyota maintained the highest investment per worker, with a growing differential over its Japanese rivals. The U.S. pattern, by comparison, was irregular: capital stock per worker remained stagnant for the Big Three through the late 1970s, but a subsequent rise in investment enabled the American firms to match, or even exceed, the average Japanese capital stock per worker by the mid-1990s. Thus, our data confirm the deficiency in American investment noted in prior economic studies, but after about a decade, the gap with Japan was closed. Moreover, the data show that Toyota, commonly regarded as the leader in lean production methods, was also the leader in investment. Hence it is important in our study to control for differences in capital input when assessing the impact of other factors.

Lean Manufacturing Capabilities

Our aim is to incorporate measures of lean production capabilities in three broad areas regarded as important in the automotive literature: (1) manufacturing,

[7] While such differences in plant scale could reflect environmental differences between the two countries, it is notable that Toyota's flagship U.S. plant in Georgetown, Kentucky, has capacity of 500,000 vehicles per year, more than twice the capacity of a standard U.S. plant.

[8] We constructed a real capital stock series for each firm using a perpetual inventory capital adjustment equation: $K_t = (1-d)K_{t-1} +$ deflated gross investment, where gross investment is defined as the change in the firm's undepreciated capital stock since the preceding year, and d is the rate of economic depreciation, which we assumed to be equal to 10%. For Japanese firms, we deflated gross investment using the gross domestic expenditure deflator for nonresidential investment reported by the Economic Planning Agency. For U.S. firms, we used the GDP deflator for nonresidential fixed investment from the 1998 *Economic Report of the President*. Values for the two countries were converted to common currency using a purchasing power parity exchange rate for capital goods of 235 yen per dollar in 1982 (OECD 1987). Our assumption of 10% annual depreciation rate is consistent with a weighted average over asset categories of the economic depreciation rates reported by Hulten and Wykoff (1981). Results were similar for alternative measures of capital stock.

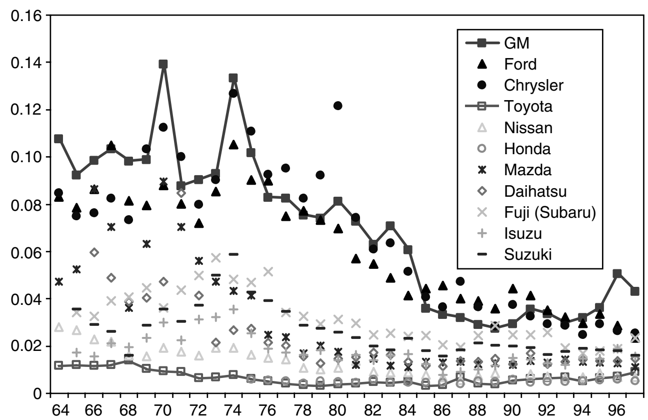
(2) supplier relations, and (3) product design. We start with capabilities on the manufacturing shop floor, where we have the best indicator measure.

Our proxy for lean production capabilities on the factory floor is the level of work-in-process (WIP) inventory. Plants with frequent production problems must hold large inventory buffers to avoid disruptions in output. The level of WIP provides a summary statistic of the firm's manufacturing capabilities, and furthermore, reductions in WIP can serve as a driver for process improvement. Lieberman and Demeester (1999) validated the WIP measure as an indicator of manufacturing skills in the context of the automotive industry. For a sample of 52 Japanese automotive suppliers and assemblers, they found that WIP reductions preceded productivity gains, and lower WIP levels were associated with higher labor productivity. In this study we follow a similar approach, using the WIP/sales ratio as a measure of factory management skills.

Figure 4 shows large variation in the WIP/sales ratio among the auto makers in our study.[9] Moreover, all firms exhibit some pattern of inventory reduction. Toyota, which began its campaign to cut inventories during the late 1950s, had the lowest WIP levels in the 1960s and 1970s and is tied with Honda in later years. Several other Japanese assemblers, including Daihatsu, Fuji, Mazda, and Suzuki, had large and widely fluctuating inventories in the late 1960s and early 1970s. By the late 1970s these fluctuations were eliminated as lean manufacturing methods became widely adopted in Japan. The one exception is Fuji (Subaru), whose WIP inventory ratio remained highest in Japan and began rising again in the late 1980s. Figure 4 shows that in the 1960s the WIP levels of U.S. producers were in the top range of the Japanese, orders of magnitude above Toyota, where they remained until the early 1980s. Over the next decade, however, WIP inventories fell substantially in the United States as the Big Three began to understand and embrace the Japanese manufacturing practices.[10]

Product design is another area where the Japanese have been influential. Multiple dimensions of design

Figure 4 **WIP/Sales Ratio**



performance are important in the automotive industry, including development time and cost, rate of new product introduction, and degree of product appeal to consumers. Recent studies (e.g., Clark and Fujimoto 1991, Nobeoka and Cusumano 1997) document organizational changes that have cut development time and cost, enabling firms to introduce a greater number of new products. These improved methods were developed in Japan in the late 1970s and 1980s, spreading later to the United States.

Product design is a difficult domain in which to gauge firms' evolving capabilities. Comprehensive historical data are unavailable, so we are forced to use a weak proxy measure. We appraise firm's capabilities based on the quality of their product designs as assessed by the staff of *Car and Driver*, a trade journal. In annual issues beginning in January 1983, *Car and Driver* identified a set of "10 best cars" from the regular production models sold in the United States.[11] While the criteria used by *Car and Driver* emphasize final product design quality rather than underlying capabilities, in a supplementary analysis we found that the *Car and Driver* award rates were correlated with firms' adoption of the "rapid design transfer strategy" identified by Nobeoka and Cusumano (1997). Honda, Mazda, Nissan, and Toyota have accounted for nearly half of all winning vehicles since 1983. Honda, in particular, has been an outlier in these ratings, accounting for more than twice as many "top 10" cars as any other firm.

Automotive assemblers also differ in their capabilities for coordination with component suppliers (Helper and Sako 1995, Dyer 1996). Firms with superior capabilities can reduce procurement costs and raise product quality. Such skills are subtle, and comprehensive measures are unavailable. We can, however, observe each firm's degree of backward

[9] The WIP inventories of Fuji, Nissan, and GM (Hughes) have been adjusted to remove inventory related to the manufacture of aerospace products, which have much higher WIP requirements than auto assembly.

[10] The inventory data are not quite comparable for the American and Japanese producers. In their financial reports, the U.S. companies give a single combined figure for WIP and raw materials inventory, which causes the U.S. inventory ratios to be overstated in our sample. Using Census data, which separates these two types of inventory, Lieberman and Asaba (1997) show that the average WIP/sales ratio of U.S. auto assembly plants may now be slightly lower than in Japan.

[11] The selection criteria include multiple categories such as "design," "ride," "value," "driveability," and "handling."

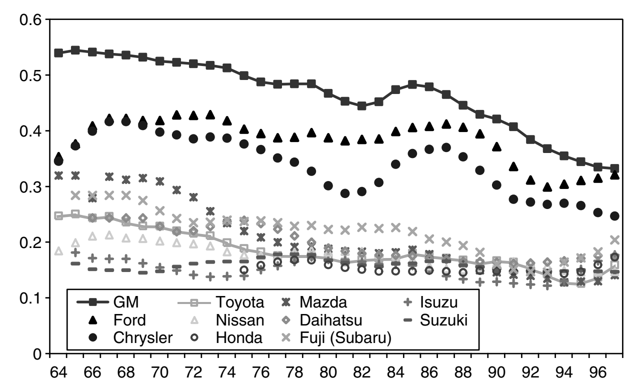
integration into parts production. For many decades, Ford and GM supported substantial in-house parts-manufacturing operations, whereas the Japanese have been known for subcontracting and close collaboration with suppliers. Thus, auto assemblers in the two countries have maintained very different capabilities with respect to the interface with parts production. Integration was considered a superior strategy in the early years of the auto industry, but as the industry has matured, the advantage has shifted to Japanese-style subcontracting (Womack et al. 1990, Dyer 1996). Indeed, after the final year in our sample GM and Ford moved dramatically toward the subcontracting model by spinning off their internal parts-making operations.

Our measure of vertical integration is the firm's value added as a proportion of sales (V/S). This measure allows a test of the relative value of integration versus subcontracting. While informative, the V/S ratio is not an indicator of the assembler's skills in coordinating with parts suppliers (whether internal or external), which are presumably more important than the degree of integration, per se. Hence, our tests of supplier-assembler coordination are quite limited.

To avoid spurious correlation with short-term output changes, we use a lagged, four-year moving average of the V/S ratio, shown in Figure 5. In the early years of our sample, the U.S. assemblers maintained about twice the integration ratio of their Japanese counterparts. Since the late 1980s, a convergence has occurred: Some Japanese assemblers such as Toyota have increased their integration, while the Americans have shed most parts-making operations. Following the spin-offs of parts plants by Ford and GM in the late 1990s (not shown in our data), the degree of vertical integration has become very similar across all producers.

The Dynamics of Organizational Design Choices
The measures presented in this section reflect organizational design choices of the automotive companies and their evolution over time. Over the three-decade period of this study, the measures show remarkable persistence and some degree of convergence. Convergence is evident for the data on investment per worker, vertical integration, and WIP/sales, suggesting the gradual imitation of industry best practice. By 1997, the American producers had closed the gap with Japan in fixed investment, moved toward the Japanese outsourcing model, and streamlined the process flow of their factories. On the other hand, the data on firm and plant scale show little if any convergence. Figure 2 shows continuing large differences in firm size (although several companies, including Chrysler, Nissan, Mazda, Daihatsu, and Isuzu, later fell under the control of other auto makers). Perhaps the most persistent differences are those for plant scale: Over the period of the sample, the American firms remained locked-in by historical investments and lack of skills in mixed-model assembly, while many of the small Japanese producers suffered from inadequate volume to fill efficient-scale plants.

Figure 5 Value-Added/Sales (Vertical Integration)



Such patterns are consistent with theoretical perspectives on industry evolution and adoption of best practice under the RBV. Winter (1987) has pointed out that the firm's tangible and intangible assets are analogous to state variables in control theory—they are difficult to change over a short time span, but evolve over time in response to management efforts (control variables) and environmental influences. Similarly, Dierickx and Cool (1989) argue that strategic asset stocks can be changed only gradually. Our data provide evidence on the speed with which automotive firms have adjusted important resources, capabilities, and operational scale.

4. Stochastic Frontier Production Function Model

The usual panel data estimation techniques—fixed- and random-effects models—are inappropriate for our study because they assume two-sided or symmetric deviations from the production frontier. We need a technique that can capture the fact that firms always lie on or beneath the "best-practice" production function. Hence, we use the SFPF methodology to estimate the production structure of Equation (2), with refinements introduced by Battese and Coelli (1995) that allow technical efficiency to be estimated as a function of firm-specific, time-varying factors.

Following standard SFPF methodology, we first add to Equation (2) a disturbance or error term that represents statistical noise in a typical regression. This term captures the effects of occurrences such as successful or unsuccessful advertising campaigns, strikes, etc., that affect the production outcome. It is hypothesized that the realized production of a firm is bounded by the product of the parametric production function and the symmetric random error term. This is the stochastic production frontier. The model can then be written as

$$Y_{it} = F(K_{it}, L_{it})\mathrm{TE}_{it} e^{V_{it}}, \tag{3}$$

where the V_{it}s are the independent and identically distributed symmetric, random errors, which have a normal distribution with mean zero and unknown variance σ_v^2.

As described earlier, TE_{it} is a scaling factor, where $0 < \mathrm{TE} \leq 1$, such that the actual outcome is always below the production frontier. We statistically operationalize TE_{it} as a second error term, U_{it}, such that

$$\mathrm{TE}_{it} = e^{-U_{it}}, \tag{4}$$

or, equivalently, $U_{it} = -\ln \mathrm{TE}_{it}$, where by definition, $U_{it} > 0$. The U_{it}s are one-sided, nonnegative unobservable random variables associated with the technical *inefficiency* of production, such that, for a given technology and levels of inputs, the observed output falls short of its potential output. A common assumption in the SFPF literature is that U is distributed as a nonnegative truncation of the normal distribution with unknown variance σ^2. In this study we use Battese and Coelli's (1995) method for parameterizing U as a function of additional, firm-specific variables.

Now, given a sample of N firms for T time periods, the stochastic frontier production function can be written as

$$Y_{it} = F(K_{it}, L_{it}) e^{V_{it}} e^{-U_{it}}. \tag{5}$$

In this study we assume that $F(\cdot)$ has a Cobb-Douglas functional form, with technical progress that occurs at a constant rate μ over time, i.e.,

$$F(K_{it}, L_{it}) = e^{\mu^t} K_{it}^{\beta_1} L_{it}^{\beta_2}. \tag{6}$$

The time trend reflects the potential outward movement or growth in the frontier after controlling for the factors that can be observed in the data.[12] The stochastic frontier specification can be written in per capita terms by combining Equations (5) and (6), taking logarithms, and dividing by labor, as

$$\ln(Y/L)_{it} = \mu t + \theta \ln(K/L)_{it} + \gamma \ln(L)_{it} + V_{it} - U_{it}, \tag{7}$$

where Y/L represents value added per employee, K/L is capital stock per employee, L is the number of employees, and V_{it} and U_{it} are the random variables described above. The coefficient, θ, which is equal to β_1, is the elasticity of output with respect to capital. The coefficient, γ, which is equal to $\beta_1 + \beta_2 - 1$, represents the deviation from constant returns to scale, where a positive value of γ signifies increasing returns to scale.

The dependent variable in this transformed model is value added per employee, or labor productivity.[13] Thus, Equation (7) can be viewed as a statistical assessment of potential determinants of labor productivity. The production function relates labor productivity to capital and labor inputs; we expect that productivity will rise with investment per worker (K/L) and possibly with the size of the firm (L). In addition, labor productivity will be influenced by other resources and capabilities of the firm, as represented by the factors in U_{it}.

Battese and Coelli (1995) specify technical inefficiency effects U_{it}s as a function of firm-specific, time-varying factors as following:

$$U_{it} = Z_{it}\delta + W_{it}, \tag{8}$$

where Z_{it} is a vector of explanatory variables, such as those collected in our study. Here, δ is a vector of unknown parameters to be estimated and W_{it}s are unobservable random variables.[14] The technical efficiency (TE) of the ith firm in the tth year then is

$$\mathrm{TE}_{it} = exp(-Z_{it}\delta - W_{it}). \tag{9}$$

The technical efficiencies are predicted using the conditional expectations of $exp(-U_{it})$, given the composed error term of the stochastic frontier. Following the suggested parameterization by Battese and Coelli, we define $\sigma_S^2 \equiv \sigma^2 + \sigma_v^2$ and $\gamma \equiv \sigma^2/\sigma_S^2$, and estimate σ_S^2, γ, vector β, and δ by maximum-likelihood estimation (MLE) methods.[15]

[12] We chose the Cobb-Douglas specification because it is a commonly used functional form, which can be estimated using single-equation methods to give consistent parameter estimates (see Zellner et al. 1966). We also tried a trans-log specification, but the likelihood function failed to converge.

[13] Value added equals the firm's sales during the fiscal year, minus the costs of purchased materials and services. This is equivalent to the sum of all payments to labor and capital, plus indirect taxes. For the Japanese companies, we used value-added figures provided by Daiwa Securities Corporation. For the U.S. companies, we computed value added by summing the factor payments. Real value added was computed by dividing nominal value added by the domestic producer price index for motor vehicles. For Japan, we used the domestic wholesale price deflator for transport equipment from *Price Indexes Annual*, published by the Bank of Japan. For the United States, we used the Bureau of Labor Statistics producer price index for passenger cars. Yen and dollar values were converted to a common currency using a purchasing power parity exchange rate of 171 yen per dollar in 1982, based on OECD estimates for motor vehicles (OECD 1987). Exchange rates for all other years are defined by the 1982 rate and the price deflators.

[14] W_{it}s, which are assumed to be independently distributed, are obtained by truncation of the normal distribution with mean zero and unknown variance, σ^2, such that U_{it} is nonnegative (i.e., $W_{it} \geq -Z_{it}\delta$).

[15] The estimates in this study were obtained by programming the Battese and Coelli (1995) likelihood function using the maxlik routine version 3.1.3. in the Gauss econometric package.

Table 1 Data Summary

Variable	Mean	Std. dev.	Units	Sources
Value added per employee (Y/L)	8.6	4.1	millions of 1982 yen	See footnotes 5 and 13.
Time (t)	17.1	9.0	count from 1965	
Capital stock per employee (K/L)	16.4	7.7	millions of 1982 yen	See footnotes 5 and 8.
Number of employees (L)	144	229	thousands of employees	See footnote 5.
WIP/sales ratio (W/S)	0.033	0.029	ratio	See footnotes 5, 9, and 10.
Value-added/sales ratio (V/S)	0.243	0.111	ratio	See footnote 5.
Design quality (CD)	0.85	0.66	number of citations	*Car and Driver*
Number of vehicles produced (Q)	1.68	1.52	millions of vehicles	See footnote 6.
Volume per plant (Q/N)	281	168	thousands of vehicles	See footnote 6.
Cumulative output ($\sum Q$)	44.97	58.85	millions of vehicles	See footnote 6.

Note. Data sample includes 336 observations.

We incorporate measures within the technical inefficiency component of the stochastic frontier as follows:

$$U_{it} = \delta_0 + \delta_1 \ln(W/S)_{it-1} + \delta_2 \ln(V/S)_{it-1,4} + \delta_3 (CD)_{it} + \delta_4 \ln(Q)_{it} + \delta_5 \ln(Q/N)_{it} + \delta_6 \ln\left(\sum Q\right)_{it} + W_{it}, \tag{10}$$

where W/S_{it} is the WIP inventory to sales ratio; $V/S_{it-1,4}$ is the four-year moving average of the value added to sales ratio; CD_{it} is a two-year moving average of the number of design citations awarded the firm by *Car and Driver*;[16] Q_{it} is the total number of motor vehicles produced by the firm in its home market during year t; Q/N_{it} is the average vehicle output per assembly plant in year t; and $\sum Q_{it}$ is the firm's historical cumulative domestic vehicle production through the start of year t. We include the latter measure as a general index of firm experience and learning (Argote 1999). We test Q_{it} in the inefficiency term to verify that the measured effects of plant scale, Q/N_{it}, and cumulative output, $\sum Q_{it}$, are not simply due to correlation with annual vehicle output.

A positive value of the δ coefficient associated with any of these variables indicates that as the level of that variable goes up, the level of technical *inefficiency* also goes up and vice versa. For example, a positive coefficient for W/S implies that technical inefficiency rises with the level of WIP inventory. We expect, potentially, a positive coefficient for W/S and negative coefficients for CD, Q/N, and $\sum Q$. The sign for V/S is not clear from a theoretical standpoint.

5. Results

Table 1 provides summary statistics on the measures in the study. With the exception of the time trend and the count measure of design quality, the values were converted to natural logarithms for the regression analysis. Table 2 reports the estimation results. All regressions include the WIP/sales ratio in the inefficiency term, given its prior validation as a proxy for lean manufacturing capabilities. In light of the correlation among some of the measures, we add other variables to the inefficiency term in various combinations.[17] To verify robustness of the results across firms in the sample, the last two regressions show the estimates when Toyota and the American producers are omitted.

The first three parameters in Table 2 relate to the production frontier. The frontier is specified as a function of capital and labor inputs and is assumed to be shifting at a constant rate. The time trend, μ, is positive and significant; its value implies that the frontier level of efficiency increased at an average rate of about 2.5% per year. This can roughly be interpreted as the rate of growth of total factor productivity associated with best-practice operation in the auto industry. The capital elasticity coefficient, θ, identifies a statistically and quantitatively significant association between greater capital investment and higher labor productivity. The returns to scale parameter, γ, is about 0.09, which suggests significant increasing returns to scale in the production function (i.e., a 10% increase in firm size was associated with an increase of 0.9% in output per worker). The estimated parameters of the production frontier change only slightly with different specifications of the inefficiency model.

The coefficients in the inefficiency model are of prime interest in this study. The WIP/sales coefficient, δ_1, is positive in all regressions and generally highly significant, suggesting that higher levels of WIP were associated with lower levels of efficiency, as expected. Thus, the results point to the importance of lean manufacturing skills on the factory floor.

[16] Given that all CD_{it} values are 0 prior to the start of the *Car and Driver* ratings, we included a separate dummy variable (set equal to 1 for these early years, and 0 otherwise).

[17] The model likelihood function failed to converge with some combinations of parameters. We were, for example, unable to include total vehicle output and output per plant in the same regression. (These measures differ only by the count of assembly plants.)

Table 2 Parameter Estimates of the Stochastic Frontier Model*

	1	2	3	4	5	6	7	8	9
Stochastic frontier									
Time μ	**0.024**	**0.027**	**0.023**	**0.025**	**0.028**	**0.025**	**0.029**	**0.029**	**0.043**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
Capital/labor ratio θ	**0.364**	**0.321**	**0.388**	**0.317**	**0.265**	**0.347**	**0.260**	**0.231**	**0.133**
	(0.051)	(0.060)	(0.062)	(0.064)	(0.061)	(0.055)	(0.061)	(0.063)	(0.074)
Employees γ	**0.090**	**0.105**	**0.089**	**0.108**	**0.114**	**0.098**	**0.113**	**0.115**	**0.126**
	(0.011)	(0.013)	(0.014)	(0.014)	(0.014)	(0.011)	(0.014)	(0.014)	(0.016)
Inefficiency model									
Constant δ_0	**3.029**	**0.747**	**1.216**	**1.182**	**3.316**	**1.117**	**3.366**	**3.705**	**1.925**
	(0.462)	(0.214)	(0.268)	(0.129)	(0.442)	(0.109)	(0.449)	(0.522)	(0.425)
WIP/sales ratio	**0.123**	**0.186**	**0.192**	**0.166**	0.062	**0.201**	**0.078**	**0.092**	**0.189**
(lagged) δ_1	(0.030)	(0.024)	(0.028)	(0.030)	(0.034)	(0.027)	(0.036)	(0.045)	(0.045)
Value-added/sales				0.105	**0.196**		**0.161**	**0.172**	−0.194
ratio (lagged) δ_2				(0.072)	(0.071)		(0.076)	(0.084)	(0.109)
Design quality δ_3						0.035	0.035	0.040	**0.066**
						(0.022)	(0.023)	(0.027)	(0.025)
Number of vehicles			−0.011						
produced δ_4			(0.021)						
Volume per plant δ_5	**−0.184**				**−0.197**		**−0.202**	**−0.230**	**−0.096**
	(0.040)				(0.039)		(0.039)	(0.045)	(0.035)
Cumulative production δ_6		0.022							
		(0.012)							
Variance parameters									
σ_S^2	0.052	0.054	0.055	0.054	0.050	0.055	0.050	0.054	0.043
	(0.006)	(0.006)	(0.007)	(0.006)	(0.005)	(0.006)	(0.006)	(0.007)	(0.006)
γ	0.563	0.700	0.599	0.633	0.577	0.649	0.589	0.711	0.682
	(0.169)	(0.149)	(0.204)	(0.184)	(0.162)	(0.164)	(0.154)	(0.118)	(0.156)
Log-likelihood function	45.03	33.28	31.95	32.78	48.62	32.00	49.75	47.65	58.08
Firms in sample	All	All	All	All	All	All	All	Exc. Toyota	Exc. US Big-3
No. of observations	336	336	336	336	336	336	336	304	240

*All the explanatory variables in the stochastic frontier and in the inefficiency model are in logarithms, except for the design quality measure. Numbers in parentheses are estimated standard errors. Coefficients in bold are significant at the 0.05 level.

Another strong result relates to plant scale. The coefficient for average output per assembly plant, δ_5, is negative and highly significant, implying that efficiency was higher for firms that produced more vehicles per plant. As discussed earlier, this finding may denote the joint influence of scale economies and manufacturing capabilities associated with mixed-model assembly. Firms with such capabilities are able to operate with lower levels of WIP inventory, which may account for the reduced coefficient for WIP/sales when volume per plant is included.

Regression 2 includes the *cumulative* number of vehicles produced, the proxy for learning curve effects. Japanese producers began in the early years of the sample with low levels of cumulative output but experienced rapid growth. Toyota ultimately surpassed the cumulative output of Chrysler, but otherwise the relative experience rankings are fairly stable, with GM remaining by far the most "experienced" firm. The coefficient of the cumulative output variable, δ_6, is not statistically significant, suggesting the absence of any simple connection between cumulative output and efficiency for the firms in our sample. Moreover, the sign of the coefficient is positive, signifying that more "experienced" firms (typically the U.S. Big Three) were less productive. Experiments that allowed the stock of production experience to depreciate over time failed to reverse this result. We conclude that firm-level cumulative output does not serve as an effective proxy for organizational learning among the automotive companies in our sample.

Regression 3 includes the firm's total vehicle production in the observation year as a component of the inefficiency model. We test this measure, Q, to confirm that the results for plant scale, Q/N, and cumulative output, $\sum Q$, are not simply due to correlation with the firm's annual vehicle output. In addition, Q serves as a potential indicator of scale economies at the firm level; it can be viewed as an alternative to the test for scale economies denoted by the parameter γ in the production frontier. In regression 3, the associated coefficient, δ_4, has the expected negative sign but is insignificant. Thus, we find evidence of firm-level economies of scale in the production function ($\gamma > 0$) but not in the inefficiency term.[18]

[18] If the production function is specified as constant returns to scale (i.e., if γ is omitted from the model), the coefficient for vehicles

Our measures relating to supplier integration and product design give weak or insignificant results. Regressions 4, 5, and 7 show that the value-added/sales measure of backward integration into parts production becomes significant when included with volume per plant. The positive sign of δ_2 implies that more integration into parts production was associated with greater inefficiency. This is consistent with views on the advantages of subcontracting. However, the result is not robust across specifications and could simply reflect the fact that labor productivity tends to be lower in parts production than in assembly. The measure of design quality collected from *Car and Driver* is statistically insignificant in regressions 6 and 7 and carries the wrong sign. Thus, there is no evidence that firms with more design awards had higher levels of efficiency.[19]

To summarize the main findings in Table 2, our estimates of the production function show that greater capital investment was associated with higher labor productivity, as expected. Moderate economies of scale are observed at the firm level. The best-practice frontier gradually shifted outward, presumably as the result of technical progress not captured by factors in our model. Furthermore, estimates of the inefficiency model show the presence of scale economies at the plant level, and a connection between WIP inventory and efficiency. Less conclusive evidence suggests that firms with more vertical integration were less efficient. We find no indication of a general "learning curve" at the firm level, and no connection between firm efficiency and our *Car and Driver* measure of design quality.

We performed a series of robustness checks to examine the possibility that our results might be contaminated by unobserved heterogeneity in our sample. A standard way to control for such heterogeneity is to include a fixed-effect parameter for each firm. Unfortunately, our SFPF model failed to converge when a full set of firm dummies was included in either the production function or the inefficiency term. As an alternative, we estimated the model with selected companies omitted from the sample, to assess whether heterogeneity specific to these firms might distort our estimates. For example, our findings could be dominated by the strong performance of Toyota (so that any measure correlated with Toyota would appear to have explanatory value), or by country-specific effects. The final columns in Table 2 provide estimates of our model with observations for Toyota (regression 8) or the three American companies (regression 9) excluded. Comparison of regressions 7 and 8 reveals that the omission of Toyota has very little impact on the estimated coefficients or their significance levels. Hence, it is clear that heterogeneity relating to Toyota is not responsible for our findings. Omission of the three American firms leads to greater changes in the estimated parameters, although the general pattern is largely unaffected. When the American producers are excluded, the coefficient of WIP/sales increases in magnitude and significance, thus confirming that the WIP/sales measure is correlated with productive efficiency in Japan. The coefficient of volume per plant becomes much smaller in regression 9 (although it remains statistically significant), indicating that the productivity differential we have attributed to plant scale exists mostly between producers in Japan and the United States. The coefficient of the value-added/sales ratio changes sign and becomes insignificant in regression 9, suggesting that our findings relating to vertical integration pertain to differences between Japanese and U.S. companies, and thus could be simply a country effect. The design quality measure achieves statistical significance in regression 9 but shows the wrong sign, a result that is likely spurious given the deficiencies of this measure.

Carrying this approach further, Appendix A (available as an electronic companion at http://mansci.pubs.informs.org/ecompanion.html) reports a set of 11 regressions based on Equation (1) of Table 2, where each producer is sequentially excluded from the sample. The estimated coefficients remain fairly stable across these regressions. Hence, there is no evidence that any single firm exerts unusual influence on our estimates. Moreover, Appendix B (online at http://mansci.pubs.informs.org/ecompanion.html) gives a set of OLS regressions, similar to Equations (1) and (7) of Table 2, but with the inclusion firm fixed effects. Most of the patterns observed in Table 2 are maintained in the OLS results when fixed effects are added. Among the notable changes are a reduction in the WIP/sales coefficient (suggesting that most of the explanatory value of this measure is across producers, rather than within firms over time), and an increase in the coefficient of volume per plant (which may pick up the effects of short-run output fluctuations when the cross-sectional variance is removed). Also, the value-added/sales ratio changes sign, again implying that our findings for vertical integration are sensitive to the model specification. (While informative, such OLS estimates suffer various deficiencies in comparison to the SFPF model, which we highlight in ongoing work.)

produced, δ_4, becomes statistically significant. Thus, firm-level scale economies show up in the inefficiency model if they are excluded from the production function.

[19] We also obtained insignificant results for a quality measure obtained from annual issues of *Consumer Reports*, which gives vehicles ratings with an emphasis on reliability and frequency of repair. We recorded the proportion of models from each manufacturer that received a "recommended" rating in each year.

6. Explaining Differences in Performance Among Firms

We now apply the estimates from Table 2 to draw comparisons among firms. One challenge is to account for the substantial differences in performance that have existed between the largest producers in the two countries, Toyota and GM. We present calculations for these companies to show how interfirm comparisons can be made.

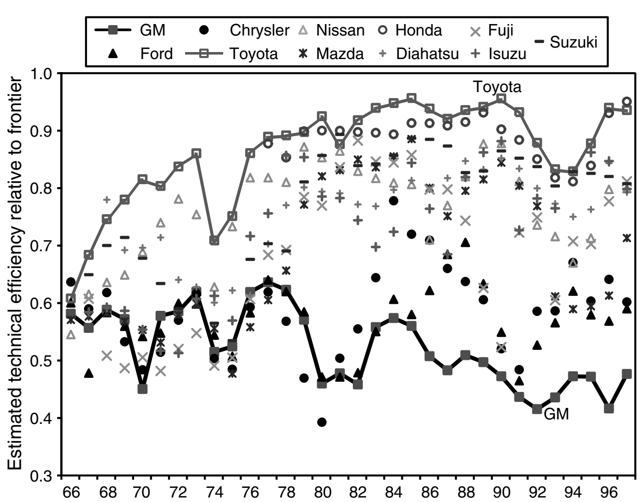
Technical efficiency is a summary measure of firms' performance. Figure 6 shows the estimated technical efficiency of producers in each year, based on regression 5. (The plotted values are the conditional estimates of TE given by formula (A.10) in Battese and Coelli 1993.) The top margin of the graph corresponds to the industry's efficiency frontier, which was increasing at a rate of about 2.8% per year, according to the value of μ in regression 5. The TE estimates in Figure 6 suggest that Toyota has operated close to the frontier since the late 1970s, whereas GM has been falling away from the frontier. Other firms typically lie in between. (Note that the TE estimates in Figure 6 exclude the effects of firm-level scale economies and capital investment, which are incorporated in the production function.)

Probing deeper, Table 3 utilizes the data values and estimated coefficients of the model to draw comparisons among firms. The calculations provide a breakdown of the labor productivity differential between GM and Toyota, based on means of the relevant variables for the two producers over the 1965–1997 period. The first part of the table shows the extent to which GM and Toyota differed along the dimensions considered in this study. On average, GM's output (value added) per worker was only 62% of Toyota's. GM had more than 13 times as many employees as Toyota, but with only 79% as much investment per worker. GM's assembly plants had about one-fourth the average volume of Toyota's. Within its plants, GM held about 10 times more WIP inventory, as a fraction of sales. GM also maintained substantially more backward integration into parts production: internal operations represented 46% of final sales revenue for GM, as compared with 18% for Toyota.

Taking the logarithm of these ratios and multiplying by the applicable regression coefficients, it is possible to make an estimate of the contribution of each factor in explaining the overall differential in output per worker. The results of these calculations are shown in the final columns of Table 3.[20] The labor productivity differential between GM and Toyota equals -0.48 in log terms. Based on the coefficients from regression 1 of Table 1, this differential can be attributed about equally to Toyota's superior positions relating to WIP inventory ($2.35 \times -0.1229 = -0.29$) and output per plant ($-1.27 \times 0.1840 = -0.23$), with an additional small effect due to Toyota's higher investment ($-0.24 \times 0.3655 = -0.09$). Our estimates suggest that these disadvantages were partly offset by GM's greater economies of scale at the firm level ($2.62 \times 0.0897 = 0.24$).[21] Thus, the four factors in combination may account for about three-fourths (=0.37/0.48) of the labor productivity differential between GM and Toyota. A similar calculation, including the effect of vertical integration, is shown in the last column of Table 3, based on the coefficients from regression 5, which includes all the major variables except design quality. Some estimates, such as the impact of WIP/sales, change magnitude between the columns, revealing sensitivity to the underlying specification of the model.

Figure 7 illustrates similar comparisons between Toyota and all other firms in the sample, using the coefficient estimates in regression 5. Over the 1965–1997 period, Toyota enjoyed substantial advantages in labor productivity relative to most producers. These advantages were based on many factors considered in this study: capital investment, firm and plant

Figure 6 **Technical Efficiency by Firm and Year**



[20] Note that the regression, composed of Equations (7) and (9), is linear in logarithms for the variables of interest. The difference between GM's and Toyota's output per worker, $\log Y/L$, is equal to differences in the (logged) explanatory variables multiplied by their respective estimated regression coefficients, plus the difference in prediction errors (or the unexplained portion). In Table 3, we convert the data into logarithms, take differences in the values for GM and Toyota, and plug these differences into the regression equation.

[21] GM's advantage in firm scale is likely to be overestimated, as the calculation compares GM's worldwide employment with the domestic employment of Toyota. Also, it is possible that scale economies may be diminishing over the range of firm sizes in our sample, which would also lead to an overestimate of the GM-Toyota differential. Otherwise, the estimates in Table 2 imply large but offsetting scale advantages of the two firms at the firm versus plant level.

Table 3 GM-Toyota Comparison Calculation

	Average data values (1965–1997)					
Dependent variable	GM	Toyota	GM/Toyota	log(GM/Toyota)		
Output per worker (Y/L)**	43.8	70.7	0.62	−0.48	(=differential to be explained)	
					Impact of factor on log(Y/L)*	
Explanatory factors					Based on reg. 1	Based on reg. 5
Resource levels						
Capital per worker (K/L)**	74.5	94.5	0.79	−0.24	−0.09	−0.06
Number of employees (L)	754,327	54,846	13.8	2.62	0.24	0.30
Capability measures						
WIP/sales	0.071	0.007	10.4	2.35	−0.29	−0.15
Value added/sales	0.461	0.182	2.5	0.93		−0.18
Vehicles/plant	170,687	607,418	0.28	−1.27	−0.23	−0.25
Total:					−0.37	−0.34

*Impact of factor = log(GM/Toyota) × regression coefficient.
**Thousands of 1982 dollars.

scale, and WIP. The calculations suggest that Toyota's greatest advantages can be linked to our measure of plant scale. Toyota lacked scale economies at the firm level relative to GM and Ford, but enjoyed scale advantages at both the firm and plant level relative to Japanese rivals.

7. Conclusions

The contributions of our study are both methodological and substantive. By combining the perspective of the resource-based view with the methods of production economics, we have outlined an approach for making the RBV operational. Applying the SFPF model of Battese and Coelli (1995) to public data on 11 automotive companies, we have identified firms' positions relative to the industry best-practice frontier. Furthermore, we have shown how the parameter estimates of the model shed light on potential determinants of firm performance in the auto industry. The Battese and Coelli model offers advantages over previous SFPF methods in that it allows for dynamic performance comparisons and is estimated in a single stage.

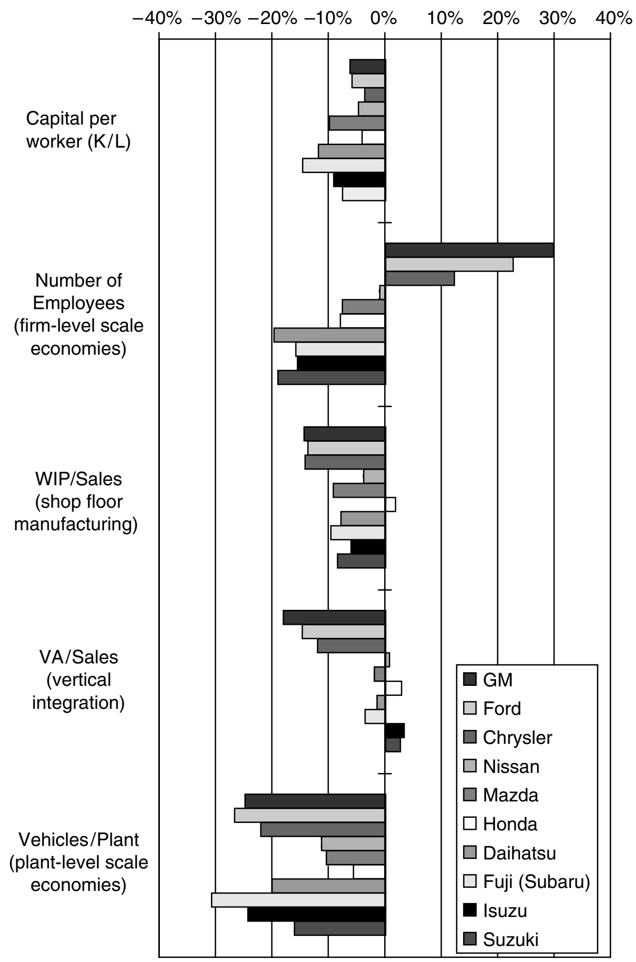
By considering a broad set of influences on company performance, our analysis adds perspective to prior work on the automotive industry. We have identified benefits associated with capabilities on the manufacturing shop floor, as well as economies of scale at the firm and plant level. Our estimates of the latter are likely to incorporate the value of capabilities for mixed-model assembly needed to effectively run the larger automotive plants. Weaker evidence in our study suggests that auto producers with higher levels of vertical integration have been less efficient. Other factors prove statistically insignificant in our analysis, perhaps because of the deficiencies of our proxy measures.

Based on the coefficient estimates, we have provided rough calculations on the sources of interfirm differences in performance. Our estimates suggest that productivity differentials among auto makers have been mostly the result of differences in organization and scale. In contrast with earlier work in the economics literature, we conclude that organization and scale are much more important than capital investment in accounting for labor productivity differences in the automotive industry.

While suggestive, our quantitative findings must be interpreted with caution. The estimates in this study may be biased, perhaps substantially, given limitations of the data. Important categories of capabilities may be omitted from the model. Those measures that we have included in our analysis are imperfect proxies. Ideally, our measures serve as valid indicators, but the results are ultimately based on correlations rather than causality. In areas where our proxies are weak, low correlation with the desired constructs biases our statistical estimates toward zero. Alternatively, if our measures are correlated with other important factors that we have failed to recognize, the estimated coefficients may be inflated. Moreover, serial correlation may cause our estimates of statistical significance to be overstated.

Despite these limitations, our findings point to the importance of operational effectiveness as a source of competitive advantage in the automotive industry. Toyota has long been the industry's most efficient producer and has increased its lead over time. Porter (1996) argues that operational effectiveness alone is not sufficient for a firm to achieve sustainable competitive advantage; the firm must also have a market position that insulates it from competitors. While this is true in industries where operational improvements can be easily imitated, the differentials we have

Figure 7 **Estimated Impact of Factors on Value-Added per Employee, Relative to Toyota**



Note. Reg. 5 coefficients and 1965–1997 avg. data values.

identified in the automotive industry have been sustained for long periods. Many years or decades have been required to achieve the imitation of superior scale and organizational skills. Consequently, lagging firms have converged only slowly to industry best practice (if at all), while stronger firms like Toyota have made continual advances, thereby maintaining or expanding their lead.

Such findings raise questions about the relative importance of operational effectiveness versus market position as sources of competitive advantage. Major firms in the automotive industry are similarly positioned as broad-line producers, and there is common agreement regarding the best practice. Such uniformity may enhance the role of operational effectiveness. Market positioning is likely to be more important in industries that support diverse competitors in specialized niches. In this study our specification of the production frontier has incorporated only limited dimensions of firms' positioning. Future refinements in SFPF models may allow a richer set of trade-offs to be explored.

An online appendix to this paper is available at http://mansci.pubs.informs.org/ecompanion.html.

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