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

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ABSTRACT

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 inter-firm 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.
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 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 provides a framework for identifying the sources of inter-firm differences in efficiency. In this paper 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.

This study links the perspective of the RBV with that of production economics, showing how the frameworks are related and how they can enrich each other. From economics we draw formal models and statistical methods that have been lacking in research on the RBV. The RBV provides insights regarding the sources and implications of firm heterogeneity, typically ignored by economists. Nevertheless, economists commonly recognize that differences in firm or plant size can lead to cost differences in the presence of economies of scale. Our study highlights the influence of scale
economies, which have been overlooked in the RBV literature despite their importance in many industries.

Our discussion is organized as follows. In the next section, 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 eleven firms in our sample over a three-decade period from the 1960s through 1997. Drawing from these estimates, we then make inter-firm 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, 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.,

\[ Y = F(K, L) \]  

where \( Y \) denotes the firm’s output, and \( K \) and \( L \) are its capital and labor inputs. Given data on a sample of firms, standard econometric methods can be used to estimate the production function. The estimated parameters show the tradeoffs 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. While 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 tradeoffs 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, Lovell and Schmidt (1977) and Meesuen and van der Broeck (1977) led to the development of “stochastic frontier production function” (SFPF) models that can be estimated to identify the production frontier and the relative positions of firms.\(^1\) Thus, the SFPF models explicitly recognize firm heterogeneity, whereas more traditional economic approaches assume it away.

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: \(0 < TE \leq 1\). The output of any firm \(i\) can be written as, \(Y_i = F(X_i) \, TE_i\), or in the case of a two input production function, \(F(K_i, L_i) \, TE_i\).

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, 2003). Although this two-stage procedure suffers from conceptual problems (Kumbhakar and Lovell, 2000: 262-266), it provides a method for assessing efficiency differences at a specific

\(^1\) 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 multi-output 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 inter-firm differences can be examined. For an overview and comparison of these methodologies, see Coelli, Rao and Battese (1998).
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,

\[ Y_{it} = F(K_{it}, L_{it}, t) \cdot TE(Z_{it}), \]  

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 inputs.\(^2\) Output is determined by the product of \( F(\cdot) \) and \( TE(\cdot) \). 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 Battese and Coelli (1995) 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 inter-firm differences in performance (e.g., Barney, 1986; Rumelt, 1987; Dierickx and Cool, 1989; and Peteraf, 1993). The RBV must be

\(^2\) 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).
regarded as a perspective rather than a theory, as debate continues over its essential constructs (Hoopes, Madsen and Walker, 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). Supporters of the RBV have proposed 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. It has proven 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.

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. Prior investigations in the strategic management field have begun to provide the RBV with greater empirical content. For example, Henderson and Cockburn (1994) found that firm effects influenced 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, Narasimhan and Rajiv (1999) have proposed a two-stage statistical approach for operationalizing the RBV: in the first stage, SFPF methods are used to obtain estimates of firms’ capabilities relative to the industry frontier; these capability estimates are then regressed on financial performance measures. While such a multi-stage procedure may be necessary to incorporate financial measures of performance with SFPF, the single-equation approach of the present study is simpler and more direct.

One contrast between the RBV and SFPF perspectives is that they have emphasized different metrics of firm performance. The RBV is commonly invoked to explain profit differentials, whereas the SFPF models address differences in efficiency.
Despite the established focus of the RBV on profits, efficiency may provide a better metric for empirical studies. Peteraf and Barney (2003) argue that the RBV is ultimately “an efficiency-based explanation of performance differences” that excludes other determinants of profitability, such as market power and collusion. Moreover, SFPF models convey a broader conception of firm performance than might be immediately apparent. In the next section we show that a simple transformation of equation (2) 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 major automakers, 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.\footnote{Over the period from 1983 to 1997, 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 automakers combined.}

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 specifics depend upon 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, Womak, Jones and Roos (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. Western firms have acknowledged these shifts but have often been slow to catch up.

Below, 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. automakers from the mid-1960s through 1997. Our data are entirely from public sources (company annual reports on business segments relating to motor vehicle production, unless otherwise indicated). Given data limitations, some of our measures serve only as weak proxies for types of capabilities that are highlighted in the applied 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 dimensions of heterogeneity considered most important in this 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. For example, large sunk investments are

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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.

5 Financial and employment data for Japanese companies are from annual issues of the Daiwa Analysts’ 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. Non-automotive 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 it was not possible to identify values specific to automotive businesses in the United States.
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 lifecycle 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. An indicator of the importance of these scale economies is the high rate of company mergers. To achieve a more efficient scale of operation, many automakers have combined in recent years, often linking across national boundaries. This continues a trend of consolidation stretching back to the early days of the industry.

One 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 needed to capture the range of size variation 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; indeed, it would seem virtually impossible for the small Japanese producers to achieve the scale of Toyota or the Big-Three, except via mergers.

Scale differentials are one of the few dimensions of firm heterogeneity considered by conventional economists. In our empirical work we incorporate a standard test for economies of scale, as described in the next section. An important question, though, is whether scale advantages can be considered a “resource” within the context of the RBV. This is a matter of interpretation that has received surprisingly little attention in the RBV literature.

In a seminal study, Barney (1991) proposed that resources contribute to sustained competitive advantage when they are valuable, rare, difficult to imitate, and difficult to substitute. These criteria provide a test for classification under the RBV. The prevalence of mergers, as well as econometric evidence presented below, suggest that greater firm size is valuable in automotive manufacturing. Large size is also rare and difficult to imitate in the auto industry, as the substantial and persistent differentials in Figure 2
Attest. While small automakers can sometimes substitute for scale by striking alliances with other producers (e.g., to share components, such as engines), such arrangements are imperfect. Thus, advantages of greater firm size would appear to fit Barney’s criteria for strategic resources in the context of the RBV.

Other interpretations of the RBV exclude firm size and associated scale economies from the category of strategic resources. In Makadok’s (2001) view, resources are observable assets that can be valued and traded, whereas capabilities are organizationally embedded and thus can be transferred only through sale of the firm or major subunits. By this definition, firm size is clearly not a resource (although it could, perhaps, be considered a capability). Hoopes, Madsen and Walker (2003), seeking to avoid a perspective where all factors that contribute to a firm’s sustained success are classified as either resources or capabilities, suggest that scale economies belong in a separate category of “cost drivers.”

Few would dispute that scale advantages can contribute to superior performance, regardless whether assigned to the category of “resources,” “capabilities,” or “cost drivers.” In the absence of universally-accepted definitions within the RBV literature, we draw upon the production frontier model (Equation 2) for conceptual structure. This model incorporates within the production function those resources that are essential to production, notably capital and labor; all other influences are included in the $Z_{it}$ vector of the technical efficiency term. This approach allows us to integrate the standard econometric production function model with the framework of the RBV. 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 (1993:35) 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 notions of the RBV run parallel to the logic of the frontier production function model.
The above discussion of scale economies focuses on savings that arise with increases in overall firm size. It may also be meaningful to consider scale economies at sublevels of the firm. For example, savings from the spread of product design and tooling costs may depend upon the annual or lifetime volume of specific vehicle models (or groups of related models that share components). We avoid incorporating vehicle-specific measures of scale in this study, as they are hard to assess, and output per model is only partially under the control of the firm. Moreover, the ability to achieve these product-level scale economies may be closely related to firm size, which is already incorporated in our analysis.

A similar dimension of scale that is both meaningful and observable is the average size of the firm’s automotive assembly plants. Early engineering studies (e.g., Pratten, 1971) suggested that most plant-level scale economies 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 conventional configuration of automotive assembly plants by combining on-site stamping with two or more vehicle assembly lines to give a much higher-volume 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 in \( Z_{it} \) each firm’s annual average output per assembly plant.

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 400,00 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 annual units. Figure 3 gives clear evidence that Toyota and other major

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\(^6\) 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.
Japanese 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: U.S. producers operate older plants dating 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 needed to efficiently operate a higher-volume plant. Output per model has been much higher in the U.S. than in Japan; this has allowed the American automakers to dedicate 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 enabled higher rates of cost reduction (Schonberger, 1982: 119-121), in addition to allowing them to exploit the potential scale economies of a higher-volume plant.

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. Thus, it suggests a connection between “mass” and “lean” production capabilities. A significant effect for plant size in our SFPF analysis would denote the potential influence of both factors. To assess their relative importance, further information is required.

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

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\(^7\) 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.
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 neither rare, difficult to imitate, nor difficult to substitute. 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.

Figure 4 plots our estimates of real capital stock per employee ($K/L$).\(^8\) 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, capital stock per employee rose steadily from the mid-1960s through the late 1980s. The figure shows that Toyota was the firm with highest investment per worker over most of the sample period. The U.S. pattern differs from that of the Japanese: 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 within about a decade the gap with Japan was eliminated. 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.

\(^8\) We constructed a real capital stock series for each firm using a perpetual inventory capital adjustment equation: $K_t = (1-d) K_{t-1} + \text{deflated gross investment}$, 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 non-residential investment reported by the Economic Planning Agency. For U.S. firms, we used the GDP deflator for non-residential fixed investment from the 1998 Economic Report of the President. Our measure with 10% 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.
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, (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 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 5 shows large variation in the WIP/sales ratio among the automakers in our study. 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 the lean manufacturing methods of Toyota and others 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 5 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

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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.
States as the Big-Three began to understand and embrace the Japanese manufacturing practices.\textsuperscript{10}

Product design is another area where the Japanese have been influential. Multiple dimensions of design 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 changes in organization and methods that 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 upon the quality of their product designs as assessed by the staff of \textit{Car and Driver}, a trade journal. In annual issues beginning in January 1983, \textit{Car and Driver} identified a set of “10 best cars” from the regular production models sold in the United States.\textsuperscript{11} While the criteria used by \textit{Car and Driver} emphasize final product design quality rather than underlying capabilities, we found in a supplementary analysis that the \textit{Car and Driver} award rates were highly 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

\textsuperscript{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.

\textsuperscript{11} The selection criteria include multiple categories such as “design,” “ride,” “value,” “driveability,” and “handling.”
subtle, and comprehensive measures are unavailable. We can, however, observe each firm’s degree of backward 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, Jones and Roos, 1990; Dyer, 1996). Indeed, GM and Ford moved dramatically toward the subcontracting model by spinning off their internal parts-making operations shortly after the final year our sample.

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. It is less informative as an indicator of the assembler’s actual skills in coordinating with parts suppliers (whether internal or external), which may be more important than integration, per se. To avoid spurious correlation with short-term output changes, we use a lagged, four-year moving average of the value-added/sales ratio, shown in Figure 6. In 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 integrated backward (particularly into electronic components that have become critical to vehicle operation), while the Americans have increasingly shed their parts-making operations. Following the spin-offs of parts operations 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

Over the three-decade period of this study, the organizational design choices of automotive companies have shown remarkable persistence and some degree of convergence. The data show convergence for 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 documents continuing large differences in firm size (although several companies, including Chrysler, Nissan, Mazda, Daihatsu, and Isuzu, were later merged or fell under the effective control of larger rivals). Perhaps the most persistent differences are those for plant scale. Throughout the sample period, the Big-Three U.S. automakers remained locked-in by their historical investments and lack of skills in mixed-model assembly, whereas most of the smaller Japanese producers suffered from inadequate volume to fill efficient-scale plants.

Such patterns are consistent with more theoretical views of industry evolution and adoption of best practice. 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 firms adjust their resources and capabilities in the automotive industry.

3. Stochastic Frontier Production Function Model

The usual panel data estimation techniques—fixed and random effects models—are inappropriate for our study as they assume two-sided or symmetric deviations from the production frontier. As shown in Figure 1, 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 the SFPF methodology, we first add 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:

\[ Y_{it} = F(K_{it}, L_{it}) \, TE_{it} \, e^{V_{it}}, \quad (3) \]

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 \( \sigma^2_v \).

As described earlier, \( TE_{it} \) is a scaling factor, where \( 0 < TE \leq 1 \), 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:

\[ TE_{it} = e^{-U_{it}}, \quad (4) \]

or equivalently, \( U_{it} = -\ln TE_{it} \), where by definition, \( U_{it} > 0 \). The \( U_{it} \)'s are one sided, non-negative 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 non-negative truncation of the normal distribution with unknown variance \( \sigma^2 \). 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:

\[ Y_{it} = F(K_{it}, L_{it} : \beta) \, e^{V_{it}} \, e^{-U_{it}}. \quad (5) \]

In this study we assume that \( F(\cdot) \) has a Cobb-Douglas functional form, with technical progress that occurs at a constant rate \( \mu \) over time i.e.,
\[ F(K_{it}, L_{it} : \beta) = e^{u_i} K_{it}^{\beta_1} L_{it}^{\beta_2}. \] (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:

\[ \ln \left( \frac{Y}{L} \right)_{it} = \mu + \theta \ln \left( \frac{K}{L} \right)_{it} + \gamma \ln (L)_{it} + V_{it} - U_{it}, \] (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, \( \theta \), which is equal to \( \beta_1 \), is the elasticity of output with respect to capital. The coefficient, \( \gamma \), which is equal to \( \beta_1 + \beta_2 - 1 \), represents the deviation from constant returns to scale, where a positive value of \( \gamma \) 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 links 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:

---

\(^{12}\) We chose the Cobb-Douglas specification as it is a commonly used functional form, which can be estimated using single equation methods to give consistent parameter estimates (see Zellner, Kemeny and Dreze (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 values were converted to U.S. dollars using purchasing power parity exchange rates. The latter were based on OECD estimates for the 1980s (OECD, 1987), which were extrapolated (using the relative price indexes for the two countries) to cover all years of the sample.
where \( Z \) is a vector of explanatory variables, such as those collected in our study. Here, \( \delta \) is a vector of unknown parameters to be estimated and \( W \)'s are unobservable random variables.\(^{14}\) The technical efficiency (\( TE \)) of the \( i \)-th firm in the \( t \)-th year then is:

\[
TE_{it} = \exp ( -Z_{it} \delta - W_{it} )
\]  \( (8) \)

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 \( \sigma^2_s = \sigma^2 + \sigma^2_v \) and \( \gamma = \sigma^2_v / \sigma^2_s \), and estimate \( \sigma^2_s, \gamma, \) vector \( \beta \) and \( \delta \) by maximum-likelihood estimation (MLE) methods.\(^{15}\)

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

\[
U_{it} = \delta_0 + \delta_1 \ln (W/S)_{it-1} + \delta_2 \ln (V/S)_{it-1.4} + \delta_3 \ln (CD)_{it}
\]

\[
+ \delta_4 \ln (Q)_{it} + \delta_5 \ln (Q/N)_{it} + \delta_6 \ln (\Sigma Q)_{it} + W_{it} ,
\]  \( (9) \)

where \( W/S \) 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 \textit{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 \( \Sigma Q_{it} \) 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 in order to verify that the measured effects of plant scale, \( Q/N_{it} \), and cumulative output, \( \Sigma Q_{it} \), are not simply due to correlation with annual vehicle output.

\(^{14}\) \( W \)'s, which are assumed to be independently distributed, are obtained by truncation of the normal distribution with mean zero and unknown variance, \( \sigma^2 \), such that \( U_{it} \) is non-negative (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.

\(^{16}\) Given that all \( CD_{it} \) values are zero prior to the start of the \textit{Car and Driver} ratings, we included a separate dummy variable (set equal to 1 for these early years, and zero otherwise).
A positive value of the $\delta$ 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 $\Sigma Q$. The sign for $V/S$ is not clear from a theoretical standpoint.

Table 1 gives the mean values of the variables and a correlation matrix. The latter shows a high degree of correlation among many of the measures in the sample. Not surprisingly, labor productivity and capital stock per employee are strongly correlated and positively trended over time. Firm size, as measured by the number of employees, is strongly correlated with the value-added/sales ratio and cumulative output, reflecting the fact that in general, the U.S. producers had much higher values than the Japanese. This U.S./Japan differential also contributes to the high correlations between WIP/sales, plant scale and the value-added/sales ratio. Clearly, a comprehensive statistical model is needed to disentangle the potential influences on firm performance in the automotive sample.

4. Results

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 measures, we add other variables to the inefficiency term in various combinations.\textsuperscript{17} To verify robustness of the results across producers, the last two regressions give estimates with Toyota excluded, and with U.S. producers excluded from the data sample.

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

\textsuperscript{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.)
constant rate. The time trend, $\mu$, is positive and significant, implying 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, $\theta$, equals about 0.3, which implies that a 10% increase in capital per worker led to a 3% increase in output. The returns to scale parameter, $\gamma$, is about 0.09, indicating 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, $\delta_1$, is positive in all regressions and generally highly significant, implying that higher levels of WIP were associated with lower levels of efficiency, as expected. Thus, the results confirm the importance of lean manufacturing skills on the factory floor.

Another strong result relates to plant scale. The coefficient for average output per assembly plant, $\delta_5$, is negative and highly significant, indicating that efficiency was higher for firms that produced more vehicles per plant. As discussed earlier, this finding is likely to denote the joint influence of scale economies at the plant level and 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. The 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, $\delta_6$, 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, $\Sigma Q$, 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 $\gamma$ in the production frontier. In regression 3, the associated coefficient, $\delta_4$, 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.\(^{18}\)

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 weakly significant when included with volume per plant. The positive sign of $\delta_2$ 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.\(^{19}\)

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\(^{18}\) If the production function is specified as constant returns to scale (i.e., if $\gamma$ is omitted from the model), the coefficient for vehicles produced, $\delta_4$, 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.
To verify that these results are not determined by outliers for a specific producer or country, we estimated the model for various subsamples. Appendix A gives a set of eleven regressions (based on equation 1 of Table 2), where each producer is sequentially excluded from the sample. The coefficients remain fairly stable across these regressions, and there is no evidence that any single firm exerts unusual influence on the estimates. Similar comparisons can be drawn across the last three regressions in Table 2, which incorporate the broadest set of measures in the model while omitting observations for Toyota (regression 8) and the three American companies (regression 9). Regression 7 includes the full sample of eleven producers. As in the Appendix, exclusion of Toyota has little effect on the estimated coefficients. Exclusion of the American firms leads to some greater changes. (This would be expected, as the variation in the sample for some measures is largely between the two countries). When the U.S. firms are excluded, the coefficient of WIP/sales increases, the coefficient of volume per plant falls (although it remains statistically significant), and the coefficient of the value-added/sales ratio changes sign. The latter suggests that the effects shown for vertical integration in the full sample pertain to differences between Japanese and U.S. companies. Finally, the design quality measure becomes significant but with the “wrong” sign.

To summarize the findings in Table 2, our estimates of the production function show that greater capital investment led to 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 the 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. There is no indication of a general “learning curve” at the firm level, nor is there a significant link between firm efficiency and our Car and Driver measure of design quality.
5. 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 inter-firm comparisons can be made.

Technical efficiency is a summary measure of firms’ performance. Figure 7 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 $\mu$ in regression 5. The $TE$ estimates in Figure 7 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 7 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 1965-97 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 ten 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. 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 x –0.1229 = -0.29) and output per plant (-1.27 x 0.1840 = -0.23), with an additional small effect due to Toyota’s higher investment (-0.24 x 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 x 0.0897 = 0.24). 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. Some estimates, such as the impact of WIP/sales, change magnitude between the columns, revealing sensitivity to the underlying specification of the model.

Figure 8 illustrates similar comparisons between Toyota and all other firms in the sample, using the coefficient estimates in regression 5. Over the 1965-97 period, Toyota enjoyed substantial advantages in labor productivity relative to most producers. These advantages were based on nearly all of the factors considered in this study: capital investment, firm and plant 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.

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.

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.
6. Conclusions

In this study we have outlined a methodology for operationalizing the resource-based view of the firm, using the SFPF model of Battese and Coelli (1995). Applying this model to historical data on the international automotive industry, we have identified firms’ positions relative to the best practice frontier. Moreover, we have shown how the coefficient estimates can be used to assess factors that may cause firms to fall below the frontier. 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.

In terms of specific findings, our analysis gives some rough quantitative evidence on the importance of resource and capability categories suggested by prior work on the automotive industry. Our estimates confirm the value of superior capabilities on the manufacturing shop floor (as indicated by the WIP/sales ratio) and economies of scale at the firm and plant level. Our estimates of the latter are likely to include the value of capabilities for mixed model assembly that are needed to efficiently run larger scale plants. We also find weak evidence that firms with higher levels of vertical integration are less efficient. Other factors prove statistically insignificant in the analysis, perhaps because of the deficiencies of our proxy measures.

We have provided rough calculations on the sources of inter-firm differences in performance. Our estimates suggest that the productivity differences between GM and Toyota are mostly the result of differences in organization and scale. Similar findings apply across the full sample of producers. One conclusion is that organization and scale have been much more important than capital investment in accounting for differences in labor productivity.

Such quantitative findings must be interpreted with caution. The estimates in this study may be biased, perhaps substantially so, 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 for firms’ true capabilities. Ideally, our measures serve as valid indicators, but the results are ultimately based upon 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 coefficient estimates may be spurious. 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 in the automotive industry. Porter (1996) argues that operational effectiveness alone is not sufficient for a firm to achieve competitive advantage; the firm must also have a market position that insulates it from competitors. Yet we have shown that efficiency advantages in the automotive industry have been sustainable for long periods of time. Many years or even decades have been required for the imitation of scale advantages and organizational skills relating to lean manufacturing. Consequently, lagging firms have converged only slowly to industry best practice, while the stronger firms that define the frontier have made steady improvements, thereby maintaining a lead. While our findings are specific to the automotive assemblers, similar features may apply in other industries. Nevertheless, two salient characteristics of the automotive industry are the prevalence of broad-line producers and general agreement regarding best practice. Operational effectiveness may be less critical in industries that support diverse competitors in specialized product niches.

We have argued that our application of the Battese and Coelli model allows a broad assessment of firm performance differentials. Even so, our analysis lacks dimensions of competitive positioning outside of those relating to efficiency or scale. Some further elements of market position, such as product quality, may be related to the lean manufacturing skills considered in this study. Potential connections between productive efficiency and the notions of competitor differentiation and positioning remain to be explored in future work.
References


Table 1. Variable Means and Correlation Matrix

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<tr>
<th>Variable</th>
<th>Mean*</th>
<th>Std. Dev.*</th>
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<tr>
<td>Value-added per employee</td>
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<tr>
<td>Time</td>
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<td>Capital stock per employee</td>
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<tr>
<td>WIP/sales ratio</td>
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<td>Value-added/sales ratio</td>
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<td>Car &amp; Driver measure</td>
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<td>Domestic vehicle production</td>
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<td>Volume per assembly plant</td>
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<td>Cumulative output</td>
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<tr>
<th></th>
<th>Y/L</th>
<th>t</th>
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* All measures except CD are in logarithms. The data sample includes 336 observations.
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*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 t-statistics.
### Table 3. GM-Toyota Comparison Calculation

#### Average Data Values (1965-1997)

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<th>log(GM/Toyota)</th>
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#### Explanatory Factors:

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<th>Based on Reg. 5</th>
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|                      |      |        |           | Impact of Factor on log(Y/L)* |
|                      | Total|        |           | -0.37            | -0.34            |

*Impact of Factor = log(GM/Toyota) x regression coefficient.

**Thousands of 1982 dollars.
Figure 1. Firms Relative to Industry Production Frontier
Figure 2. Number of Employees
Figure 3. Average Vehicle Output per Plant

GM
Ford
Chrysler
Toyota
Nissan
Honda
Mazda
Daihatsu
Fuji (Subaru)
Isuzu
Suzuki

[Graph showing the average vehicle output per plant for various car manufacturers from 1964 to 1996.]
Figure 4a. Capital Stock per Worker (Japan)

- Toyota
- Nissan
- Honda
- Mazda
- Daihatsu
- Fuji (Subaru)
- Isuzu
- Suzuki

Thousands of 1982 dollars
Figure 4b. Capital Stock per Worker (United States)

Thousands of 1982 dollars

GM
Ford
Chrysler
Figure 5. WIP/Sales Ratio

- GM
- Ford
- Chrysler
- Toyota
- Nissan
- Honda
- Mazda
- Daihatsu
- Fuji (Subaru)
- Isuzu
- Suzuki
Figure 6. Value-added/Sales (Vertical Integration)
Figure 7. Technical Efficiency by Firm and Year

Estimated technical efficiency relative to frontier

- GM
- Ford
- Chrysler
- Toyota
- Nissan
- Mazda
- Honda
- Diahatsu
- Fuji
- Isuzu
- Suzuki
Figure 8. Estimated impact of factors on value-added per employee, relative to Toyota (Reg. 5 coefficients and 1965-97 avg. data values)

-40% -30% -20% -10% 0% 10% 20% 30% 40%

- Capital per worker (K/L)
- Number of Employees (firm-level scale economies)
- WIP/Sales (shop floor manufacturing)
- VA/Sales (vertical integration)
- Vehicles/Plant (plant-level scale economies)
### Appendix A. Parameter Estimates of the Stochastic Frontier Model When One Firm is Excluded

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<td>Chrysler</td>
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*All the explanatory variables in the stochastic frontier and in the inefficiency model are in logarithms. Numbers in parentheses are t-statistics.