Product Variety and Manufacturing Performance: Evidence from the International Automotive Assembly Plant Study

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This paper examines the effect of product variety on manufacturing performance, defined here as total labor productivity and consumer-perceived product quality. Using data from the International Motor Vehicle Program (M.I.T.) study of 70 assembly plants worldwide, the paper examines three dimensions of product variety, at fundamental, peripheral, and intermediate levels. The international sample reveals great variation in the distribution of each type of product variety in different regions, reflecting in part different strategies for variety. Furthermore, the impact of different kinds of product variety on performance varies, and is generally much less than the conventional manufacturing wisdom would predict. However, an intermediate type of product variety, here called parts complexity, was found to have a persistent negative impact on productivity. Finally, the study provides partial support for the hypothesis that management policies, in both operations and human resource areas, can facilitate the absorption of higher levels of product variety, i.e. that "lean production" plants are capable of handling higher levels of product variety with less adverse effect on total labor productivity than traditional "mass production" plants.
(*Product Variety; Labor Productivity; Product Complexity; Lean Production; Automotive Assembly; Mass Production; Flexible Production*)

1. Introduction

Companies can no longer follow the trail blazed by Henry Ford, capturing market share and high profits by producing large volumes of a standardized product. Today, consumers' needs and wants change rapidly. Companies that understand these changing preferences (or create new preferences) and respond to them quickly, with appropriate products, have a substantial advantage over their competitors (Dertouzos et al. 1989; Stalk and Hout 1990). In the automotive industry, increasing product variety arises from such factors as changes in energy prices and trade structures, internationalization of the market, and the growing sophistication of customers (Clark and Fujimoto 1991). The result has been a steady increase in the number of car models that are being offered worldwide. In the U.S., the world's largest automotive market, this trend has been particularly dramatic—from 84 models in 1973 to 142 models in 1989, an increase of almost 70%. The volume of production per model sold in the U.S. has dropped as well. During this same period, the average annual sales per model, over the lifetime of the product, have dropped by 34% from 169,000 units to 112,000 units per model (Womack et al. 1990).

These trends create considerable manufacturing challenges for assembly plants. As the model mix and array

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of options increase in a plant, assembly line task balancing is more problematic and parts planning and production scheduling systems become increasingly complex. Thus one goal of this paper is to evaluate the impact of increased product variety on manufacturing performance.

Japanese and American auto manufacturers have strikingly different strategies with respect to product variety. The U.S. domestic car manufacturers have traditionally believed that extremely high production volumes were required to achieve the economies of scale needed to keep production costs low. Hence they adopted the strategy of minimizing the variation in fundamentally different models (fundamental variety), while offering a large number of options that could be varied without altering the core design (peripheral variety) in order to differentiate products for the consumer. In comparison with the U.S., Japanese manufacturers, at least in Japan, offer more distinct models from which customers can choose, but far fewer possible option combinations. For example, the number of possible option combinations on the 1982 models of Honda Accord and the Ford Thunderbird were 32 and 69,120 respectively ("Where is The Niche?", Forbes, September 1984).[1] A second goal of this paper is to evaluate the consequences of these different product strategies.

A final goal is to explore the ways in which companies and plants attempt to minimize the impact of complexity on manufacturing performance. Previous research (Krafcik 1988a, b; Krafcik and MacDuffie 1989; Womack et al. 1990; MacDuffie and Krafcik 1992; MacDuffie 1995) has identified the performance advantages, in terms of productivity and quality, associated with "lean production" management practices. The paper tests (and finds partial support for) the hypothesis that "lean production" plants are capable of handling higher levels of product variety with less adverse effect on manufacturing performance than traditional "mass production" plants.

This paper uses data from the International Assembly Plant Study, carried out under the auspices of the International Motor Vehicle Program (IMVP) at M.I.T.[2] It examines five measures that capture different aspects of the products and product mixes built in assembly plants around the world: Model Mix Complexity, Parts Complexity, Option Content, and two measures of Option Variability. Model Mix Complexity corresponds to fundamental variety, and is based on the number of different platforms, body styles, and models, scaled by the number of different body shops and assembly lines in each plant. Parts Complexity results from an intermediate category of variety that is partially driven by consumer choice (e.g. exterior color, the combinations of engines and transmissions) but also reflects the impact of higher variety on product design (e.g. the number of main wire harnesses, the commonality of parts across models) and the supply system (e.g. the number of assembly area part numbers, the number of suppliers to the assembly area).

The third, fourth, and fifth measures all relate to peripheral variety. The Option Content measure reflects the overall level of installed options, and equals the percentage of vehicles built with various options, aggregated across all models in a plant. Option Variability, in contrast, refers to the variance in option content within each model and across models manufactured in the plant. There are two measures based on this variable, each reflecting different assumptions about variability; the derivation of each measure is discussed below. High option content does not, in itself, necessitate high option variability. If 100% of all vehicles built have

[1] This dramatic difference in the level of options narrowed considerably during the 1980s. In the mid-1980s, American companies undertook major programs of "option deproliferation," and Japanese companies began building larger, more expensive cars that included more options. However, a major difference in option strategy remained, with U.S. companies more likely to allow customers to choose from a list of individual options, and the Japanese companies more likely to install many so-called "options" as standard equipment on the base model. Finally, it should be noted that Japanese plants in the U.S. (the transplants), all of which opened between 1982 and 1989, began production with low levels of both fundamental and peripheral variety, and have added more fundamental variety over time, although they still don't match the complexity levels of plants in Japan.

[2] The International Motor Vehicle Program (IMVP) operated from 1985–90 and was sponsored by virtually every automotive manufacturer in the world. During that time, the International Assembly Plant Study was carried out by John Krafcik and John Paul MacDuffie. IMVP continues now as one of the Sloan Foundation-funded studies of industrial competitiveness, and a second round of assembly plant data is being collected by John Paul MacDuffie and Frits Pil.

every available option, the option content will be at its highest possible level, while option variability will be zero. However, this would be an extremely unusual occurrence in automobile manufacturing. The inclusion of both option content and variability measures allows consideration of any possible combination of high/low option content with high/low option variability.

One note on terminology. We use the term "variety" to refer to what the company wants to offer to consumers—its product market strategy. These choices about the breadth and depth of different product lines affects manufacturing. We use the term "complexity" to refer to one dimension of the manufacturing task that results from the product strategy. Thus, a company's choice about product variety requires manufacturing plants to cope with a certain level of product mix complexity. For example, when a company offers consumers a variety of options, the manufacturing plant faces a particular option complexity, which in turn reflects both a particular level of option content and a particular variability in options across individual car models. When a company decides what variety of platforms to offer consumers and distributes those platforms to its plants, any given plant will face a particular level of model mix complexity.

2. Literature Review

Coping with product variety forces a manufacturing firm to confront a fundamental tradeoff—the increased revenue that can result from more variety versus increased costs through the loss of scale economies. Faced with this tradeoff, manufacturers may follow one of two divergent paths: 1) low variety and a "focused factory," or 2) high variety and flexible manufacturing.

There has been considerable disagreement among researchers as to which of the two strategies is better. Skinner (1974) suggested that by focusing manufacturing operations, a firm can outperform competitors whose plants attempt a broader mission. On the other hand, Abernathy and Wayne (1974) warn manufacturers that consistently choosing a "focus" strategy to speed movement down the learning curve will result in a narrowly specialized work force and a reduced ability to innovate or respond quickly to changes in the competitive environment. De Meyer et al. (1989) find that both U.S. and Japanese manufacturing managers view product mix flexibility as a manufacturing capability crucial for competitive success. Similarly, Abegglen and Stalk (1985) argue that rapidly-changing customer needs warrant investments in manufacturing flexibility, both to hold existing customers and attract new ones.

Scale economies result when fixed cost inputs can be distributed over an increasingly high volume of a standardized output. In contrast, economies of scope result from complementarities in production processes that allow a variety of products to be produced more cheaply in combination, using low-volume batches, than individually in high-volume batches (Panzer and Wilig 1981, Goldhar and Jelinek 1983). Flexible, programmable technologies increase the feasibility of achieving economies of scope and offer managers the possibility of customizing products for the consumer without paying the increasing costs of product variety. However, as observed by Jaikumar (1986), simply procuring flexible manufacturing systems is no panacea for handling the complexity arising from product variety. Management has an important role in making the entire production system more flexible, both by insuring that production scheduling, equipment setup, and maintenance policies support the effective utilization of flexible tooling and by training workers in multiple skills so they can handle the demands of higher variety.

On the empirical side, the existing research on the impact of product variety on manufacturing operations has been both limited and inconclusive. Some researchers have observed an adverse effect of variety on manufacturing performance, while others have found no impact. Kekre and Srinivasan (1990), for example, investigated the market benefits and cost disadvantages of broader product lines using the Profit Impact of Marketing Strategies (PIMS) data base. They found that significant market share benefits can accrue from broader product lines, but observed that the increases in production costs widely believed to be associated with product variety were not empirically supported. Foster and Gupta (1990) studied manufacturing overhead cost drivers in an electronics firm and also observed only limited correlation between manufacturing overhead costs and complexity based cost drivers such as total number of parts, number of suppliers and breadth of product line. The authors concluded that the lack of correlation may be due to problems in developing more appropriate measures of complexity in each of the facilities that were studied.

In contrast to the previous studies, Banker et al. (1990) studied an auto component (head and tail lights) manufacturer and observed that product complexity (defined as number of moving parts in the mold) did have a significant impact on the cost of supervision, quality control, and tool maintenance. Their methodology applied the activity based costing (ABC) accounting philosophy by analyzing the determinants of activity costs in terms of product and process design features. By relating complexity factors to costs, they identified those factors that act as explanatory variables for the consumption of overhead resources. In a follow-up article on the same auto component manufacturer, Datar et al. (1990) stated that the production of complex products results in high manufacturing costs for activities such as supervision, quality control, inspection, and machine and tool maintenance. But incurring additional costs in supervision and tool maintenance may also reduce the costs required for quality control. Hence they stressed the need to recognize the interrelationships and interdependencies among these costs, failing which corporations are led to a biased analysis of costs of manufacturability and product profitability.

Although these studies have produced useful insights, each of them has used relatively simple measures of product complexity and aggregate performance measures. For instance, Kekre and Srinivasan (1990) looked only at the implications of the number of products in the portfolio on total production costs. The assembly plant study data allow us to investigate more refined models of product complexity than any of the previously conducted studies, and to evaluate the possibility that some kinds of complexity have implications for manufacturing performance while others do not.

3. The Impact of Product Variety on Manufacturing Performance

There are many ways in which product variety might be expected to decrease productivity and quality in automotive assembly plants. As the number of platforms and body styles increases within a plant, it may lead to higher set-up costs at the body framing area due to switching between platforms and body styles. As both parts and option complexity increase, direct labor productivity and quality might suffer, as production workers face a more complicated array of different parts—and less predictable combinations of parts—to install. Balancing the assembly line for consistent cycle times at each work station also becomes more difficult due to multiple models and varied option combinations. Line speed must be set to accommodate the vehicles (and sequence of vehicles) requiring the most assembly time. These latter types of complexity may have an even greater negative impact on **indirect** labor productivity. The tasks facing production support staff become more complex, both within the assembly plant (e.g. scheduling machines, performing setups, parts inspection and delivery, rework for quality defects) and in dealing with suppliers (e.g. scheduling parts deliveries, expediting parts orders, and coordinating negotiations and other communications).

But the benefits of variety must be considered as well. The costs of additional complexity may be unwarranted for options that prompt little interest from consumers. But these costs may be more than justified where customers base their purchase decisions on obtaining the features they want. Product variety—and the associated complexity that confronts the manufacturing plant—is therefore "good" if it provides market place advantages at little cost, while it is "bad" if it offers no value to customers, no matter what the cost.

In any case, a company that can minimize the costs of product variety has more flexibility in choosing how much variety to offer in the marketplace. For example, flexible tooling and fixturing systems in the body shop can eliminate most of the setup costs associated with a complex model mix. Given the increasing availability (and affordability) of this technology and the market share gains associated with higher product variety, most companies are likely to invest in such flexible tooling. Even if companies intend to build only one platform at a time, the savings in retooling costs every four to eight years when the platform does change may exceed the additional cost of flexible rather than fixed tooling. But at this point in time, flexible body shops are likely to be unevenly distributed among an international sample of assembly plants, so model mix complexity might still be expected to have a negative impact on performance.

Technology is not the only means of reducing the potential costs of product variety. We expect that a lean production organization should have several advantages over traditional mass production systems in coping with increased complexity. For example, among the many benefits of an effective Just-in-Time inventory system is the ability to deliver parts to the assembly line in the precise build sequence, thus eliminating lineside stocks of inventory for all possible build combinations. While this is logistically complicated,[3] it does reduce the potential confusion for production workers by greatly simplifying parts presentation. Firms must have well-developed capabilities in logistics and production control to manage a JIT system effectively, and these capabilities also enable the absorption of more product variety without penalty.

Work teams, job rotation, and extensive training for multiskilling also increase worker capabilities for dealing with high parts and option complexity, and offer the potential to minimize line imbalance by redistributing tasks when a high-content build sequence occurs. Continuous improvement activities by team members and engineers can also help achieve a smooth production flow, further reducing line imbalance. The orientation towards learning in a lean production system helps to generate process control knowledge that is both deep and systemic and yields insights into how best to handle increased complexity levels.

Long-term contracts with a small number of suppliers—another common characteristic of lean production—reduce the coordination costs of dealing with the higher number of parts typically associated with high product variety. Finally, to the degree that lean product development yields more manufacturable designs—with fewer parts, greater modularity, and standardized interfaces for easier connections—product variety will have less impact on the assembly plant.

To summarize, the conventional wisdom in manufacturing would suggest that product variety, and related complexity, will have a negative impact on direct and indirect labor productivity and quality. We argue that a lean production system and flexible tooling can shift this tradeoff point to allow a company to absorb a higher level of complexity at a given cost, thus effectively reducing the cost of increasing variety. This hypothesis sets the stage for our analysis of the International Assembly Plant Study data.

4. The International Assembly Plant Study: Sample, Variables, and Methodologies

For the International Assembly Plant Study, 90 assembly plants were contacted, and survey responses were received from 70 plants during 1989 and early 1990, representing 24 producers in 16 countries, and approximately 60% of total assembly plant capacity worldwide. Plants were chosen to achieve a balanced distribution across regions and companies, and to reflect a range of performance within each participating company, minimizing the potential for selectivity bias. Questionnaires were sent to the plant manager, who was asked to distribute different sections to the appropriate departmental manager or staff group. Plants and companies were guaranteed complete confidentiality and, in return for their participation, received a feedback report comparing their responses with mean scores for different regions. All 90 plants that were contacted were visited between 1987 and 1990. Early visits provided the field observations that became the foundation of the assembly plant questionnaire. Later visits provided an opportunity to fill in missing data, clarify responses, and carry out interviews that aided the interpretation of data analyses.

For this paper, we analyzed a subset of the sample, the 62 volume plants; omitted were 8 plants making luxury/specialist products.[4] Missing data for some key variables reduces the sample for all multivariate analyses to 57 plants. Table 1 provides the distribution of plants in six regional groupings, reflecting both plant ownership and location, and sample means for dependent and independent variables (discussed below). The

[3] Indeed, the growing opposition expressed in the Japanese media to high levels of product variety and the high rate of change in products (due to the rapid product development cycle) is based in part on the traffic congestion resulting from frequent JIT deliveries of parts required by high complexity plants (Cusumano 1994).

[4] The dividing line between the "volume" and "luxury/specialist" categories was a 1987 selling price in the U.S. market of $22,000.

rest of this section describes the dependent and independent variables used in our study. (For other analyses based on these variables, see Krafcik 1988a, 1988b; MacDuffie and Krafcik 1989; MacDuffie 1991; MacDuffie and Krafcik 1992; and MacDuffie 1995.)

4.1. Plant Performance Measures

Productivity: Productivity reflects the efficiency with which physical inputs have been transformed into outputs. Different productivity measures can be computed depending on the treatment of inputs and outputs (Hayes et al. 1988). Single factor productivity measures the output per unit of a single input such as labor, capital, or materials. Total factor or multifactor productivity measures the ratio of output to a weighted sum of all input types. The measure of productivity used here falls in the single-factor category, and is defined as the *hours of actual working effort* required to build a vehicle at a given assembly plant, with adjustments for vertical integration, product size differences, and absenteeism. Using labor hours rather than financial data alleviates the problems associated with differences in wages, accounting treatments, and exchange rates that are typically encountered in international comparisons, but overlooks differences in capital inputs between plants. While it is theoretically desirable to include measures of capital and other inputs, it can be difficult to acquire these data and ensure their comparability across countries. Consequently, we rely on two measures of capital intensity to control for capital-labor substitutions, total automation and a robotics index, described as control variables below. While these do not capture total capital investment (since they exclude most facility costs), they do represent the investment (in process equipment) that is most directly linked to labor productivity.

The productivity methodology used here focuses on a set of standard activities that are common across all plants in the survey, to control for differences in vertical integration. Since a large vehicle will require more effort to assemble than a small vehicle, adjustments are made to standardize for vehicle size. Adjustments are also made to standardize for the number of welds, which differs across designs and therefore affects headcount in the body shop. Labor hours are also adjusted for absenteeism, for two reasons. First, the study examines the effort involved in building vehicles and not total costs, and so does not include employees on the payroll to cover a particular level of absenteeism. Second, absenteeism rates may have more to do with national and social welfare policies affecting work absences than with how the plant is managed.

This measure of total labor hours per vehicle is not adjusted for differences in employee skill levels. Hammer and Champy (1993) argue that employee skill levels are a function of two factors: training (which teaches workers the "how" of a job) and education (which increases workers' insight and understanding and enhances their ability to learn). Plant-level differences in training are captured in our Human Resource Management variable, discussed below. To control for differences in education, we repeated the analyses reported in the paper with the average number of years of formal education as an additional independent variable. The education measure was available for 44 of the 62 plants. Although years of education was negatively correlated with direct labor hours per car, it did not have a significant effect on productivity. Given the already small sample size and the minimal association between the variable and productivity, the education level measure is omitted in the analyses shown here.

There is one critical difference in the productivity figures used here from those in previous papers using the IMVP data base (e.g. Krafcik and MacDuffie 1989). Before, the productivity measure was corrected for the option content of the vehicle, in order to insure an "apples to apples" comparison of plants. Here, we use the option uncorrected productivity and make Option Content an independent variable, in order to study its relationship to performance.

Quality: The quality measure is derived from the 1989 survey of new car buyers in the U.S., carried out by J. D. Power, a market research firm. It measures the number of defects per 100 vehicles, and is constructed to reflect only those defects that an assembly plant can affect, i.e. omitting defects related to the engine or transmission, while emphasizing defects related to the fit and finish of body panels, paint quality, and the integrity of electrical connections.

4.2. Product Complexity Measures

i) *Model Mix Complexity* measures fundamental variety, based on the mix of different products and product variants produced in the plant.[5] It includes the number of distinct platforms (i.e. each having a unique underbody and floor pan and serving as the foundation design for multiple models), models (i.e. variants on a common platform with more than 50% different exterior body panels), body styles (i.e. 3-door, 4-door), drive train configurations (i.e. front-wheel vs. rear-wheel drive), and export variations (i.e. right-hand vs. left-hand steering). Each item is weighted in accordance with interview data from plant managers about its contribution to the plant's overall model mix complexity (Krafcik 1988b):

- 10 points for each unique platform
- 5 points for each unique model
- 5 points for each body style
- 3 points (total) for front, rear and all wheel drive
- 3 points (total) for left and right hand drive option per model.

The measure is adjusted to account for the number of assembly lines and body shops in the plant. For instance, a plant with two parallel assembly lines producing a single model on each is given the same model mix score as that of another plant that builds one model with one assembly line. First, an overall complexity value is computed for body and assembly, using the weights above, which is then divided by the number of body shops and assembly lines respectively. After adjusting for the number of body and assembly shops, we combine the two scores using weights that reflect the amount of direct labor each functional area requires in the few plants in the sample with virtually no automation: 38% for the body shop and 62% for the assembly department. Finally, the resulting measure is scaled to yield a score from 0 to 100, where 0 represents the plant with the least model mix complexity and 100 the plant with the most complexity in the sample. All the complexity measures are converted to the same 0 to 100 scale to enhance the comparability of results.

ii) *Parts Complexity*, which measures an intermediate level of complexity between fundamental and peripheral, is an index compiled from two subgroups of variables. The first subgroup includes three measures of parts or component variation—the number of engine/transmission combinations, wire harnesses, and exterior paint colors—that affect the sequencing of vehicles, the variety of required sub-assemblies, and material and parts flow through the system. The second subgroup includes three measures—the number of total parts to the assembly area, the percentage of common parts across models, and the number of suppliers to the assembly area—that affect both the logistical requirements of material and parts flow and the administrative/coordination requirements for dealing with suppliers. All these variables are scored on a 1 to 6 scale, where 1 is the lowest and 6 the highest complexity level; the percentage of common parts is reverse scored, with 1 reflecting the most parts commonization. They are additively combined and the resulting index is rescaled from 0 to 100, as above. The Cronbach's adjusted alpha for this index is 0.75.[6]

iii) *Option Content* is often referred to as peripheral variety, because it consists of product variations that are independent of the core design and therefore can be installed without affecting the level of fundamental variety.[7] Here we measure the percentage of all vehicles actually built in a plant that have a particular option, from a list of eleven options (including air conditioning; power steering, doors, locks, and windows; cruise control; left and right hand remote mirrors; sun roof; four-wheel drive; and anti-lock brakes). The options for each product are weighted by their cost, and the total cost of options as a percentage of selling price is calculated. This assumes that the price of the option reflects the amount of labor required to install the option. By calculating the price content of the options in all the cars

[5] This differs from Boon (1992), which focuses on a single product and defines "fundamental variety" as the number of model variants for a product multiplied by the number of available engines. We include model variants in Model Mix Complexity and the number of engine/transmission combinations in Parts Complexity, as described below.

[6] Cronbach's alpha is a statistical test for scale reliability. Scores approach 1 when the intercorrelations among items in a scale are high, indicating internal consistency. Since the size of the reliability coefficient increases as items increase, the alpha is commonly adjusted to reflect the number of items in the scale. The expectation for reliability of a new scale is a Cronbach's adjusted alpha of at least 0.6 (Nunnally 1978).

[7] It differs from the peripheral variety index of Boon (1992), which is based on the number of **potential** option combinations that *could* be built for a single product.

built in the plant, and dividing that total cost by a standard wage rate, we compute the labor hours that are spent installing options on the car. After computing the option content for each vehicle built in a plant, we derive total option content through a weighted average that is based on the percentage of total production volume devoted to each vehicle.

iv) *Option Variability* is computed from plant data on the *extent to which vehicles contain* each of the eleven options considered. Variability in the options installed on different cars complicates vehicle assembly by creating imbalances in the workload at different work stations and by requiring a wide variety of parts to be delivered to various points on the line at exactly the right time. For these reasons, most auto manufacturers have developed sophisticated computer algorithms to determine the sequence in which cars will be built on the line so as to smooth out the impact of variability. For example, if exactly half of the cars have a sunroof installed, these algorithms would try to establish a sequence in which every other car had a sunroof. However, there are so many differences among cars to be considered in sequencing that the ability to minimize the impact of all option variability is limited. Moreover, contingencies such as paint defects usually upset the optimized sequence to some degree.

Let μ_i denote the fraction of cars that have option i, $i = 1, \ldots, 11$. We regard each option for a given car as a random variable and treat μ_i as the probability that a random car has option i. Then total option variability is measured as the sum of the standard deviation of these random variables:

$$\sum_{i=1}^{11} \sqrt{\mu_i(1-\mu_i)}.$$

This measure is designed to be computed for a given assembly line. For plants with multiple lines, we take a weighted average to determine the plant-level measure of variability, weighting by the percentage of each model built on each line.

We considered a second approach to measuring option variability. At many companies, options are bundled to reduce the total possible variants that can be ordered by consumers. In the second measure, we assume that if $\mu_i \geq \mu_j$, then any car with option j also has option i. With this assumption we can compute the fraction ρ_i of cars that have exactly i options. Assume for notational simplicity that $\mu_1 \geq \mu_2 \cdots \geq \mu_{11}$. Thus the second option variability measure equals the standard deviation of the number of options per car:

$$\rho_i = \mu_i - \mu_{i+1}, \quad i = 1, \ldots, 10, \quad \rho_{11} = \mu_{11} \quad \text{and}$$

$$\rho_o = 1 - \sum_{i=1}^{11} \rho_i = 1 - \mu_1, \sqrt{\left(\sum_{i=0}^{11} i^2 \rho_i\right) - \left(\sum_{i=0}^{11} i\rho_i\right)^2}.$$

For this sample, these two measures are correlated at $r = 0.95$ and the first measure demonstrated greater explanatory power in initial analyses. Hence we work only with the first measure in the analyses that follow.

4.3. Production Organization Index

The Production Organization index, a broad measure of how the plant organizes and manages its production system and its workforce, is developed for several reasons. We argue elsewhere (MacDuffie 1991; MacDuffie and Krafcik 1992; MacDuffie 1995) that lean production plants have a distinctive "organizational logic" that differs dramatically from traditional mass production plants. We hypothesize here that this "logic" gives lean production plants greater organizational flexibility with respect to various contingencies, including a greater ability to absorb high product variety without a corresponding performance penalty.

Under mass production, scale economies are of paramount importance, so buffers (e.g. extra inventories or repair space) are added to the production system to protect against potential disruptions, such as sales fluctuations, supply interruptions, and equipment breakdowns. Such buffers are seen as costly under lean production because they hide production problems. Consequently, buffers are minimized (e.g. through a Just-in-Time inventory system) to serve a cybernetic or feedback function, providing valuable information about production problems for improvement activities (Schonberger 1982).

Under the philosophy of continuous improvement that characterizes lean production, problems identified through the minimization of buffers are seen as opportunities for organizational learning (Ono 1988, Imai 1986). Ongoing problem-solving processes on the shop floor, alternating between experimentation with procedural change and the careful standardization of each improved method, yield a steady stream of incremental improvements (Tyre and Orlikowski 1993). This requires a multiskilled and committed workforce. In order to identify and resolve quality problems as they appear, workers must have both a conceptual grasp of the production process and the analytical skills to identify the root cause of problems. To develop such skills and knowledge, lean production utilizes a variety of multiskilling practices, including work teams, quality circles, job rotation within a few broad job classifications, and the decentralization of quality responsibilities from specialized inspectors to production workers. Furthermore, to insure that workers are motivated to contribute the attentiveness and analytical perspective necessary for effective problem-solving, lean production is characterized by such "high commitment" human resource policies as employment security; compensation that is partially contingent on performance and a reduction of status barriers between managers and workers (Shimada and MacDuffie 1986).

To measure this difference in "logic," we develop the Production Organization Index (POI) as the average of three component indices: Use of Buffers, Work Systems, and Human Resource Management (HRM) Policies. Each of the component indices are made up of multiple variables, described below, all of which are standardized by conversion to z-scores before being additively combined. Then each component index is standardized on a scale from 0 to 100 before being averaged for the overall index. The combined Production Organization Index places a plant on a continuum of production system management practice, where a low score indicates a traditional mass production system and a high score indicates a lean production system.

i) *Use of Buffers*: This index measures a set of production practices that are indicative of overall production philosophy with respect to buffers (e.g. incoming and work-in-process inventory), with a low score signifying a "buffered" system and a high score signifying a "lean" system. It consists of three items:

- the percent of the total assembly area dedicated to final assembly repair
- the average number of vehicles held in the work-in-process buffer between the paint and assembly areas, as a percentage of one shift production
- the average level of inventory stocks, in days for a sample of eight key parts, weighted by the cost of each part.

ii) *Work Systems*: This index captures how work is organized, including the allocation of work responsibilities and the participation of employees in production-related problem-solving activity. A low score for this variable indicates a work system that is "specializing" in orientation while a high score indicates a "multiskilling" orientation. We assume that a high score also indicates that a plant follows a "continuous improvement" philosophy, given the extensive use of small group activities and suggestion systems to address production system problems in such a plant. The index consists of six items:

- the percentage of the workforce involved in formal work teams;
- the percentage of the workforce in employee involvement groups;
- the number of production-related suggestions received per employee;
- the percentage of production-related suggestions implemented;
- the extent of job rotation within and across teams, (0 = no job rotation, 1 = infrequent rotation within teams, 2 = frequent rotation within teams, 3 = frequent rotation within teams and across teams of the same department, 4 = frequent rotation within teams, across teams and across departments);
- the degree to which production workers carry out quality tasks, (0 = functional specialists responsible for all quality responsibilities; 1, 2, 3, 4 = production workers responsible for 1, 2, 3, or 4 of the following tasks: inspection of incoming parts, work-in-process, finished products; gathering Statistical Process Control (SPC) data).

iii) *HRM Policies*: This index measures a set of policies which affects the "psychological contract" between the employee and the organization, and hence employee motivation. A low score for this variable indicates "low commitment" HRM policies and a high score indicates "high commitment" policies. It consists of four items:

- the hiring criteria used to select employees in three categories: production workers, first line supervisors, and engineers, (sum of rankings of the importance of various hiring criteria for these groups of employees, with low scores for criteria that emphasize the fit between an applicant's existing skills and job requirements ("previous experience in a similar job") and high scores for criteria that emphasize openness to learning and interpersonal skills ("a willingness to learn new skills" and "ability to work with others");

• the extent to which compensation system is contingent upon performance, (0 = no contingent compensation; 1 = compensation contingent on corporate performance; 2 = compensation contingent on plant performance, for managers only; 3 = compensation contingent on plant performance or skills acquired, production employees only; and 4 = compensation contingent on plant performance, all employees);

• the extent to which status barriers between managers and workers are present, (0 = no implementation of policies that break down status barriers and 1, 2, 3, 4 = implementation of 1, 2, 3, or 4 of these policies: common uniform, common cafeteria, common parking, no ties);

• the level of training provided to newly-hired production workers, supervisors, and engineers in the first six months of employment, (0 = Up to one week of training for newly-hired production workers, first line supervisors, and engineers; 1 = One to two weeks of training for newly-hired employees in all three groups; 2 = two to four weeks of training for newly-hired employees in all three groups; and 3 = over four weeks of training for newly-hired employees in all three groups);

• the level of ongoing training provided to experienced production workers, supervisors, and engineers, (0 = 0–20 hours of training for experienced (over 1 year of service) production workers, first line supervisors, and engineers per year; 1 = 21–40 hours of training per year for all 3 groups; 2 = 41–80 hours of training/year; and 3 = over 80 hours of training/year).

Reliability tests for the three component indices reveal a significant intercorrelation among the included variables. The Cronbach's standardized alpha score for the Use of Buffers index is 0.63, for the HRM index is 0.70 and for the Work Systems index is 0.81. The three component indices are also highly intercorrelated—for Use of Buffers and Work Systems, $r = 0.62$; for the Use of Buffers and HRM Policies, $r = 0.48$; and for Work Systems and HRM Policies, $r = 0.62$. Although we examine these indices separately, they are also combined into the Production Organization Index; the Cronbach's standardized alpha for the combined index is 0.80. Thus in addition to the conceptual reasons to expect that the three component indices will be highly integrated, there is strong empirical support for their statistical interdependence.

4.4. Control Variables

Automation: The main technology variable, *Percent of Direct Production Steps Automated*, captures the level of both flexible and fixed automation. For each functional area, a proxy measure for direct production activities was developed, as described below.

Functional Area	Proxy Measure of Automated Production Steps
Body Welding	Percentage of spot and seam welds applied by automation
Paint: Joint Sealing	Percentage of total length of joint sealer applied by automation
Paint: Primer/color	Percentage of total square inches of paint applied by automation
Assembly	Number of automated assembly tasks, weighted by labor content

Then, a weighted average level of automation for the plant is calculated, using weights based on the amount of direct labor each functional area requires in an average unautomated plant: 31% for body welding, 19% for paint, and 50% for assembly. Since the index measures the percentage of total direct production steps that are automated, it is expected to correlate with the productivity measure, which includes the labor hours required for nonautomated direct production steps as well as indirect and salaried hours.

The second technology measure, the Robotic Index, measures the number of robots (defined as programmable with at least three axes of motion) in the body, paint, and assembly departments, adjusted for the plant's production volume. This measure captures only a subset of the automation in the plant and thus is less effective as a proxy for capital investment. It does, however, provide some indication of the flexibility of the plant's toolstock. The two measures are highly correlated, at $r = 0.81$.

Plant Scale is defined as the average number of vehicles built during a standard, non-overtime day. In most cases, the data correspond to a high level of capacity utilization. For example, if a plant faced a short-term reduction in capacity due to poor market conditions or other circumstances, data was gathered to reflect recent or projected full capacity operation. When long-term operations reflect a reduced capacity level, these data were used. Therefore, differing levels of capacity utilization over time in a given plant will not significantly affect the data analyses.

Product Design Age is defined as the weighted average number of years since a major model change for each of the products currently being built in a plant. The measure is a proxy for manufacturability, under the assumption that products designed more recently are more likely to have been conceived with ease of assembly in mind than older products.[8] According to the product development literature, designing a product for manufacturability reduces the number of parts and eliminates unnecessary steps, leading to lower coordination costs, reduced material handling, and fewer defects (Whitney 1988, Dean and Susman 1989).

5. Descriptive Statistics

As shown in Table 1 (above), sizeable differentials are found for nearly every measure across regions. The Japanese plants in Japan and their transplants in North America have higher average productivity and quality than U.S.-owned plants in North America, and plants in Europe, Australia, and newly-industrialized countries (NIC) (see also Krafcik 1988b; Krafcik and MacDuffie 1989; and Womack, Jones, and Roos 1990). However, these averages conceal considerable variation in performance within each of these regional groupings.

Table 1 also documents significant differences in the product complexity measures across regions, consistent with the different product strategies discussed above. The Japanese plants tend to have higher model mix and parts complexity while U.S.-owned plants in North America tend to have lower model mix complexity but higher option content. The Japanese transplants in North America tend to have less complexity, of all kinds, than their sister plants in Japan. Despite the low levels of option content at Japanese plants in Japan, they face the highest levels of option variability in the sample, a consequence of their high levels of model mix complexity.

In terms of the Production Organization Index, Japanese plants in Japan are the leanest plants in the sample, followed by the Japanese transplants in North America. The average score for most regions on this index is much closer to the mass production endpoint, although there is considerable within-region variation. The data also reveal that the level of automation differs considerably: highest for the consistently automated Japanese plants, somewhat lower for the U.S. and Europe, where the average reflects a mix of high-tech and low-tech plants, and very low for the nearly unautomated plants in the newly industrialized nations. The design age of products also shows high variance across regions. The age of products in Japanese plants average only 2 years while newly industrialized nations cope with outdated designs averaging 8 years in age.

6. Regression Analyses

We hypothesize above that the product complexity measures will be important predictors of variability in productivity and quality outcomes. We further hypothesize that the "leanness" of an assembly plant plays a role in coping with higher complexity arising due to product variety. In other words, we expect that adverse effects of the product complexity measures on performance will be reduced if the plant follows "lean" management policies.

To test these hypotheses, a "base case" regression on the dependent variables (first total labor productivity and then quality) was performed using seven independent variables—four measures of product complexity (model mix and parts complexity, option content and

[8] This assumption must be qualified. Although newer models may be more likely to reflect the movement to more manufacturable designs, older models may be associated with fewer labor hours per vehicle due to learning curve effects. Most evidence, however, suggests that the benefits from more manufacturable designs outweigh learning curve gains (Womack et al. 1990).

Table 1 **Descriptive Statistics for Full Sample and Regional Groups**

Variables	All Plants							
	Mean	Std. Dev.	Japan/Japan	Japan/NA	U.S./NA	Europe	NIC	Australia
Number of plants	57	—	8	4	14	14	11	6
Plant Performance Measures								
Total Labor Productivity (hrs/vehicle)	32.90	12.16	18.13	22.58	27.15	37.47	44.98	40.04
Quality (assembly defects/100 vehicles)	78.07	31.47	51.51	49.25	91.64	83.67	70.24	113.00
Product Variety Measures								
Model Mix Complexity (0—low; 100—high)	30.64	21.23	40.98	15.05	21.13	28.98	42.63	31.21
Parts Complexity (0—low; 100—high)	54.50	22.48	72.08	27.50	41.42	75.72	51.51	35.55
Option Content (0—low; 100—high)	39.83	26.85	24.49	22.52	63.91	33.77	41.05	27.51
Option Variability Index (0—low; 100—high)	46.29	20.55	59.87	46.24	51.44	43.31	37.88	38.56
Production Organization Index (0—*Mass*; 100—*Lean*)	45.99	20.89	85.24	67.08	34.74	38.41	40.39	33.82
Control Variables								
Total Automation (% of production steps automated)	25%	14%	38	36%	30%	29%	8%	10%
Scale of Production (no. of units/day)	936	651	1385	790	836	1368	606	268
Product Design Age (in years)	4.74	3.29	2.00	2.03	4.50	5.15	8.02	3.72

Japan/Japan = Japanese-owned plants in Japan.
Japan/NA = Japanese-owned plants in North America.
US/NA = U.S.-owned plants in North America.
Europe = All European plants.
NIC = Newly Industralized Countries (Brazil, Korea, Mexico, Taiwan).
Australia = All Australian plants.

option variability) and three control variables (the level of automation in the plant, scale of production, and product design age).[9] Then, the production organization index variable was added to the regression analysis so its impact could be evaluated. Finally, to test whether our results could be attributed to a "Japan effect," we replace the production organization index with a dummy variable for plants located in Japan.

Table 2 contains the regression analyses. In Eq. 1 (the "base case"), the level of automation and scale of production have the expected negative signs—i.e. higher automation results in higher productivity, defined as fewer hours per vehicle. But only the level of automation is a highly statistically significant (at 99% confidence level) predictor of productivity differences.[10] Scale has no statistically significant impact on labor

[9] Correlations among the product complexity measures are relatively low ($r < .40$) and correlations among the other independent variables (particularly scale, design age, and the production organization index) are not much higher ($r < .60$), suggesting little risk of collinearity distorting the regression results.

[10] When the Robotic Index was used in place of the Automation Level variable, the results for the product complexity measures were similar, but the Robotic Index was not statistically significant and the Scale variable *was* statistically significant. The Robotic Index has a skewed distribution, with many plants having few or no robots, and it is more strongly correlated with scale, creating greater collinearity problems. Since Automation Level is a more comprehensive measure and therefore a better proxy for capital investment, we use it exclusively in all regression analyses.

Table 2 Regression Results on Total Labor Productivity (std. errors in squared brackets)

Production Organization Index and Component Indices

	Specification					
Independent Variables	1	2	3	4	5	6
Constant	33.55***	39.086***	32.14***	35.36***	35.73***	36.56***
Scale of Production	−0.001	−0.002	−0.002	−0.001	−0.001	−0.002
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Automation Level	−39.942***	−33.671***	−34.446***	−39.473***	−36.062***	−32.68**
	[11.131]	[11.235]	[11.099]	[11.29]	[10.70]	[11.75]
Product Design Age	1.261***	1.044**	1.137***	1.184***	1.135***	1.187***
	[0.394]	[0.397]	[0.386]	[0.44]	[0.378]	[0.389]
Production Organization Index	–	−0.129**	–	–	–	–
		[0.064]				
Japan Location Dummy	–	–	−7.189**	–	–	–
			[3.475]			
i) Use of Buffers Index	–	–	–	−0.025	–	–
				[0.064]		
ii) Work System Index	–	–	–	–	−0.118**	–
					[0.048]	
iii) Human Resource Policies Index	–	–	–	–	–	−0.077*
						[0.046]
Option Content	0.113**	0.072	0.088**	0.106**	0.074*	0.085*
	[0.043]	[0.046]	[0.043]	[0.047]	[0.044]	[0.045]
Modex Mix Complexity	−0.055	−0.039	−0.033	−0.049	−0.03	−0.061
	[0.054]	[0.053]	[0.053]	[0.56]	[0.052]	[0.053]
Parts Complexity	0.145**	0.145**	0.164***	0.141**	0.144**	0.157***
	[0.059]	[0.058]	[0.058]	[0.061]	[0.056]	[0.059]
Option Variability Index	−0.129**	−0.104*	−0.104*	−0.127**	−0.085	−0.119**
	[0.061]	[0.059]	[0.059]	[0.06]	[0.059]	[0.059]
Adjusted *R*-squared	0.618	0.64	0.642	0.611	0.654	0.0631
Number of Observations	57	57	57	57	57	57
F for equation	13.92	13.453	13.53	11.99	14.245	12.991
P(*F*)	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001

***—significant at 0.01 level.
**—significant at the 0.05 level.
*—significant at the 0.1 level.

productivity, which is surprising given economy of scale arguments but may be due to collinearity between the automation and scale variables. The product design age is also a statistically significant (at 99% confidence interval) predictor of productivity, with newer designs associated with fewer hours per vehicle.

Among the complexity measures, model mix complexity has no statistically significant explanatory power with respect to productivity, while parts complexity, option content, and option variability **are** statistically significant. Parts complexity and option content have the expected positive signs, i.e. more complexity increases hours per vehicle. But the coefficient for option variability is **negative**, counter to the expectations that higher variability should lead to more hours per car, i.e. lower productivity.

The minimal effect of model mix complexity on performance in this equation could be due to the fact that plants have the appropriate tooling in the body shop for whatever level of model mix they produce. Model mix mainly affects the body shop, which is heavily automated. The tooling of a plant's body shop may establish a clearcut ceiling of model mix that can be handled. If body shops have equipment dedicated to a single product, it will be impossible to build any other product in that plant without retooling. But if body shops have flexible welding equipment, there should be no labor productivity penalty for multiple models. Put differently, a plant's capacity for model mix complexity can be underutilized but not overutilized. Since there is no reason to expect that underutilizing a plant's capacity for model mix has a negative effect on performance, we might hypothesize that model mix complexity should have no impact on a plant's productivity and quality.

The negative coefficient for option variability requires some explanation. We have no conceptual reason to expect that it should be easier for a plant to deal with high (rather than low) variability of option content from vehicle to vehicle. However, it may be the case that companies do not attempt to build a complex product mix with high option variability except in plants that have developed the capability—either organizational or technical—to handle it. Furthermore, it may be the case that traditional mass production plants are always associated with low variability because they attempt to minimize such variability for maximal economies of scale. In this sense, different plants can be said to be on different production frontiers with respect to option variability. Although the correlation between option variability and the production organization index is rather low ($r = .18$), there is some evidence in the regional averages of different strategies towards option variability.

In Eq. (2), we add the production organization index in order to examine the hypothesis that "lean production" plants are able to minimize the adverse effects of product complexity. The evidence here is mixed. The production organization index does have a strong, statistically significant impact on productivity (the greater the "leanness" of the plant, the lower the hours per vehicle). Also, once the production organization index variable is introduced, the option content measure is no longer a statistically significant predictor of productivity. However, the interpretation of this result is not clearcut. It may be due to collinearity, although the correlation between the POI and option content is modest ($r = -0.38$). If in fact lean production policies are responsible for eliminating the negative effect of option content on productivity, there should be an interaction effect between option content and the POI. However, when an interaction term for the POI and option content was introduced into the equation, it was not statistically significant. Thus this analysis only supports the conclusion that the POI absorbs the explanatory power of the option content measure, and does not necessarily support the hypothesis about lean production.

Furthermore, lean production policies appear to have little impact on parts complexity—the coefficient for this variable is essentially unchanged and still statistically significant. Model mix complexity is still unrelated to productivity when the production organization index is added. Indeed, the probability that the model mix coefficient is zero in these equations is rather high; the t-statistic for the coefficient is $t = 0.74$, which corresponds to a p-value of $p = 0.464$. Option variability also remains statistically significant, but still with a negative coefficient.

To test whether the production organization index captures more than a general "Japan effect," we added a dummy variable for plants located in Japan (Eq. 3) to the "base case" regression. Because the POI and the Japan dummy are correlated ($r = 0.66$), use of either variable will produce some results which are similar, but results based on the POI differ in a number of important ways from those based solely on a Japan dummy. When the Japan dummy is substituted for the production organization index, it has the same significance level (95%) and the adjusted R-squared is unchanged.[11] While most coefficients for the independent variables are unchanged, those for option content and parts complexity increase in size and statistical significance. Particularly noteworthy, compared with Eq. (2), is that option content becomes significant at the 95% significance

[11] When **both** the production organization index and the Japan dummy are entered in the equation, the adjusted r-squared is unchanged and neither is statistically significant—undoubtedly because of collinearity between these two variables.

level, albeit with a smaller coefficient than the "base case" in Eq. 1, and parts complexity moves from the 95% to the 99% significance level. Since Japanese plants are not equally "lean" (their POI score ranges from 68 to 93), this suggests that lean production policies may have more to do with moderating the negative impact of option content and parts complexity on productivity than some other factor unique to plants in Japan.[12]

The final three equations in Table 2 examine the three component indices of the production organization index—use of buffers, work system and human resource management policy. When these indices are included in separate regressions for productivity (Eqs. (4), (5), and (6), together with the control variables, the use of buffers index is not statistically significant while the work systems and HRM policies indices are. While the use of buffers index has a statistically significant bivariate correlation with productivity of $r = -0.49$, its lack of significance in the multivariate analysis may be due to its collinearity with product design age, with which it is correlated at $r = -0.58$.

In order to explore the interaction between the production organization index and measures of product complexity more carefully, we divided the plants into mass and lean production subsamples based on the production organization index of the plants, with a score of 50 marking the dividing line between categories. Table 3 presents the results obtained when running the "base case" equation for these two subgroups. There is no statistically significant relationship between any of the product complexity measures and total labor productivity for the lean production plants. In contrast, for the subsample of mass production plants, the parts complexity variable displays a strong positive association with hours per vehicle. Comparing the subsamples, the coefficients for model mix, parts complexity, and option content are smaller for the "lean" plants (only option variability's positive but not significant coefficient is larger), suggesting that these plants are indeed on a different production frontier with respect to variety. This supports the conclusion that assembly plants adopting lean production principles seem to be more capable of minimizing the complexity penalty arising from higher product variety than traditional mass production plants.[13]

Table 3 **Regression Results on Total Labor Productivity (std. errors in square brackets)**

A Comparison Between Lean and Mass Production Systems

Independent Variables	Lean Production Systems	Mass Production Systems
Constant	21.54***	33.47***
Scale of Production	−0.004*	−0.001
	[0.002]	[0.003]
Automation Level	−1.498	−43.19***
	[16.08]	[15.857]
Product Design Age	2.521**	1.022**
	[0.892]	[0.478]
Option Content	0.05	0.106
	[0.059]	[0.067]
Model Mix Complexity	−0.047	−0.052
	[0.059]	[0.078]
Parts Complexity	−0.02	0.184**
	[0.07]	[0.082]
Option Variability Index	0.029	−0.114
	[0.062]	[0.10]
Adjusted R-square	0.568	0.45
Number of Plants	19	38
F for Equation	4.387	5.333
$P(F)$	0.01	0.0005

Statistical Significance: *** = 0.01, ** = 0.05, * = 0.1.

[12] In separate analyses (not shown), we use Spearman correlations to compare plants located in Japan and "lean" plants (as defined above). This non-parametric test is necessary because of the small size ($n = 8$) of the Japan subsample. For the Japan subsample, both option content and parts complexity have a statistically significant positive correlation with productivity—the higher the option and parts complexity, the higher the hours per car. In contrast, for the "lean" subsample, none of the correlations between the complexity measures and productivity are statistically significant. The fact that higher complexity has a negative effect on productivity within the subset of Japan plants but does not for the subset of "lean" plants supports the conclusion that the production organization index is not picking up a "Japan effect" but captures fundamental process capabilities helpful in handling product complexity in any location.

[13] Since the precise score on the production organization index varies among the plants in the "lean production" and "mass production" subgroups, we repeated this analysis and included the index among the independent variables. It was not statistically significant for either subgroup, and the results for the other variables were unchanged.

Next, we examine which variables in the parts complexity index are most strongly related to labor productivity by introducing each individual variable into the regression equation in place of the overall index. As Table 4 reveals, the three variables that directly generate product variation (the number of engine/transmission combinations, the number of exterior colors, and the number of wire harnesses) are statistically significant predictors of labor productivity. In addition to the direct complexity effect of these variables, they may also have important indirect effects. For example, a high number of exterior colors multiplies the number of color-dependent small exterior and interior parts that must be provided to the assembly line, either from inventory or from suppliers on a Just-in-Time basis. Wire harnesses could be viewed as the "infrastructure" for many different electrical options (and combinations of options, such as high-powered audio systems). The higher the number of wire harnesses, the higher the number of different option packages the plant may have to install. Indeed, there is some evidence that these indirect effects are greater than the direct effects. For example, despite being a strong predictor of overall labor productivity, the number of exterior colors had no effect on paint department productivity, as noted below.

In contrast, of the three variables in the index related to material handling and coordination with suppliers (number of assembly area parts, number of suppliers to the assembly area, and percentage of common parts across models), only commonality of parts is significant (at the 90% confidence level), i.e. the more parts commonality, the fewer hours per vehicle. We did expect labor hours, particularly for indirect labor, to increase with a higher number of parts and a larger number of suppliers. We will need further research to determine why this hypothesis was not supported.[14]

In regression analyses for quality (not shown), we found that none of the complexity variables and none of the control variables were statistically significant. Only the production organization index was a significant predictor of quality. For automation, this finding is consistent with other evidence (e.g. Krafcik and MacDuffie 1989) of substantial variation in quality for plants with equally high levels of automation, with "high-tech" mass production plants having substantially more defects per vehicle than "high-tech" lean production plants. But it is surprising that neither design age, the proxy for manufacturability, nor parts complexity, both of which had a strong relationship with productivity, are significant factors here. Given the weak relationship between most of these variables and quality, we do not present a full set of analyses that parallel those for productivity. Clearly, further investigation of the relationship between product complexity and quality is required.

7. Conclusion

There has been conflicting evidence to date in research outside the automotive industry on the relationship between complexity arising due to product variety and manufacturing performance. In this paper, we use multiple product complexity measures derived from the International Assembly Plant Study to test the impact of product variety on productivity and quality. We sought to investigate conventional hypotheses that expect complexity to have a negative impact on manufacturing performance, as well as alternative hypotheses that technology or, more importantly, lean production manufacturing and management policies allow an assembly

[14] In analyses not reported here, we explore the relationship between the product complexity measures and direct labor productivity in the welding, paint and final assembly areas; indirect and salaried labor hours cannot be separated by functional area. For the final assembly area, model mix and option variability are not statistically significant, but both parts complexity and option content measures explain a significant fraction of the variance in labor productivity. When the production organization index is added, it is statistically significant for final assembly labor productivity and option content is no longer significant, but parts complexity remains significant; this replicates results above. None of the complexity measures are statistically significant predictors of productivity in either the weld or paint departments. For the weld department, this is consistent with our view that plants tend to have a level of model mix complexity that does not exceed the capabilities of their process equipment. For the paint department, this confirms our impression, drawn from discussions with managers at various plants, that product variety does not pose any problem for the paint department. This is true even when the plant produces vehicles in many different exterior colors. When we substituted the number of exterior colors for the full parts complexity index in the paint department regression equation, it was not statistically significant.

Table 4 Regression Results on Total Labor Productivity (std. errors in square brackets)

Components of Parts Variety

	Specification						
Independent Variables	1	2	3	4	5	6	7
Constant	39.086***	40.442***	36.361***	37.567***	40.766***	43.86***	38.698***
Scale of Production	−0.002	−0.0004	−0.002	−0.001	−0.0002	0.001	−0.0002
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Automation Level	−33.671***	−35.409***	−32.338***	−32.415***	−31.085**	−29.573**	−29.833**
	[11.235]	[11.54]	[10.784]	[11.365]	[11.77]	[12.092]	[11.608]
Product Design Age	1.044***	1.143***	1.043***	1.282***	1.16***	1.342***	1.123***
	[0.397]	[0.399]	[0.378]	[0.393]	[0.413]	[0.419]	[0.406]
Production Organization Index	−0.129**	−0.141**	−0.207***	−0.134**	−0.139**	−0.162**	−0.128**
	[0.064]	[0.065]	[0.065]	[0.065]	[0.067]	[0.076]	[0.066]
Option Content	0.072	0.071	0.034	0.084*	0.049	0.061	0.074
	[0.046]	[0.047]	[0.044]	[0.048]	[0.049]	[0.049]	[0.048]
Model Mix Complexity	−0.039	−0.007	−0.025	−0.003	−0.02	0.011	−0.038
	[0.053]	[0.051]	[0.048]	[0.05]	[0.057]	[0.052]	[0.057]
Option Variability Index	−0.104*	−0.103*	−0.097*	−0.088	−0.081	−0.078	−0.102
	[0.059]	[0.06]	[0.056]	[0.059]	[0.061]	[0.061]	[0.061]
Parts Complexity	0.145**	–	–	–	–	–	–
	[0.058]						
Engine/Transmissions Combinations	–	1.569**	–	–	–	–	–
		[0.75]					
External Colors	–	–	3.498***	–	–	–	–
			[1.065]				
Wire Harnesses	–	–	–	1.317**	–	–	–
				[0.592]			
Assembly Area Parts	–	–	–	–	0.946	–	–
					[0.762]		
Suppliers to the Assembly Area	–	–	–	–	–	−0.79	–
						[0.825]	
Commonality of Parts	–	–	–	–	–	–	1.26*
							[0.697]
Adjusted R-squared	0.64	0.627	0.667	0.631	0.605	0.6	0.619
Number of Observations	57	57	57	57	57	57	57
F for equation	13.453	12.748	15.043	12.95	11.733	11.509	12.355
$P(F)$	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001

***—significant at 0.01 level.
**—significant at the 0.05 level.
*—significant at the 0.1 level.

plant to absorb greater product complexity with little adverse effect on performance.

We found that most of the product complexity measures did not have a negative impact on labor productivity or quality. The lack of any impact of model mix complexity may be due to the fact that plants (especially the body shops) are usually designed to handle a certain number of body styles and models. Switching between these body styles and models incurs very little penalty, but any style outside this mix is essentially infeasible. The negative coefficient for option variability, implying that higher variability was associated with **fewer** hours per car (rather than more, as we expected), suggests that plants with very high option variability are on a different, more flexible production frontier with respect to all kinds of product variety, and hence are less affected by this variability than more inflexible plants. In contrast, option content **was** a statistically significant predictor of productivity, at least in the analyses of the complexity measures (and controls) alone.

This combination of findings about options—a positive relationship with hours per vehicle for option content but a negative relationship for option variability—is intriguing. One avenue to explore is the impact of a company's product policy. If many features we think of as options are offered not as choices for consumers to make but are included as "standard equipment," the cost of a base model may increase but for the manufacturing plant, the complexity problems are much less because a higher standardized content can be anticipated for all vehicles. However, even on this point, we find the paradox that the Japanese companies that follow this product policy also have the highest levels of option variability, at least in their plants in Japan. The high level of model mix complexity in these plants—and the option variability that results—may outweigh the reductions in option variability from a high "standard equipment" product policy.

The persistent and statistically significant negative effect of parts complexity on productivity is one of the most striking findings of this paper. This type of complexity is less commonly examined than the familiar categories of fundamental and peripheral variety. But it arguably the area where the trend to increasing product variety is most problematic for manufacturers, due to the powerful multiplier effects of choosing to increase the number of exterior colors, or wire harnesses, or engine-transmission combinations. Japanese automotive companies, struggling with problems of recession and overcapacity, have made several announcements recently of their intention to reduce product variety in their plants. Yet our interview data from recent trips to Japan reveals that their focus is not so much on reducing the number of platforms or the options offered, but rather reducing the number of body variations per platform and the amount of parts complexity for each body style. Our results suggest that this will be particularly important for the less "lean" Japanese plants. Given the empirical findings presented here and the evidence that auto companies are taking actions to reduce parts complexity, further exploration of this underemphasized category of complexity is warranted.

Our hypothesis that "lean production" policies give plants the capability to handle product variety more effectively was partially supported for option content, with more mixed results for parts complexity. The statistical significance of option content in the "base case" regression changed to no significance when the production organization index was introduced—although in the absence of a significant interaction effect, we must be cautious in interpreting this as evidence of the impact of lean production policies. In contrast, when the Japan dummy variable was substituted for the production organization index, option content remained statistically significant. For parts complexity, its coefficient in regression analyses for the full sample was virtually unchanged when the production organization index was introduced and increased when the Japan dummy was substituted. However, in regressions for the subsamples of lean and mass production plants, three complexity measure coefficients (model mix, parts complexity, and option content) were lower for the subsample of lean plants, and parts complexity, which was statistically significant for the "mass production" subsample, was not significant for the "lean" subsample.

These findings suggest that such lean production policies as Just-in-Time inventory systems; work teams, job rotation, and extensive training to develop a multiskilled workforce; continuous improvement efforts involving production workers and engineers (through suggestion systems and quality circles) and directed at smoothing production flow and improving line balance; and product development approaches that yield highly manufacturable designs can all play a role in helping "lean" plants absorb complexity successfully. This partly explains how the "leanest" Japanese plants have been able to achieve higher overall performance with much higher levels of parts complexity and option variability (albeit lower levels of option content) than most of their competitors.

These findings suggest a shift in the nature of the debate about product variety. If the negative performance impact of product complexity is in fact limited across the world's assembly plants, and "lean" plants can potentially minimize this penalty more successfully than their mass production competitors, it may make more sense to focus on how variety can be "free" to companies, in the same sense that quality can be "free." The argument here is that companies can invest in process improvements and other organizational capabilities that shift the tradeoff point between cost and product variety (as with cost and quality) considerably. This means that, for a fixed investment in systems (e.g. JIT or teams), a plant has greater latitude to absorb product variety without facing the variable costs that a more inflexible production system would face with any variety increase. As long as the marketplace gains from higher variety outweigh the investment costs, variety can in fact be described as "free".[15,16]

[15] We develop this line of reasoning further in Fisher et al. (1995).

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