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MEASURING MANUFACTURING FLEXIBILITY: THE IMPACT OF PRODUCT MIX ON OPERATING PERFORMANCE

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**Measuring Manufacturing Flexibility:
The Impact of Product Mix on Operating Performance**

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ABSTRACT

Managers identify the ability to produce a broad line of continually changing products with minimal degradation of performance--- "product mix flexibility"--- as a critical source of competitive advantage. However, flexibility has received little attention as a component of manufacturing performance. This apparent inconsistency reflects firms' reliance on traditional, financial performance measures. Critics argue that financial measures must be augmented by nonfinancial performance measures to create a "balanced scorecard" (Kaplan & Norton, 1991) for manufacturing environments that employ advanced technology or modern management methods. Product mix flexibility is a candidate for inclusion in the "balanced scorecard" of firms that compete on the ability to produce a wide range of rapidly changing products.

This paper measures product mix flexibility as the impact of actual product mix complexity on nonfinancial measures of performance. The performance measures considered are: total factor productivity, operating efficiency, and output quality. Measures of product mix complexity are developed using a product attribute model derived from the group technology literature of operations management. These measures are used to investigate the relation between product mix complexity and operating performance in three weaving plants of a leading U.S. textile firm during 1986-90.

The paper makes four contributions to the emerging literatures on manufacturing flexibility and multi-dimensional performance measurements. First, the paper develops a measure of product mix complexity that incorporates similarities and differences among products in the demands placed upon manufacturing. Previous research has relied, with limited success, on proxy variables such as the number of products produced to assess product mix complexity. The results indicate that a measure of product mix complexity that distinguishes similarities and differences among products has greater power to describe manufacturing performance when compared to previous attempts to operationalize product mix complexity. Second, the paper estimates the longitudinal relation between product mix complexity and operating performance and compares the flexibility of three plants facing different levels of product mix complexity. Thus it complements previous studies that use cross-sectional or longitudinal analysis alone. Third, the paper provides evidence on sources of increased flexibility. By disaggregating products into underlying characteristics that influence manufacturing activities, the paper identifies forms of product mix complexity that degrade performance. The paper also provides weak evidence that experience producing these forms of product mix complexity mitigates their performance impact --- that "complexity-based learning" may obtain with sustained experience producing a heterogenous mix of products. Finally, the results indicate that different forms of product mix complexity adversely affect the three measures of operating performance. This suggests that the "balanced scorecard" must balance different measures of nonfinancial performance as well as financial and nonfinancial performance measures.

(Keywords: Performance Measurement, Flexibility, Product Mix, Complexity)

INTRODUCTION

In recent surveys, U.S. and Japanese manufacturing managers assert that product mix flexibility is the most critical manufacturing capability for future success (Stewart, 1992; De Meyer, et. al. 1989; Slack, 1987). From the perspective of manufacturing, product mix flexibility implies an ability to produce a wide range of products, to accommodate modifications to existing products, and to assimilate new products, all with minimal degradation of performance (Slack, 1984; Upton, 1991). These capabilities correspond to what Sethi and Sethi (1990), in their comprehensive literature review, call: 1) process flexibility, the ability to produce a wide range of products without setups; 2) product flexibility, the ability to add new products at low cost; 3) volume flexibility, the ability to operate profitably at different volumes; and 4) market flexibility, the ability to adapt to changing market conditions.[1]

The practical difficulty of becoming flexible hinges on assessing the flexibility of existing manufacturing operations as well as identifying avenues for improvement. Despite its importance, product mix flexibility is rarely included among firms' internal performance measures and applied research has been "neglected" (Gerwin, 1993). This apparent conundrum reflects the empirical challenge of measuring flexibility as well as the myopic, financial focus of traditional performance measurement systems (Drucker, 1990; Kaplan & Norton, 1991; Eccles, 1991; Eccles & Pyburn, 1992; Nanni, Dixon & Vollman, 1992). Critics claim that a "balanced scorecard" (Kaplan & Norton, 1991) that reports financial as well as nonfinancial measures is needed to assess organizational performance in the new manufacturing environment and that accountants must broaden the scope of their activities to include these new measures if they are to play a strategic role in management. Product mix flexibility is a strong candidate for representation on the balanced scorecard of firms that face rapidly changing, fragmented product markets.

The theoretical operations literature suggests measuring product mix flexibility as the impact of realized product demands on the performance of existing operations (Son & Park,

[1] Sethi and Sethi (1990) identify 11 fundamental forms of flexibility from the over 50 types of flexibility described in the operations literature. This study addresses four of the 11 fundamental forms of variety. As Slack (1987) argues, all flexibilities are not equally important to all production environments. The nature of the textile weaving process, the longitudinal research design, and the time frame of this study are incompatible with studying the remaining seven forms of flexibility.

1987; Gupta & Goyal, 1989; Sethi & Sethi, 1990; Roll, Karni & Arzi, 1992). Theories developed in the economics, operations management and management accounting disciplines relate manufacturing cost and nonfinancial measures of operating performance to product mix complexity (Skinner, 1974; Panzar & Willig, 1977; Willig, 1979; Panzar & Willig, 1981; Porter, 1980; Hayes & Wheelwright, 1984; Hill, 1985; Miller & Vollman, 1985; Johnson & Kaplan, 1987; Cooper & Kaplan, 1987; Karmarkar & Kekre, 1987; Kekre, 1987; Banker, Datar & Kekre, 1988; Cooper, 1990). The general conclusion of these models is that producing a changing mix of heterogeneous products reduces operating performance and increases manufacturing costs--- that plants typically are not flexible. The root cause of performance degradation is posited to be heterogeneity in the production activities required to produce a mix of products. Heterogeneous production activities disrupt experience-based learning, create complex material and information flows that require coordination, and cause congestion of shared resources that requires complex scheduling and balancing routines (Skinner, 1974; Hill, 1985; Miller & Vollman, 1985).

Although theoretical models and widespread anecdotal evidence supports the claim that product mix heterogeneity impairs operating performance, empirical evidence to substantiate the impact of product variety is mixed (Hayes & Clark, 1985; Foster & Gupta, 1990; Kekre & Srinivasan, 1990; Datar, Kekre, Mukhopadhyay & Srinivasan, 1990; Banker, Datar, Kekre & Mukhopadhyay, 1990; Banker & Johnston, 1991; Banker, Potter & Schroeder, 1992; Cooper, Sinha & Sullivan, 1992). One explanation offered by many authors for ambiguous results is that the constructs used to measure product mix complexity are inadequate. Variables commonly used to measure product mix breadth (e.g. number of products produced) and the degree of product mix change (e.g. number of engineering changes or new product introductions) fail to assess similarities and differences among products that precipitate heterogeneous production activities and consequently affect operating performance. This failure suggests that previous tests of the impact of product mix complexity on operating performance are mispecified. By ignoring similarities and differences among products these studies lack the power to distinguish between the strategy implemented successfully by some Japanese firms, careful product proliferation around core commonalities to create product breadth that is transparent to manufacturing, and the experience of U.S.

manufacturers, that product variety wrecks havoc on manufacturing.

This paper uses an approach developed in the group technology field of operations management to create measures of product mix complexity that distinguish products on the basis of similarities and differences of demands that they place on manufacturing. These measures are used to test the hypothesis that operating performance--- defined as total factor productivity, weaving efficiency, and percent off-quality output--- is negatively related to product mix heterogeneity using monthly data from 1986-90 for three weaving plants of a leading U.S. textile firm. The paper makes four contributions to the emerging literature on manufacturing flexibility and multi-dimensional performance measurement. First, the paper develops a measure of product heterogeneity that incorporates product similarities and differences that are related to manufacturing activities and documents its superiority to previous approaches. Second, the paper estimates the longitudinal relation between product mix complexity and operating performance and compares the flexibility of three plants that face different levels of product mix complexity. Thus it complements previous papers that use cross-sectional analysis or longitudinal analysis alone (Foster and Gupta, 1990; Banker, Potter and Schroeder, 1992; Cooper, Sinha & Sullivan, 1992). Third, the paper is the first to provide evidence on sources of increased flexibility. In particular, it is the first to address whether flexibility is correlated with experience producing a broad range of continually changing products. Finally, the results indicate that different forms of product mix complexity affect different measures of nonfinancial performance. Thus accountants' "balanced scorecard" must balance different nonfinancial performance measures as well as financial and nonfinancial performance measures.

The paper is organized in five sections. The first section reviews previous efforts to assess the impact of product mix complexity on performance and suggests an alternative approach for measuring product mix complexity that is derived from the group technology literature. The second section describes the research sites and provides summary statistics about product mix complexity and performance during the period, 1986-90. Section 3 outlines the research methods and develops measures of product mix complexity. Tests of the relation between product mix complexity and performance are provided in the fourth section. Section 5 summarizes the paper's contributions to the literature and to management practice.

1. PRODUCT MIX COMPLEXITY AND OPERATING PERFORMANCE

The literature addressing the impact of product mix complexity on manufacturing is spread across three fields: economics, management accounting, and operations management. Each discipline has contributed different theoretical and empirical approaches. The theoretical literatures have coalesced; economists have derived conditions that promote (dis)economies of scope in multi-product production (Panzar &Willig, 1977; Willig, 1979; Teece, 1980; Panzar & Willig, 1981; Gorman, 1985) while researchers in accounting and operations have gone within the "black box" of the production function to provide rich descriptions of multi-product production environments and analytic models to explain the micro-structure of diseconomies of scope (Skinner, 1974; Hayes & Wheelwright, 1984; Hill, 1985; Miller & Vollman, 1985; Johnson & Kaplan, 1987; Cooper & Kaplan, 1987; Karmarkar & Kekre, 1987; Kekre, 1987; Banker, Datar & Kekre, 1988; Cooper, 1990). The empirical literatures have not coalesced, in large part because measures of product mix complexity have eluded researchers.

Empirical efforts in economics (Baumol and Braunstein, 1977; Pulley and Braunstein, 1992) center on determining economies of scope by econometric estimation of the joint production cost function. This approach is fruitful when a limited number of products or product families are produced with few inputs for a lengthy period. However, in the more common production environment of several hundred products produced in varying combinations, data limitations typically cause the joint cost function to be under-identified. Accounting researchers circumvent this problem by adopting the more modest goal of estimating total costs of all product interactions, rather than specific interactions between individual products. They identify probable interaction costs from firms' accounting records--- manufacturing overhead costs--- and relate these costs to variables that proxy for product mix complexity (Foster and Gupta, 1990; Banker, Potter and Schroeder, 1992; and Cooper, Sinha, and Sullivan, 1991).[2] The approach has provided mixed evidence to support our intuition that product mix complexity is positively correlated with overhead cost.

Operations management researchers take a similar approach of indirectly measuring

[2] Banker, Datar, Kekre & Mukhopadhyay (1990) and Datar, Kekre, Mukhopadhyay & Srinivasan (1990) take a different approach of first assigning overhead costs to products and then estimating the relation of the revised product cost to product characteristics. Thus they estimate the costs of product complexity rather than the joint costs of product mix complexity.

the effects of product mix complexity on nonfinancial measures of operating performance. Rearranging the production function, Hayes and Clark (1985) create a total factor productivity (TFP) index to assess plants' effectiveness of transforming inputs into outputs. In theory TFP equals one if production occurs according to the linear, separable production function hypothesized. However, if product interactions reduce a plant's ability to transform inputs to outputs, TFP falls short of one. This shortfall is hypothesized to be well-explained by product mix complexity. Regressing TFP on proxies for product mix complexity such as the number of products produced, Hayes and Clark find weak evidence of a negative relation.

Although they circumvent the problem of estimating individual product interactions, methods used by accounting and operations researchers to estimate the net effect of product interactions create the new empirical challenge of measuring product mix complexity. Typically two types of variables are used: those that are the result of product mix complexity (i.e. the number of engineering changes, product shipments, and vendors); and, variables that are crude proxies for product mix complexity (i.e. the number of products, component parts, and production batches). None of these variables measure differences among products that generate heterogeneous demands on manufacturing--- the hypothesized source of diseconomies of scope and burgeoning overhead (Miller & Vollman, 1985) and the proposed object of "factory focus" (Skinner, 1974; Hill, 1985).

The group technology literature of operations management offers an alternative method for directly assessing product mix heterogeneity. Developed as a means for classifying products on the basis of production and design similarities, group technology assumes that products are uniquely described by a well-defined but limited set of N attributes (Hyer & Wemmerlov, 1984). Wilson and Henry (1977) identify two categories of attributes used to assess similarity for purposes of group formation: "graphical" data describe the product in engineering terms, and "manufacturing" data describe process specifications for production. The difficulty of implementing group technology is determining the relative importance of different attributes, and establishing the optimal number and composition of groups (Miltenburg & Zhang, 1991). However, the objective of this study is to empirically link the product attribute space occupied by plants' product mixes to changes in plant performance. Consequently, it is possible to use the strengths of group technology--- description of the product attribute space--- without inheriting its implementation problems.

Skinner (1974) proposed several objects of "factory focus" to reduce the variety of manufacturing activities within one facility, including: product focus, process focus and customer focus. This suggests that the relevant set of product attributes for assessing the impact of product mix complexity on manufacturing are those that describe the product ("graphical" parameters), the process ("manufacturing" parameters), and the demands of customers for a particular product. If a product is described by its N-attribute vector of product, process and customer parameters, then product heterogeneity is defined by differences in the attribute vectors of two products. Product mix complexity arises when heterogeneous products are produced simultaneously or in sequence.

In a single-process (weaving) production facility, such as those examined in this study, product mix complexity arises in two ways. If the facility is equipped with many identical, parallel machines, product mix complexity may arise with simultaneous production of heterogeneous products. Whether a plant has one or many machines, product mix complexity may arise with sequential production of heterogeneous products. Relating simultaneous and sequential product mix heterogeneity to plant performance yields a measure of flexibility: uniformity of performance.[3] A flexible manufacturing facility produces a wide range of continually changing products with consistent, strong performance.

Simultaneous and sequential product mix heterogeneity create different demands for manufacturing activities and thus can be expected to affect performance measures differently. Skinner (1974) argues that simultaneous production of heterogeneous products engenders confusion and goal incongruence among production workers and creates demands on management to resolve the ensuing conflicts. Proponents of cell manufacturing argue that co-locating similar products improves performance by reducing the need for coordination and by concentrating responsibility and authority at the point of production (Burbidge, 1989). Thus,

[3] This definition of flexibility is Upton's (1991) multi-product analog to Stigler's (1939) definition of flexible technologies. Stigler defines a flexible technology as one with a relatively flatter average cost curve over a wide range of output quantities. Though a less flexible technology might offer lower average costs at some particular output, X^*, in the presence of demand uncertainty that is resolved after the technology choice is made (Marschak & Nelson, 1962) the more flexible technology offers lower expected costs for the distribution of expected demand.

performance measures that comprehend coordination and production efficacy are expected to be influenced by simultaneous product mix heterogeneity.

The impact of sequential product heterogeneity on operating performance is twofold: fixed effects and sequence dependent effects of setup. The downtime associated with machine setups reduces production capacity and consequently, productivity. Although a "fixed" level of downtime is typically associated with all setups, an additional variable component of setup time may depend on characteristics of the products produced before and after the setup. Sequence dependent setups are common in process-flow industries such as chemical (Bitran & Gilbert, 1990) and paper manufacture (Upton, 1991). The minimum cost path of producing several products on a machine is a sequence that maximizes similarity of adjacent products according to one or several critical attributes (i.e. weight, color). Performance measures that include setup performance are expected to be influenced by sequential product mix heterogeneity.

In sum, performance is hypothesized to be best when products are tightly clustered in attribute space with little change from period to period--- products reflect a consistent set of manufacturing priorities, fixed and sequence dependent setup costs are minimized and cross-product learning is maximized.

2. RESEARCH SITES

The research sites are three weaving plants of a leading U.S. textile manufacturer, "Weaving Industries". During the period of this study, 1986-1990, the firm was recognized in the trade and business press as being well managed. Even so, like its U.S. competitors, Weaving Industries experienced declining demand for its high volume products. The erosion of commodity markets in combination with demands for greater customization accelerated product proliferation in Weaving Industries' product lines. The three plants were selected by management for three reasons: first, they employ an advanced weaving technology and represent substantial capital assets, second they experienced little additional investment during the period of study, and finally, management wanted to verify and quantify their intuition that product mix complexity impairs performance.

The challenge of field-based research is finding research sites that differ in the variable being studied but are similar along other dimensions. This section demonstrates that Plants A, B, and C are similar along dimensions previously shown to impact operating performance. At the same time the plants have experienced different levels and rates of growth of product variety. Similarities among the plants minimize confounding effects of variables that fall outside the research domain while differences provide the basis for measuring the impact of product variety on measures of operating performance. The following section uses qualitative and quantitative data obtained during field visits to describe the plants and provide a context for interpreting subsequent results.

2.1 Plant Profiles[4]

Plants A, B and C are cost centers of the firm's Woven Fabric manufacturing division. The firm operates many plants with similar technical capabilities and further limits each plant's product range through a facilities focus strategy. The focus strategy for the Woven Fabrics Division assigns each plant a raw material specialty. Plants A, B, and C specialize in products made of inputs 1, 2 and 3, respectively. In addition to its specialty, Plant C is a "swing" plant, used to balance capacity utilization across all three plants.

A plant's facilities focus strategy and scheduling practices determine whether observed product mix variation is adequate to reveal a relation between product mix heterogeneity and operating performance. Weaving Industries' broad product offering does not limit the plants' product range; however, its facilities focus strategy and production scheduling practices do. Plants A and B, specialize in weaving products of inputs 1 and 2, respectively. Plant C, which specializes in input 3 but frequently weaves products of inputs 1 and 2, promises the greatest range of observed variety. The plants produce fabrics that are engineered for specific customers and production is to order rather than to replenish inventory stock. Production planning permits intervention in the composition and timing of demand; however, the scope of these interventions is limited. Fabric demand is heavily influenced by "fashion"; it is fleeting and if not quickly satisfied, evaporates. Thus, if demand is badly forecasted schedulers modify the schedule to meet market demands. Consequently, the plants experience

[4] Technical terms that are used in subsequent discussions are capitalized in their first use.

significant product mix change even within the bounds of their assigned facilities focus.

Located in small towns in the textile intensive southeastern United States, the plants employ nonunion workers and pay identical wages for comparable job classifications. Self-sufficient production teams of four to five employees are responsible for approximately 100 looms each and with few exceptions the plants operated 24 hours a day seven days per week throughout the period. Absenteeism was less than one percent annually during 1986-90. Consistent with industry averages, turnover among hourly employees was 20-25 percent annually for all three plants. As a result of normal promotions, the plants have been marked by high management turnover; Plants A and B had four and Plant C three plant managers from 1986 to 1990. In contrast, the engineering and administrative staffs were stable.

The plants were built within a decade of each other and there is little to distinguish the physical facilities or infrastructure. The production equipment is the same make and vintage, reflecting the firm's decision in the early 1980's to upgrade to an advanced weaving technology. The plants acquired the majority of their looms at the same time (mid-1984) from the same vendor. Employees of all three plants were trained in the same courses offered at the firm's central training facility and at the equipment vendor's training facility. The scale of the plants is similar; Plant B has the largest number of looms, L, followed by Plant C with .91L and Plant A with .83L.

The plants use the same advanced weaving technology. Weaving is the process of interlacing lengthwise WARP yarns and cross-wise FILL yarns at right angles. Warp yarns are wound onto a metal core, called a WARP BEAM, in an upstream process. During machine setup, the warp beam is mounted in the loom in an operation known as a DRAW setup. Alternatively, if a second batch of a product is produced on a machine, the threads of the new warp beam are tied to those of the exhausted beam and pulled through the loom. This minor form of setup is called a TIE. The loom raises and lowers alternate warp yarns and inserts the fill thread to form a panel of fabric. Next the woven fabric is inspected, packed and shipped.

In sum, the plants are virtually indistinguishable along dimensions known to affect operating performance and cost; specifically, employee skills and work practices, equipment age and type, and plant facilities and infrastructure. In contrast, as the following section demonstrates, the plants have experienced different levels of product mix variety caused in part by their focus on different inputs.

2.2 Product Mix Complexity

From 1986 to 1990, the number of products that Plants A, B, and C produced each 4-week period increased and the stability of the product mix from period to period decreased.[5] Growth in the number of products produced over the five years provides a crude approximation of increasing product mix complexity. The different ways that product heterogeneity emerged are evident in a comparison of the number of products produced that considers three definitions of "product": 1) a warp beam; 2) a unique combination of a warp beam and a fill thread; and, 3) warp beam and fill thread combinations that exclude different generations of a product.

Controlling for minor differences in plant scale (number of looms), Panel A of Table 1 characterizes the growth of product variety, by treating as a single product all products that share common warp beams. Each plant experienced increased product mix breadth, with Plants B and C having the highest level of product variety by the end of the period. Panel B characterizes product variety by treating unique warp-fill combinations as a different product. Again, product variety increased for all of the plants, though this increase took different forms. Comparing Panels A and B, Plant B proliferated products by combining different fill threads with existing warp beams. The ratio of warp-fill combinations (Panel B) to warps (Panel A) indicates that on average warps are combined with two fills in Plant B, as compared to 1.5 for Plants A and C. In the language of manufacturing, Plant B proliferated products using common components.

Over time products undergo generational change. In theory the new product generation replaces the old; in practice some customers are unwilling to adopt the new product generation. As a result, multiple product generations may coexist. Panel C characterizes product variety by treating generations of a unique warp-fill combination as one product. The definition of a multi-generation product family is derived from company records; product codes for generations of a product differ by one digit. Comparing Panels B and C

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[5] Throughout the paper a production "period" is defined to be four weeks, or approximately 28 days. Each calendar year includes 13 periods and the study encompasses five years, or 65 periods.

highlights differences between the plants in how product heterogeneity emerged. In 1986 one third of the products that Plant B produced were generations of existing products. This compares to one tenth and one seventh for Plants A and C, respectively. Differences are less pronounced but still present by 1990. Again, Plant B's product mix is substantially more homogeneous than either Plants A or C despite producing a large number of products.[6]

Table 1 indicates growth in the number of products produced in a period. It does not address product mix change. A crude measure of product turnover, computed by dividing the number of products produced in five years by the average number produced each period, indicates the degree to which increasing product mix variety was accompanied by changing product mix composition (Table 2). Product mix change surfaces in all three plants; however, Plant C was marked by significantly more change than either A or B. Removing the effect of generational change, Plant C produced six entirely different product portfolios from 1986 to 1990. In contrast, Plants A and B produced 3.4 and 3.9 product portfolios in the same period.[7]

Summarizing, the plants experienced similar growth in the number of products produced; however, this similarity masks important differences in how product variety emerged. Plant A produced a small number of heterogeneous products that were rarely produced from common warps or generations of existing products. Plant B went from having the fewest to having the most products. However, product heterogeneity was minimized by proliferating through incremental change to existing products --- combining new fills with

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[6] One facet of product variety not addressed by Table 1 is the distribution of products over operating capacity. Examining the share of operating machine hours dedicated to the highest volume product revealed no difference among the plants. Approximately 20 percent of capacity was devoted to producing the highest volume product in 1986, falling to 17 percent by 1990. The plants concentrate a substantial share of machine hours on one product and concentration declined slightly with increased product variety.

[7] An empirical question is whether "change" reflects introductions of new products or production discontinuities that interrupt a product's lifecycle. For example, Panel B of Table 1 indicates that Plant C produced 404 products in five years, on average producing 53 different products each period. This might mean that products run for 8.6 periods (65 periods/7.6 turns) before being discontinued. Alternatively products might run one period every 7.6 months, a total of 8.6 periods over five years. Comparing the duration of continuous product runs, short product runs are prevalent for all three plants; approximately 10 percent of all production runs were completed in one period and 50 percent were completed in fewer than four periods. Thus erratic production schedules are as much to blame for product mix instability as new product introductions.

existing warps and modifying products through generational change. Plants A and B had similar low levels of product mix change. In contrast, Plant C experienced the same dramatic growth in the number of products as Plant B but was unable to contain product mix heterogeneity. Products produced in a period were dissimilar and changed substantially from period to period. This volatility is consistent with its role as the "swing" plant in the firm's focus strategy. Differences in the plants' levels of simultaneous and sequential product mix heterogeneity provides a powerful research design for testing the impact of product mix heterogeneity on nonfinancial measures of operating performance.

2.3 Operating Performance: Total Factor Productivity, Efficiency and Off-Quality Output

This study examines the impact of product mix complexity on three nonfinancial measures of performance: total factor productivity, weaving efficiency, and output quality. Total factor productivity was used by Hayes and Clark (1985) in their study of determinants of plant productivity and was constructed specifically for this study. Weaving efficiency and output quality are measures that Weaving Industries' top management reviewed in their monthly plant performance evaluations throughout the period 1986-90.

As the following sections indicate, all of the performance measures are imperfect either by construction or as a result of data limitations and together provide different perspectives on manufacturing effectiveness, as indicated by their low correlation (Table 3). Consequently, product mix flexibility--- the impact of product mix complexity on operating performance--- must be examined for each aspect of performance. The following sections describe how the performance measures are constructed and provide summary statistics (Table 3) of plant performance along each dimension.

2.3.1 Total Factor Productivity

Economic studies of productivity typically start by determining an appropriate production function. In a recent study of advanced weaving technologies, Pack (1987, pp. 51-2) argues that textile engineering supports a long run, constant elasticity of substitution (CES) production function with an elasticity of substitution, σ, equal to .5. This paper uses a special case of the CES in which no short run input substitution

(σ=1) is assumed possible. Thus weaving transforms four inputs: material (M), labor (L), capital (C), and energy (E), into output (Y) according to a linear, homogeneous production function.

The total factor productivity (TFP) index, a measure of the effectiveness with which inputs are transformed to outputs, is the quotient of output and inputs. In order to combine quantities that are measured on a variety of scales, the N outputs, Y_i are weighted by their 1990 standard cost, S_i^{90}, and inputs: C, E, L, and M_k, by their 1990 standard price, P^{90}. [8]

$$TFP_t = \frac{\sum_{i=1}^{N} S_i^{90} Y_{it}}{P_K^{90} K_t + P_E^{90} E_t + P_L^{90} L_t + \sum_{k=1}^{M} P_k^{90} M_{kt}} \tag{1}$$

TFP data are gathered from archival records. Actual output quantities (excluding scrap, waste, and off-quality that exceeds contractually negotiated allowances) of each product are multiplied by the product's 1990 standard cost. Inputs are measured as follows:

Direct and Indirect Hourly Labor: Actual straight time, overtime and premium shift hours multiplied by the average hourly wage paid in the last six months of 1990, including benefits and applicable premia for overtime and shift hours.

Salaried Labor: Salaried headcount multiplied by the average monthly wage paid during the last six months of 1990, including benefits.

Materials: Actual pounds or yards of raw material, by type, multiplied by the 1990 standard cost (internally procured materials) or price (externally procured materials) per unit.

Energy: Kilowatts of electricity and gallons of water consumed multiplied by the average 1990 price.

Capital: The period capital stock (determined from the 1990 replacement value of assets and

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[8] Weighing actual quantities by costs from a distant period causes the period to appear inefficient relative to the period in which quantities are paired with actual prices. Thus the Paasche index, which weights quantities by their 1990 costs, is biased toward increasing productivity over time. In light of increasing product variety, hypothesized to reduce productivity, any finding of a statistically significant negative impact of product variety will be underestimated, and thus all the more convincing.

Three factors influence the decision to use costs rather than prices in valuing output: differences in gross margin between different textile markets, lack of reliable market prices for internally transferred fabrics, and limited availability of historical price data. The 1990 standard cost for discontinued products is estimated by applying a material specific inflation factor to the last available standard cost.

the record of asset acquisitions and disposals from 1986-90) multiplied by the sum of the depreciation rate and the firm's cost of capital (Hall & Jorgenson, 1967). Straight line depreciation methods are applied to engineering estimates of the useful lives of the equipment, building and infrastructure.

Materials are typically issued to production in advance of realized output in processes with lengthy throughput times. The average material throughput rates for each of the three raw material inputs was used to correct this temporal mismatch between material inputs and output..

Another source of measurement error in TFP arises with the distinction between input consumption and input provision during periods of reduced demand. As formulated, the TFP index requires a restrictive assumption about input markets; namely, that inputs are sold each period in infinitely divisible quantities. In practice capital investments are long-lived, with no alternate short run use. Energy and labor are also relatively fixed expenses. Consequently, C, E, and L are poor measures of input consumption and TFP is depressed in periods of low plant utilization. To separate this influence from the hypothesized influence of product mix heterogeneity, excess capacity is included as an exogenous variable in subsequent tests of the determinants of TFP. Excess capacity is calculated as one minus the machine hours (including setup time) needed to produce realized demand divided by the product of the number of machines and hours in a week.

2.3.2 Weaving Efficiency

Weaving efficiency measures the degree to which the plant operates according to expectations, or "standards". Plant engineers calculate the expected output per machine hour, or "rated efficiency", for each product based on its specifications. Period weaving efficiency is calculated as the actual machine hours divided by the standard allowable machine hours for the actual product mix. Thus weaving efficiency measures *unexpected* production difficulty. As its name suggests, weaving efficiency excludes setup time focusing instead on downtime caused by machine failures, thread breakage, and machine cleaning. Also, because it is calculated for operating machines, weaving efficiency excludes excess capacity. Product standards are independent of product mix; consequently, it is reasonable to suspect product mix complexity as a contributing factor to weaving inefficiency.

The informativeness of weaving efficiency as a measure of performance depends critically on timely, accurate updates of engineering standards. As the plant becomes more proficient at weaving a product, consistently exceeding 100 percent efficiency, the standard must be changed to reflect higher performance expectations. The policy at Weaving Industries is to revise product standards every six months if production experience suggests that the standard is outdated. To the extent that standards drift during the six month period in which no revisions are permitted, weaving efficiency measures unexpected production problems with error.

2.3.3 Output Quality

Percent off-quality, calculated as the standard cost of off-quality output divided by the standard cost of all output, measures the share of output unfit for sale at full price. Off-quality output does not include engineered scrap or waste, but does include a pre-negotiated level of off-quality (defects per unit length) that the customer agrees to accept, as well as off-quality output that exceeds the customer's allowance. Customer returns of off-quality fabric are included in the off-quality measure and are credited to the most recent period in which the product was produced prior to receipt of the returned shipment.

Unlike weaving efficiency, percent off-quality is not a measure of deviation from expectation, it is a measure of deviation from zero defects. Thus, it includes off-quality fabric that is statistically "expected" from a stochastic production process as well as unexpected off-quality. The majority of expected off-quality fabric is produced at the beginning of a warp beam, immediately after the setup technicians return the machine to production. This "setup effect" includes the effect of loom operators' making small adjustments even after the setup is technically complete, as well as the abrasion that outer threads on the warp beam sustain during material handling. The number of major (DRAWS) and minor (TIES) machine setups are included in subsequent regressions to control for this "fixed" effect of sequential product mix complexity. Off-quality is also common at the end of a warp beam. The percent of off-quality represented by losses at the beginning and end of a beam is greater for plants that consistently produce fabric from shorter beams than for plants that produce long, continuous lengths of fabric. Consequently, a measure of average warp beam length for the product mix is included in the estimated models to control for setup frequency.

Like weaving efficiency, the definition of "first quality" may change over time as customers become more demanding. If production skills don't keep pace with customer demands, off-quality output increases over time. A measure of the average customer tolerance for off-quality for each period is included in subsequent regressions to control for "quality inflation". Of course this is an imperfect measure of changing quality standards because it only comprehends decreases in the acceptable number of defects per unit length and assumes consistency in what constitutes a defect.

Another contributing factor to the statistically predictable component of off-quality is machine downtime (Appendix A). The primary cause of fabric defects in the body of a bolt of fabric is loom stoppage. Process interruptions leave a perceptible line across the fabric. A measure of the average expected uptime of machines for the given product mix is included as a further control for expected off-quality output.

Having established controls for sources of expected off-quality output, the question that remains is whether the unexpected component of off-quality is related to product mix complexity.

3. RESEARCH METHOD

Three preparatory steps are necessary to test the relation between operating performance and product mix heterogeneity: 1) Identifying product attributes; 2) Constructing measures of simultaneous and sequential product mix heterogeneity; and 3) Conducting univariate time series analysis of the performance and the product mix heterogeneity measures to remove predictable seasonality and persistence from the series. The following sections describe the methods and results of each step.

3.1 Identifying Product Attributes

Skinner (1974) argues that product, process and customer variety are likely to reduce manufacturing performance. A natural starting point for identifying product attributes that describe the product, its process and its customer demands is engineering specification records (See Appendix). Interviews with engineers and production workers revealed that product specifications for woven fabrics fall into five categories: those which describe 1) warp and fill threads, 2) warp beam construction, 3) how the warp and fill are combined, termed "fabric construction", 4) how the plant runs the product, termed the "product-process interface", and 5) customers' quality requirements[9]. Each category includes several parameters. The problem, evident in employees' descriptions of woven fabric is that the specifications are not independent and are too numerous to incorporate simultaneously in a test of the impact of product variety on performance. Common factor analysis is used to reduce the product specifications to a parsimonious set of attributes that retain the information of the original data (Harmon, 1976; Rummel, 1970).

3.1.1 Factor Analysis

One a priori test of whether a common factor model is reasonable is that partial correlations between pairs of variables controlling for all other variables are smaller than the original correlations between the variables. Kaiser's measure of sampling adequacy ($0 \leq$ MSA ≤ 1), measures the amount by which the original correlations are reduced when the other variables are included. The variables included in the factor analysis have a high overall MSA of .81, indicating that a common factor model is reasonable and that the variables adequately define product attribute space.

The maximum likelihood method[10] of extracting common factors is used to identify a smaller set of orthogonal product attributes from engineering specifications of products produced from 1986 to 1990 (Table 4). The maximum likelihood method was chosen because, if as in this study an entire population is analyzed, the data is not required to be

[9] Customer quality requirements may seem to be an unusual component of engineering specifications. However, virtually all of the plants' products are designed for a specific customer. Consequently there are rarely multiple uses or quality standards for a product.

[10] Factor analysis is performed using the FACTOR (Method=ML, Priors=SMC) and SCORE procedures of the SAS software package (ver. 6.02). The Maximum Likelihood methodology "is equivalent to Rao's (1955) canonical factor solution" (SAS User's Guide: Statistics, 1985 p. 340). Estimated communalities used to start the iterative procedure are squared multiple correlations, the best value when a population of cases is examined (Rummel, p. 122). The iterative procedure weights individual variables by the reciprocal of unique variance; thus variables with the greatest portion of their variance in common factor space are most influential in defining factor space. Iteration stops when successive values of factor loadings agree to within .001 (Harmon, pp. 207-11).

multivariate normal and the factor solution obtained is invariant to the scale of the raw data. Moreover, "the appropriate number of factors will be those with eigenvalues greater than or equal to unity " (Rummel, p. 122). The resulting factor solution is rotated using the varimax rotation criteria of minimizing the number of variables that contribute to each of the factors.

Two criteria are used to evaluate the goodness-of-fit of the factor model. One is the extent to which the model predicts actual correlations between variables. The square root of the mean squared difference between predicted and actual correlations of all variables with one another measures this aspect of fit. A value of .02 for the factor solution of Table 4 is evidence of a good fit between the estimated factor model and the actual product data. A second test of goodness-of-fit is that correlations among variables, removing the effects of common factors, are approximately zero. The square root of the mean squared partial correlations for all variables with one another provides a measure of this aspect of fit. A value of .07 for the factor solution further validates the model.

3.1.2 Factor Interpretation

The sum of squared factor loadings for a variable, termed "communality", reflects the extent to which the variable is found in common factor space. With orthogonal factor solutions, the correlation between the variables and factors is equal to the variable's factor loading. Thus factor loadings are the basis for interpreting the product attributes underlying the seven factors. The following section describes the variables which weigh heavily in identifying the factors (Table 4).

The dominant factor that explains product variation distinguishes differences in product's raw material content. Consistent with the firm's facilities focus strategy, products produced in Plants A and B are tightly clustered in different segments of the raw material scale while products produced in Plant C span the scale and overlap the products of Plants A and B. The firm's use of raw material as the basis for defining facilities focus indicates that raw material variety is believed to be detrimental to operating performance.

The second factor differentiates products on the basis of fabric weight. This factor is influenced by the weight of a linear yard of fabric, which in turn is correlated with the weight of constituent warp and fill threads, the density of fabric construction, and the warp contraction that results from intertwining warp and fill threads. Unlike Factor 1 which revealed a tight clustering of products in Plants A and B, Factor 2 identifies a form of product variation in which Plant A's product mix is almost as broad as Plant C's.

Factor 3 distinguishes products on the basis of expected machine downtime as reflected by the product-specific rated machine efficiency and stop level. A critical source of downtime and off-quality fabric is thread breakage, or the "machine stop level", expressed as breaks per 100,000 picks. Stop levels are statistically predictable given the thread thickness (denier); the thicker the thread the lower the expected downtime. Breakage rates may be reduced by adding extra sizing to strengthen the warp threads or by running the machine slower to reduce the force on the threads. Thus Factor 3 is positively related to the amount of size applied and negatively related to machine speed. Products produced in Plant C have a wider range of anticipated production difficulties than products of Plants A or B.

The fourth factor segments products on the basis of warp beam construction. Warp beam length, machine speed and fabric density (picks per inch) determine the batch size and throughput time for a typical production run. The diameter of the full warp beam is limited by the loom's capacity. Given the permissible warp beam diameter, warp beam length is determined by the denier (thickness) of individual warp threads and the number of individual threads on the beam (as measured by the weight of warp threads in a linear yard of fabric). Thus Factor 4 is heavily influenced by warp length, warp denier, warp weight, and because warp thread comprise approximately half of fabric weight, by fabric weight. The plants' products differ little in warp beam variety.

Factors 5 and 7 distinguish differences in fill and warp thread constructions, respectively. Both factors are influenced by the denier or thickness of the individual fill and warp threads. In addition, Factor 5 depends on whether the fill has been "finished" or treated to have a luster or shine and Factor 7 depends on how many individual warp filaments are twisted together to form a single, stronger warp thread. Plant C's products exhibit the widest range of warp and fill thread variation, followed closely by Plant A .

Factor 6 distinguishes products based on their defect tolerance. Standards for acceptable quality depend largely on a product's eventual use. For example, fashion apparel fabrics typically are produced to tighter tolerances than industrial fabrics. An artifact of

Weaving Industries' product mix is that the highest quality standards are required by customers for high density (picks per inch) fabrics, thus the dependency of Factor 6 on fabric density. Differing tolerances are likely to result in confusion and mistakes. Evidence of this emerged when while touring one plant I noticed pieces of paper taped to the looms. The operator left notes to remind herself of problems encountered earlier so that she would monitor the condition on subsequent visits to the machine. Plant A's products exhibit the widest range of tolerances, followed closely by Plants C and B.

In summary, factor analysis identifies systematic patterns of variation among products but leaves to the researcher the task of interpreting and linking the factor solution to meaningful constructs. Before the factor solution was calculated engineers, schedulers and production workers were interviewed to discover anticipated sources of product variation. In the course of the interviews they were asked to describe the production process, to explain differences among products, and to discuss the impact of the these differences on performance (Appendix A). Confidence in the interpretation of the factors that emerge to explain sources of product variation is provided by the extent to which the factors mirror the four categories that were consistently used to describe woven fabrics. Moreover, the linkages among product specifications that engineers described are borne out in the factor loadings. Finally, the emergence of raw material as the dominant factor and the observation that the raw material factor scores of products exhibit large between-plant variation and small within-plant variation for the focused plants (A and B), links the factor solution to an independent assessment of critical sources of product variation: the firm's facilities focus strategy.

3.2 Measuring Product Mix Heterogeneity

Factor analysis specifies the attribute space, which in turn provides the basis for determining product similarities and differences. The next step is aggregating the factor scores of products produced in a period to create measures of product mix heterogeneity. One possibility is the Euclidean distance in attribute space between products (Rummel pp. 490-513). The problem with this approach is its implication that equal changes in magnitude along each attribute scale have the same impact on performance. The common factor model extracts factors which explain variation among products. It does not follow, however, that the attribute which explains the greatest source of product variation is the primary determinant of productivity. For this reason the multi-attribute distance measure is rejected and separate measures of product heterogeneity for each attribute are used.

The measure of product mix heterogeneity used for each product attribute is the standard deviation of factor scores of products produced at time t, weighted by the number of machine hours devoted to the product in the four week period.[11] There is no basis provided in the theoretical literature for selecting a method to aggregate product information into a single statistic of product mix complexity. The standard deviation was chosen because it is a widely understood measure of dispersion. The scores are weighted to control for the distribution of products across machines. Thus a plant that produces 2 products equally divided among 100 machines is distinguished from a plant that specializes in producing one product, devoting only a fraction of capacity to the second product. The weighting scheme is consistent with the underlying theory that performance declines when employees divide their efforts among a variety of activities.

Figures 1.a-g plot the longitudinal product mix heterogeneity series for the seven product attributes. Two insights emerge. Unlike the number of products produced, product mix heterogeneity did not increase steadily over the period. On the contrary, some forms of product heterogeneity changed very little while others decreased. Another insight concerns the relative product mix complexity of the three plants. While the number of products produced and the level of product mix change (Section 2) cause the plants to be ordered from most to least complex: C, B, A, during 1986-90, Figures 1.a-g indicate that the plant ranking is neither unambiguous nor constant.

3.4 Univariate Time Series Properties of Performance and Product Mix Heterogeneity

There are several difficulties in establishing the relation between performance and product mix heterogeneity using time series data. First, it is likely that performance and product mix heterogeneity are nonstationary because production experience and product

[11] Machine hours differ from linear output because fabrics are produced at different rates. The actual number of machine hours by product was unavailable. Consequently, the number of hours devoted to a particular product are calculated from the actual yardage produced (including off-quality production), the fabric density and the rated machine speed.

heterogeneity have grown over time. Second, performance levels and product mix heterogeneity are likely to persist because production of a single batch typically spans two production periods. Nonstationarity and persistence increase the probability of spurious correlations being documented if performance is regressed directly against measures of product mix variety (Box & Jenkins, 1976; Harvey, 1981; McCleary & Hay, 1981). To counter this possibility, the dependent and independent variables are first subjected to univariate time series modelling to remove variation that is predictable given the historical pattern of the variable itself. Then innovations in product heterogeneity variables --- the residual variation of the time series models--- are regressed against innovations in performance to determine whether heterogeneity is negatively related to performance. Excluding as they do sources of performance variation that are predictable without explicit knowledge of the product mix, the results of Section 4 are strong tests of the relation between operating performance and product mix heterogeneity (Cook and Campbell, 1979 p. 331).

Modelling product mix heterogeneity, capacity utilization (EXCESS), the number of major (DRAWS) and minor (TIES) setups, the number of products produced (WPFL: unique warp-fill thread combinations) and operating performance as ARIMA processes, most of the variables are found to be well represented by first order autoregressive processes.[12] In order to distinguish whether a variable is more accurately modelled as a random walk process or a first-order autoregressive process with a large value of ρ, equation 2 is estimated.

$$(Y_t - Y_{t-1}) = (\rho - 1) Y_{t-1} + a_t \tag{2}$$

The t-statistic of the Y_{t-1} coefficient is used to test whether $\rho=1$. However, because the t-statistic obtained under the null hypothesis is not asymptotically normally distributed, modified critical t-values (τ-values) tabulated by Schmidt (1990) are used.[13] The Box-Jenkins Q-statistics of the specified ARIMA models' residuals are statistically insignificant, indicating that sources of variation that arise from predictable patterns in the variables are removed.

[12] The specified ARIMA models are available from the author upon request.

[13] This class of tests for a unit root are known as Dickey-Fuller tests. See Kennedy (1992, p. 265).

4. EMPIRICAL RESULTS

Previous attempts to empirically establish whether product mix complexity impairs operating performance have used the number of products produced as a proxy for product mix complexity. The results have typically not supported widespread management beliefs that product mix complexity impairs performance. One explanation is that the proxies used to capture product mix complexity are inadequate because they do not distinguish products based on the similarities and differences of demands they place on manufacturing. This suggests that a useful baseline for evaluating the descriptive validity of the product mix heterogeneity measures developed in this paper is the improvement these measures provide over the number of products produced in explaining performance variation.

The section begins by replicating the traditional approach of measuring product mix complexity as the number of products produced. The results are consistent with previous work, finding no evidence that the number of products produced is related to TFP, efficiency or off-quality. Subsequent sections examine the relationship between measures of product mix heterogeneity and operating performance. Three results emerge. First, the measures of product mix heterogeneity developed in this paper provide significant incremental explanatory power for TFP, efficiency and off-quality relative to previous efforts to establish a relation between product mix and operating performance. Second, some forms of product mix heterogeneity impair performance; although, each performance measure is influenced by different aspects of product mix heterogeneity. Finally, there is weak evidence that the penalty associated with producing a heterogeneous product mix is mitigated with experience.

4.1 Replication of Previous Research Findings

The results of regressing innovations in TFP, actual efficiency and percent off quality on innovations in excess capacity, the number of products (defined as a unique warp-fill combination), and the number of major (draws) and minor (ties) machine setups using the method of seemingly unrelated regressions are found in Table 5.[14] With the exception of

[14] Since the plants produce similar products for similar markets it is likely that the vectors of disturbances of independently estimated OLS regressions are correlated between the plants (Kmenta, 1986 p. 637). The method of seemingly unrelated regressions exploits this linkage to increase the efficiency of the coefficient estimates.

weaving efficiency in Plant B, none of the performance measures are significantly related to the number of products produced. This is consistent with previous studies that have reported limited correlation between manufacturing performance or cost and the number of products produced.

As predicted, TFP is significantly related to excess capacity. The productivity depressing effect of excess capacity indicates the presence of inputs that are fixed in the short run. Setups, the fixed effect of sequential product mix heterogeneity, also play a significant role in explaining productivity. TFP increases with more minor setups and fewer major setups. These variables provide significant explanatory power for productivity in Plants A and C, but offer little explanatory power for TFP in Plant B.

The estimated models for weaving efficiency are poor for all of the plants. This is not particularly surprising since the weaving efficiency measure does not include machines idled by depressed market conditions or time spent in setup. However, the absence of a significant positive influence of excess capacity does suggest that the fixed inputs that become idle during periods of depressed demand are not redeployed in a manner that increases the operating efficiency of the productive machines. There is weak evidence that increasing the number of products decreased weaving efficiency in Plant B. The number of products produced has no significant influence for Plants A or C.

Off-quality production is expected to be related to setups and product mix complexity. The estimated models do not support the latter claim when product mix complexity is represented by the number of products produced. Setups have the predicted effect of increasing off-quality output in Plants A and C. The absence of this effect for Plant B could imply that setups are performed better at Plant B; that after being returned to production the machine produces first quality output. Alternatively, it could mean that setups are more debilitating for Plant B, and as a result the fabric produced after setup is of such poor quality it is classified as waste rather than off-quality output. Lacking measures of waste it is impossible to distinguish between these alternatives.

In sum, the results of Table 5 are consistent with findings of other researchers; there is little or no relation between the number of products produced and measures of operating performance. If managers' intuition that product mix complexity impairs performance is to be empirically supported, new measures of product mix complexity are required.

4.2 Product Mix Heterogeneity and Operating Performance

This section examines whether measures of simultaneous product mix heterogeneity have greater incremental explanatory power for operating performance than the number of products produced. Tables 6, 7 and 8 present the results of regressing innovations in product mix heterogeneity on innovations in performance (TFP, Weaving Efficiency and Percent Off-Quality, respectively) using the method of seemingly unrelated regressions. The tables include the results of three separate regressions: innovations in performance regressed on 1) innovations in excess capacity utilization and setups--- the "base" model; 2) innovations in excess capacity, setups and product mix heterogeneity--- the "complete" model; and, 3) on variables which are most significant in the previous regression--- the "best" model. A caveat to interpreting the "best" model is that it is selected *after* examining the results of the complete model; the data is "overfit". Lacking a theory on which to base hypothesized differences in the impact of different forms of product mix heterogeneity on operating performance, this research is best classified as exploratory data analysis and should be evaluated in this light. Nonetheless, in almost every instance the complete model outperforms the traditional approach of measuring product heterogeneity as the number of products produced. Thus the claim that the product attribute model is superior to previous attempts to measure product mix complexity does not depend on the overfit model. The following sections discuss each table.

4.2.1 Productivity and Product Mix Heterogeneity

In contrast to the results of Table 5, increased product mix complexity is related to decreased productivity in Plants A and B when direct measures of product mix complexity that comprehend product mix heterogeneity are used (Table 6). Plant C's productivity is influenced by setups and excess capacity but is less influenced by diversity in the characteristics of products produced. Surprisingly, the least focused of the three plants is able to produce substantially more complex product mixes without sustaining a significant productivity penalty. One possible explanation is that Plant C invests more in resources devoted to coordination and control than its sister plants. Since these resources are typically considered fixed in the short term, we expect Plant C's productivity to suffer more in periods of excess capacity if this is the case. In fact, as Table 6 indicates, the effect of excess capacity on productivity is virtually identical for all three plants. It would seem that Plant C has developed a proficiency in producing a heterogeneous product mix.

Table 6 also provides evidence on the specific types of product mix heterogeneity that influence productivity. Productivity decreases are related to increased warp thread variety in Plants A and C. As Figure 1.g illustrates, Plant A experienced the lowest level of warp thread variety although the range of warp threads produced during the five years did not differ greatly from that of Plant B. One possibility is that weaving machines are inherently more productive producing products with warp threads that fall in a certain range of the warp thread spectrum. If this were the case we would expect the average warp thread factor score of products produced to have greater explanatory power than our warp thread variety measure. In a separate test that included both variables, warp thread variety remained statistically significant while the average warp thread factor score did not enter significantly in the estimated model. Thus I conclude that productivity in Plants A and C is impaired by increased variety in warp threads produced. Since productivity of Plant B is not influenced by warp thread variety despite experiencing consistently higher levels of warp thread variety (Fig. 1.g), this type of product mix heterogeneity may be amenable to experience-based learning.

Significant determinants of Plant B's productivity include raw material variety and warp beam variety. The firm's facilities focus strategy, in which Plants A and B are limited to producing fabrics from particular raw material inputs, suggests that management believes raw material variety is most likely to impair plant performance. Indeed, the focus strategy was so well implemented in Plant A that no measurable raw material variety emerged during the five years (Fig. 1.a); thus, raw material variety is excluded for Plant A in Tables 6, 7 and 8. In contrast, Plant B was subjected to raw material variety when in 1988 managers decided to produce very long continuous bolts of fabric from the input that had historically been Plant A's specialty. The demand for long bolts was driven by an unusual customer request. The decision to produce the products in Plant B reflects the avoidance of an investment in auxiliary equipment for Plants A or C that was already present in Plant B (customers for Plant B's specialty input have historically required long, continuous fabric bolts). The injection of raw material variety into a production environment that had never been exposed to and had been consciously spared such variety had significant negative consequences (Table 6). Plant C, which was strategically positioned as the "swing" plant and was exposed to high levels of raw material variety, exhibited no ill-effects of raw material variety.

More puzzling is the significant positive coefficient on warp beam variety for Plant B. When faced with these results the engineers of the plant explained that from 1986 to 1990 they worked closely with product designers to encourage them to use existing warp beams wherever possible and to use existing warp threads to create new warp beams. The pattern of declining warp thread variety in combination with increasing warp beam variety (Fig. 1.d and g) in conjunction with the result that warp beam variety increases productivity may simply reflect the relative merit of the new strategy. Another possible explanation is that multi-collinearity between measures of product mix heterogeneity and excess capacity reduces our ability to interpret individual regression coefficients for Plant B. The significant change in the coefficient for excess capacity that occurs with the inclusion of product heterogeneity measures is symptomatic of this problem. Multi-collinearity between capacity utilization and product mix heterogeneity is not surprising; there is often a tendency to accept marginal business during periods of depressed demand in an effort to recoup fixed costs. This tendency appears to have been more pronounced in Plant B than in the other plants.

A final result that emerges in examining the relation between productivity and product mix heterogeneity is the relative improvement in descriptive power of the product attribute model (Table 6) over traditional approaches of measuring product mix complexity as the number of products produced (Table 5). The power to explain changes in productivity is increased with the inclusion of measures of critical forms of variety--- typically those with which the plant has little experience. This improvement is more pronounced for Plants A and B. For Plant C, product mix heterogeneity offers little improvement in explaining productivity over a simple model that includes only the fixed effects of sequential product mix heterogeneity--- setups. This is consistent with the explanation that Plant C, faced with the highest level of product mix heterogeneity learned to accommodate it, in effect becoming flexible. In its strongest form this conclusion raises an interesting argument against factory focus and reinforces Abernathy and Wayne's (1974) point that focused plants lose the ability to adapt to product mix change.

4.2.2 Weaving Efficiency and Product Mix Heterogeneity

Weaving efficiency--- the degree to which actual operating performance exceeds or falls short of expectations--- is better explained by product mix heterogeneity (Table 7) than by the number of products produced for all of the plants (Table 5). Moreover, increased product mix heterogeneity is correlated with reductions in production efficiency. Table 7 confirms that excess capacity and setups play no role in explaining changes in weaving efficiency.

In Plant A expected downtime variety and defect tolerance variety are found to significantly reduce efficiency. That *variety* in expected downtime, distinctly different from average expected downtime, reduces weaving efficiency suggests that basing weaving standards on the ability to produce a product in isolation misses the important effect of product mix interactions.[15] Defect tolerance variety acts to reduce efficiency in Plant A, the plant that consistently served the widest range of quality tolerances (Fig. 1.f) but exhibits a puzzling positive relation to efficiency in Plants B and C.

Plant B's weaving efficiency is negatively related to fabric weight variety. Plant C's efficiency is also negatively related to fabric weight variety. However, fabric weight variety is approximately twice as costly for Plant B as they are for Plant C. Referring to Figure 1.b we find again that Plant B has the lowest and Plant C the highest level of experience with fabric weight variety. Performance penalties associated with fabric weight variety appear to be mitigated with experience.

Weaving efficiency in Plant C is also adversely effected by fill thread variety and warp thread variety. As Figures 1e and g illustrate, Plant C's product mix changed rather dramatically in 1988. The firm adopted a new product development strategy of proliferating products by combining new fill threads with existing warp threads. This strategy was most applicable from a technical standpoint to products made of inputs on which Plant C was focused; thus the pronounced increase in fill thread variety accompanied by reductions in

[15] When included in the regression, average expected downtime is not found to be significantly related to actual operating efficiency for any plant, precluding the explanation that actual efficiency measures arise as a result of systematic over or under-estimation of expected efficiencies.

warp thread variety. However, the coefficients on fill and warp thread variety for Plant C (Table 7) indicate no significant difference in the impact of fill and warp thread variety. There is no evidence that substituting fill thread variety for warp thread variety improved operating efficiency. However, Table 6 provides evidence that productivity was improved when warp thread variety was reduced in Plants A and C. It seems that balancing nonfinancial performance measures will be as great a challenge in the era of multi-dimensional performance measurement as balancing financial and nonfinancial performance measures.

4.2.3 Off-Quality Output and Product Mix Heterogeneity

As section 2.3.3 described, Off-quality output includes both expected and unexpected off-quality production. Expected off-quality arises with setups, with scheduled and unscheduled (but statistically predictable) machine downtime, and with customer demands for higher quality over time. Unexpected off-quality is hypothesized to arise with product mix heterogeneity. Table 8 presents the results of regressing innovations in the percent of off-quality output on innovations in product mix heterogeneity. The first column for each plant provides the results of regressing off-quality on variables designed to capture expected levels of off-quality output: the number of setups, the average downtime factor score, the average warp beam factor score (a measure of warp length, hence setup frequency) and the average defect tolerance factor score. The second and third columns present the results of the "complete" model--- including all product heterogeneity variables, and the "best" model--- including only those variables that emerge as significantly related to off-quality. For Plant A the third column is omitted because the results of the first column represent the "best" model.

Off-quality in Plant A is little affected by product mix heterogeneity. One possibility is that expected off-quality so greatly exceeds unexpected off-quality that the tests lack the power to distinguish the effect of product mix heterogeneity on unexpected off-quality. The best model is the model that includes only sources of expected off-quality. Nonetheless, the product attribute model is valuable for identifying sources of expected off-quality and offers considerable improvement over the traditional approach of Table 5. The fixed effect of sequential product mix heterogeneity is revealed in a reduction of off-quality with increased minor setups and in the increased off-quality that accompanies short warp beams (high average warp factor scores) that cause more frequent setups. The greatest contributor to off-quality is expected downtime. Plant A produces products made of fine thread that breaks at a higher rate than threads used in other products. Depending on customers' tolerance for minor flaws the break may cause the fabric to be rated as second quality. Thus high average defect tolerance factor scores (low tolerance for flaws) increase the rate of off-quality production.

Off-quality in Plants B and C is determined by measures of both expected and unexpected off-quality. Like Plant A, off-quality in Plant B is increased with decreased tolerance of customers for fabric flaws. Warp thread variety is correlated with reductions in off-quality production; however, multi-correlation between warp thread variety, setups and average warp beam length cause this coefficient to be suspect. Given the low overall significance of the model, the most reasonable conclusion is that off-quality output in Plant B differs from Plants A or C in some fundamental way that defies explanation using the traditional theory of what causes off-quality production. Off-quality in Plant C is increased with major setups and with expected downtime variety. However, the changing coefficient of expected downtime variety between the complete and the best model suggests that multi-collinearity is a problem that limits the precision of the coefficient estimates.

In sum, the product attribute model provides better measures of control variables that are expected to influence off-quality output than were available in previous studies, but provides little evidence that producing heterogeneous products increases off-quality. One possibility is that the unexpected component of off-quality is swamped by the larger component of expected off-quality. Measures of unexpected off-quality are required before this question can be fully explored.

5. CONCLUSION

Empiricists have long sought a useful measure of product mix complexity. The inability to operationalize concepts of similarity and difference in a measure of product mix complexity limited the power of tests of the relation between product mix complexity and operating performance. This paper uses an attribute-based model of product mix heterogeneity developed in the group technology literature to test the relation between plant operating performance and product mix heterogeneity. The attribute model is made operational by factor analyzing product engineering specifications. Regression analysis is used to test the hypothesis that performance--- total factor productivity, efficiency and off-quality production--- is negatively related to product mix heterogeneity. The results provide support for the hypothesis that product mix heterogeneity reduces performance through increased setup costs and through interaction costs of producing different products. Moreover, weak evidence that the cost of product mix complexity declines with experience in producing a broad product mix is provided by comparing the impact of setups and product mix heterogeneity on Plant C's performance with their impact on performance of the focused plants, Plants A and B.

The attribute model of product mix heterogeneity improves the explanatory power of tests of the impact of product mix on plant operating performance relative to previous approaches. Using measures of product mix complexity that offer greater power to discriminate among products, the paper offers the first empirical evidence that product heterogeneity impairs manufacturing performance. In addition, by specifying different forms that product heterogeneity takes, the attribute model provides a richer context in which to consider managerial actions to enhance flexibility. As Adler (1988, p. 51) writes:

> "For managers, flexibility is potentially advantageous--- and indeed, only becomes meaningful as a concept--- against a backdrop of potential stabilities. The managerial question is therefore not simply how to reduce rigidities, but how to find the right mix of stabilities and flexibilities."

Unlike the traditional approach which suggests that performance improvements are possible only with gross reductions in the number of products produced, the product attribute model offers helps managers identify the right mix of stabilities and flexibilities.

Identifying especially costly forms of product heterogeneity, this paper offers managers three avenues for improved performance in an environment of rapidly changing, fragmented demand. First, they can discontinue products that are "attribute outliers". This has the same effect of reducing the number of products produced as the traditional approach would suggest; however, the selection of products to discontinue is based on performance costs of complexity. Second, managers can reassign products among the plants to minimize costly forms of product heterogeneity. By reducing product mix heterogeneity instead of reducing the number of products produced, managers create the illusion of broad product lines by proliferating products along dimensions of product heterogeneity that are easily accommodated by the plant. These solutions operationalize Skinner's prescription of factory focus. As such they are subject to Abernathy and Wayne's (1974) criticism; namely, that if the environment changes and the focus strategy is inappropriate to new competitive conditions, the plant may be unable to adapt. A third avenue for improving performance in an environment of increased product mix heterogeneity is learning through experience--- becoming flexible. The evidence of this study shows that Plant C, the plant with the highest level of variety, was least influenced by variety. Though this may hold only up to a point--- suggesting that firms may need to experiment to discover the limits of product mix heterogeneity--- that point seems beyond our current definition of high product mix heterogeneity. In sum the findings of this paper provide managers a road map for becoming flexible and a measure for assessing flexibility. Management accountants' role in supporting manufacturing's effort to become more responsive includes assessing the impact of product variety on plant performance, identifying channels through which variety undermines performance, and devising yardsticks for evaluating progress in achieving product mix flexibility. This paper is a first attempt to address these challenges.

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Appendix A: Product Diversity of Woven Fabrics

Heterogeneity of woven fabrics stems from unlimited combinations of different threads. In order to determine product attributes that contribute to product mix complexity and degradation of operating performance and to identify relationships between product attributes, I conducted interviews with process and industrial engineers at each plant and at the manufacturing division. Though over 30 engineering parameters were mentioned in these interviews, they can be loosely organized into four categories: filament construction, warp beam construction, fabric construction. and the product-process interface.

Filament construction parameters describe the warp and fill threads that comprise a fabric. One aspect of filament construction is fiber specifications: fiber content, weight, and filament treatments. Fiber content refers to the raw fibers used (i.e. rayon, polyester). "Denier" is the industry's measure of weight per unit length. Chemicals used in the extrusion of manmade filaments may further differentiate filaments of the same fiber, changing their luster or shine, or imparting color. A second aspect of filament construction reflects upstream textile processes: spinning, twisting, dyeing and texturing.

The above discussion applies to warp and fill threads. Warp threads require additional description of the warp beam construction. The denier of the warp thread and the width of the warp beam indicates the density of the warp threads on the beam and the maximum width of the finished fabric. A related parameter is the length of each thread on the warp beam. Warp length determines the duration a loom runs before requiring set-up. Warp threads must be stronger than fill threads because they are under constant tension on the loom and are abraded with each pick. Consequently a chemical, called "size", is applied to warp threads during warp beam construction. There are two size-related specifications: size take-up, the absorption of size as a percent of warp weight, and slasher stretch, the extent to which warp contraction caused by sizing is reversed in weaving.

The third category of product specifications, fabric construction, describes the way that warp and fill threads are combined. The weave pattern describes designs on the fabric face. Common weave patterns are: satin, twill, and herringbone. Complex patterns are produced at slower machine speeds. Another aspect of fabric construction is the dimension of the finished product. Though largely governed by warp construction and raw material content, product dimensions are also determined by fabric density (picks per inch)--- how tightly the threads are packed together, and by warp contraction--- the percent of warp length lost in weaving as a result of inserting picks.

The most important feature of fabric, its uniformity, is largely a function of machine settings, or process specifications. The primary cause of fabric defects is loom stoppage. Process interruptions leave a perceptible line across the fabric. Loom stops occur with thread breakage, preventive maintenance or machine failures and are influenced by machine speeds, raw material uniformity and fabric construction complexity. Machine speeds are set to the fastest rate consistent with quality requirements of the customer. The machine speed chosen implies an expected operating efficiency, stop level, and quantity of off-quality production.

The following table summarizes engineering parameters and specifications of products:

VARIABLE	VARIABLE MEASURE
I. Raw Material	
1. Fiber Content	Binary Variable, 0-1 for each of 3 input types
2. Denier or Count	Weight per unit length
3. Finish	Categorical Variable, 1-5, 1=bright, 4=dull, 5=unfinished
* 4. Dye	Binary Variable, 1=dyed
* 5. Texture	Binary Variable, 1=textured
* 6. Twist Multiple	Twists per unit length
7. Number of Filaments	Number of threads twisted to form a single strand
II. Warp Beam Construction	
1. Warp Length	Length of a warp thread
2. Slasher Stretch	Percent warp length increase in weaving
3. Size Take-up	Percent warp weight increase in sizing
4. Reed Width	Fabric Width
III. Fabric Construction	
* 1. Type Weave	Pattern on face of fabric
2. Picks per inch	Fabric thread density
3. Fabric Weight	weight per linear yard
4. Warp Contraction	Percent Warp length reduction in weaving
5. Filament Weight	Warp Weight and Fill weight per linear yard
IV. Product-Process Interface	
1. Picks per Minute	Machine Speed
2. Machine Stop Level	Thread Breakage rate
3. Expected Efficiency	Run time as a percentage of machine throughput time, excluding setup time
V. Customer Quality Requirements	
1. Defect Tolerance	Categorical Variable, 1-5, 1= wide tolerance range, 5= narrow tolerance range

* Although these variables were mentioned in several interviews, upon further investigation they related to fewer than 10% of the 600+ products produced during 1986-90. Rummel (1970) advises against including variables in a factor solution that are relevant for fewer than 10% of the observations. Thus these product attributes are excluded in the factor analysis..

TABLE 1

Average Product Mix Breadth

The average number of products produced in the 13, 4-week production periods of 1986-1990 using three definitions of "product"

Panel A: Product= A unique Warp Beam, which may be combined with a variety of crosswise fill threads

	1986	1987	1988	1989	1990
Plant A	23	24	24	29	29
Plant B	14	15	22	25	35
Plant C	21	31	28	27	35

Panel B: Product= A unique combination of a lengthwise warp beam with a crosswise fill thread

	1986	1987	1988	1989	1990
Plant A	31	29	30	42	37
Plant B	30	30	42	51	67
Plant C	35	54	55	56	59

Panel C: Product= A unique combination of a lengthwise warp beam and a crosswise fill thread, treating generations of the same product as a single product

	1986	1987	1988	1989	1990
Plant A	28	28	28	34	33
Plant B	21	23	30	39	54
Plant C	30	45	45	46	51

NOTE: Adjustments are made for minor differences in plant scale, measured by the number of looms. The adjustment factors applied to the actual number of products produced are: Plant A: .83, Plant B: 1, Plant C: .91.

TABLE 2

Product Mix Change

The average number of times the product mix changed during the five years, 1986-1990, calculated by dividing the total number of products produced during 1986-90 by the average number of products produced in a 4-week period for each of three definitions of a "product".

Product =	Number Products 1986-90	Avg. Number Products/ Period	Product Mix Turnover
Warp Plant A	77	25	3.0
Plant B	62	22	2.8
Plant C	155	29	5.3
Warp-Fill Plant A	162	34	4.8
Plant B	237	44	5.4
Plant C	404	53	7.6
Multi-Generation Warp-Fill Plant A	102	30	3.4
Plant B	128	33	3.9
Plant C	275	45	6.1

TABLE 3

Summary Statistics for Operating Performance Measures

	N	Mean	Std. Dev.	MAX	MIN	Correlation: Efficiency	Correlation: Off-Quality
PLANT A							
TFP	63	.87	.07	1.1	.72	.10	.00
Efficiency	65	92.2 %	2.1	95.3 %	86.7 %	---	-.34
Off-Quality	65	8.2 %	1.6	11.6 %	2.2 %	---	---
PLANT B							
TFP	50	.92	.04	1.0	.81	-.15	-.21
Efficiency	65	93.1 %	1.3	95.2 %	89.8 %	---	-.34
Off-Quality	65	1.9 %	1.3	6.5 %	.3 %	---	---
PLANT C							
TFP	48	.92	.06	1.1	.79	-.02	-.17
Efficiency	65	90.7 %	2.2	94.4 %	84.6 %	---	-.54
Off-Quality	65	4.2 %	1.7	8.3 %	1.0 %	---	---

NOTE: Reliable, complete series of raw material inputs were not available for Plants B and C in 1986. Thus TFP reflects approximately four years of data for these plants.

TABLE 4

Rotated Factor Pattern

The results of using the maximum likelihood method of factor extraction and the varimax rotation criteria to identify independent sources of product variation from product engineering specifications.

Variable	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	C(1)
Slasher Stretch	.95	-.09	-.24	.10	-.05	-.01	.03	.87
Input 2 Warp	.95	-.09	-.26	.08	-.03	-.02	.04	.67
Input 2 Fill	.68	-.18	-.18	-.14	.52	-.09	-.07	.98
Reed Width	-.55	.05	.19	.07	-.18	.26	-.06	.88
Input 1 Fill	-.67	-.22	-.22	-.15	-.04	.19	-.11	.55
Input 1 Warp	-.84	.11	-.22	-.32	-.08	.06	-.01	.96
Fill Weight	-.08	.85	.23	.24	-.13	-.15	.07	.63
Warp Contraction	-.23	.78	-.15	.08	-.25	-.11	.07	.69
Fabric Weight	.11	.66	.16	.56	-.08	-.10	.05	.84
Fill Finish	-.06	.52	.39	.08	-.40	-.16	.08	.63
Size Pick up	-.06	-.03	.80	-.13	.06	.23	-.11	.69
Machine Stop Level	-.14	.25	.72	.18	-.40	-.01	-.13	.81
Rated Efficiency	.14	-.14	-.76	-.30	.26	.12	.20	.88
Warp Weight	.23	.26	-.05	.91	.03	-.07	.07	.46
Rated Machine Speed	.18	-.20	-.12	-.34	.22	-.13	-.20	.77
Warp Length	-.11	-.08	-.12	-.70	-.05	.02	-.17	.98
Fill Denier	.30	-.12	-.27	.14	.70	-.10	-.06	.73
Input 3 Fill	.18	.42	-.01	.04	-.66	-.20	.08	.31
Quality Tolerance	-.22	-.26	.16	-.01	.08	.79	.06	.83
Picks Per Inch	-.42	-.43	-.29	-.29	-.07	.52	-.12	.81
No. Warp Filaments	.03	.13	-.24	.19	-.08	.06	.75	.78
Warp Denier	.44	.04	-.17	.51	-.09	-.19	.58	.80
% Common Product Variation Explained	27%	17%	16%	15%	11%	7%	7%	
NAME:	Raw Material Content	Fabric Weight	Expected Downtime	Warp Beam	Fill Thread	Defect Tolerance	Warp Thread	
Squared Multiple Correlation of Variables with Factors	.98	.88	.90	.94	.85	.80	.80	

(1) C= Variable Communality

TABLE 5
Replication of Previous Research Methods:

The relation of the three measures of operating performance to setups and the number of products produced, where a product is defined as a unique warp-fill combination.(1)

Seemingly Unrelated Regression Results

	c	Excess Capacity	Major Setups	Minor Setups	Number of Products	F-Stat	Adj. R^2
TFP:							
Plant A	.868 (113)**	-.433 (3.49)**	-.947 E-3 (1.07)	.459 E-3 (2.16)*	-.217 E-3 (.10)	4.94 **	.20
Plant B	.927 (169)**	-.082 (.41)	-.131 E-2 (2.16)*	.915 E-4 (.98)	-.773 E-3 (.79)	1.20	.02
Plant C	.920 (125)**	-.343 (2.02)*	-.192 E-2 (3.45)**	.183 E-3 (1.63)	-.645 E-4 (.05)	5.40 **	.27
Weaving Efficiency:							
Plant A	.070 (.46)	-.705 (.29)	-.792 E-2 (.43)	.319 E-2 (.79)	-.047 (1.12)	.80	-.01
Plant B	.014 (.15)	2.05 (.82)	.013 (1.51)	-.267 E-3 (.16)	-.036 (1.87)*	1.20	.01
Plant C	-.15 E-2 (.01)	1.09 (.37)	.143 E-2 (.14)	.382 E-3 (.18)	-.013 (.54)	.07	-.06
Percent Off-Quality							
Plant A	.042 (.29)	-3.37 (1.46)	-.010 (.60)	-.011 (2.86)**	.029 (.73)	1.96	.06
Plant B	-.266 E-2 (.04)	-1.72 (.93)	-.217 E-2 (.34)	.954 E-3 (.79)	-.013 (.92)	.76	-.02
Plant C	-.981 E-2 (.07)	-2.83 (.90)	.032 (2.96)**	.149 E-2 (.66)	.031 (1.21)	2.99 *	.11

Absolute t-statistics in parentheses; N=63 for all plants and all performance measures, except TFP for Plants B (N=50) and C (N=48).
** = significant at 1%, one tail
* = significant at 5%, one tail

(1) The results are substantially unchanged using the alternative definitions of a product.

TABLE 6

Product Mix Heterogeneity and Total Factor Productivity:
The relation of TFP to capacity utilization, setups and product mix heterogeneity

Seemingly Unrelated Regression Results

	Plant A	Plant A	Plant A	Plant B	Plant B	Plant B	Plant C	Plant C	Plant C
c	.868 (113)**	.868 (120)**	.868 (118)**	.926 (170)**	.924 (191)**	.925 (185)**	.920 (125)**	.919 (123)**	.920 (129)**
excess capacity	-.428 (3.59)**	-.441 (3.47)**	-.404 (3.57)**	-.122 (.63)	-.378 (1.98)*	-.411 (2.19)*	-.343 (2.10)*	-.260 (1.52)	-.293 (1.82)*
Major Setup	-.96 E-3 (1.06)	-.69 E-3 (.78)		-.12 E-2 (2.06)*	-.12 E-2 (2.20)*	-.14 E-2 (2.56)*	-.19 E-2 (3.47)**	-.19 E-2 (3.28)**	-.19 E-2 (3.45)**
Minor Setup	.46 E-3 (2.17)*	.47 E-3 (2.27)*	.42 E-3 (2.09)*	.94 E-4 (1.00)	-.34 E-4 (.34)		.19 E-3 (1.73)*	.20 E-3 (1.95)*	.20 E-2 (1.89)*
Product Variety:									
Raw Material Variety					-.030 (1.27)	-.041 (2.11)*		.088 (.39)	
Fabric Weight Variety		.214 (.69)			-.138 (.81)			.015 (.14)	
Expected Downtime		-.303 (.87)			.877 (1.53)			-.026 (.27)	
Warp Beam Variety		-.030 (.87)			.403 (1.97)*	.492 (2.84)**		.019 (.12)	
Fill Thread Variety		-.108 (.33)			-.173 (1.00)			.050 (.35)	
Defect Tolerance		-.199 (1.09)			.366 (1.63)	.190 (1.13)		.186 (.74)	
Warp Thread Variety		-.348 (1.86)*	-.408 (2.72)**		-.074 (.37)			-.368 (1.89)*	-.292 (1.94)*
F-Statistic	6.69**	3.07**	8.65**	1.63	1.78	2.89*	7.37**	2.31*	6.31**
Adjusted R^2	.22	.23	.27	.05	.17	.20	.29	.22	.31

N=63 Plant A, N=50 Plant B and N=48 Plant C, absolute t-statistics in parentheses
** indicates significant at 1%, one-tail
* indicates significant at 5%, one-tail

TABLE 7

Product Mix Heterogeneity and Weaving Efficiency:
The relation of weaving efficiency to capacity utilization, setups and product mix heterogeneity

Seemingly Unrelated Regression Results

	Plant A	Plant A	Plant A	Plant B	Plant B	Plant B	Plant C	Plant C	Plant C
c	.075 (.49)	-.008 (.07)	-.069 (.50)	.003 (.03)	-.060 (.66)	-.020 (.22)	-.004 (.03)	.004 (.03)	.042 (.34)
excess capacity	-1.93 (.86)	1.62 (.79)		1.80 (.70)	1.75 (.74)		.810 (.30)	.810 (.30)	
Major Setups	-.01 (.59)	.84 E-2 (.60)		.010 (1.18)	.012 (1.51)	.012 (1.46)	.11 E-2 (.10)	-.32 E-2 (.33)	
Minor Setups	-.32 E-2 (.79)	-.26 E-2 (.80)		-.23 E-3 (.14)	-.52 E-3 (.32)		.16 E-3 (.08)	.65 E-3 (.35)	
Product Variety: Raw Material Variety					.380 (1.10)			-2.68 (1.18)	
Fabric Weight Variety		4.19 (.84)			-3.76 (1.41)	-5.54 (2.18)*		-2.42 (1.35)	-3.11 (1.79)*
Expected Downtime		-12.5 (2.24)*	-20.0 (3.64)**		-6.32 (1.17)			-.954 (.58)	
Warp Beam Variety		-3.17 (1.38)			-3.93 (1.75)			-3.13 (1.20)	
Fill Thread Variety		2.33 (.44)			-2.42 (.71)			-3.50 (1.51)	-3.45 (1.59)
Defect Tolerance		-4.43 (1.52)	-6.43 (2.07)*		7.07 (1.85)*	6.69 (1.99)*		7.15 (1.63)	
Warp Thread Variety		3.27 (1.10)			-5.00 (1.12)			-6.40 (2.13)*	-4.07 (1.72)*
F-Statistic	.66	1.60	7.51**	.57	1.49	3.31**	.02	1.18	2.67
Adjusted R^2	-.02	.08	.17	-.02	.07	.10	-.05	.03	.07

N=63 for all plants, absolute t-statistics in parentheses
** indicates significant at 1%, one-tail
* indicates significant at 5%, one-tail

TABLE 8

Product Mix Heterogeneity and Off-Quality Output: The relation of Off-Quality output to capacity utilization, setups, sources of expected off-quality output, and product mix heterogeneity

Seemingly Unrelated Regression Results

	Plant A	Plant A	Plant B	Plant B	Plant B	Plant C	Plant C	Plant C
c	-.036 (.31)	-.051 (.44)	-.009 (.12)	-.040 (.58)	-.013 (.19)	-.002 (.01)	-.004 (.03)	.00 (.00)
excess capacity	-2.88 (1.26)	-2.84 (1.13)	-1.43 (.80)	-1.40 (.79)		-2.25 (.72)	-2.66 (.85)	
Expected Off Quality:								
Major Setups	-.018 (1.30)	-.023 (1.61)	-.19 E-2 (.32)	-.17 E-2 (.29)		.036 (3.02)**	.032 (2.57)**	.034 (3.09)**
Minor Setups	-.010 (3.14)**	-.010 (2.95)**	.90 E-3 (.76)	.48 E-3 (.39)		.21 E-2 (.95)	.15 E-2 (.68)	
Average Expected Downtime	13.1 (2.15)*	12.6 (1.72)*	2.96 (.89)	5.61 (1.09)	4.40 (1.35)	1.93 (.75)	-5.04 (1.00)	
Average Warp Beam	6.15 (2.11)*	4.59 (1.24)	-.75 (.36)	1.91 (.73)		.69 (.25)	-.71 (.21)	
Average Defect Tolerance	5.93 (5.41)**	6.00 (4.56)**	2.90 (2.15)*	3.81 (2.03)*	3.35 (2.48)**	-1.38 (.46)	-2.51 (.73)	
Product Variety:								
Raw Material Variety				-.059 (.20)			-.91 (.33)	
Fabric Weight Variety		-2.93 (.52)		1.88 (.85)			-1.08 (.48)	
Expected Downtime Variety		.861 (.14)		-4.15 (.70)			5.92 (1.63)	1.78 (1.13)
Warp Beam Variety		-.68 (.27)		-.93 (.51)			.88 (.26)	
Fill Thread Variety		7.70 (1.33)		-2.32 (.73)			2.95 (1.07)	
Defect Tolerance Variety		1.05 (.30)		1.50 (.43)			-5.06 (.93)	
Warp Thread Variety		-.809 (.24)		-6.76 (1.79)*	-4.96 (1.59)		1.26 (.34)	
F-Statistic	6.30**	3.07**	.98	.85	2.64*	1.78	1.16	5.16**
Adjusted R^2	.34	.28	.00	-.03	.07	.07	.03	.12

N=63 for all plants, absolute t-statistics in parentheses
** indicates significant at 1%, one-tail ; * indicates significant at 5%, one-tail

Figure 1
Seven Forms of Product Mix Heterogeneity, 1986-90

Plots of the standard deviation of factor scores for products produced at time t, from 1986 to 1990

Figure 1.a

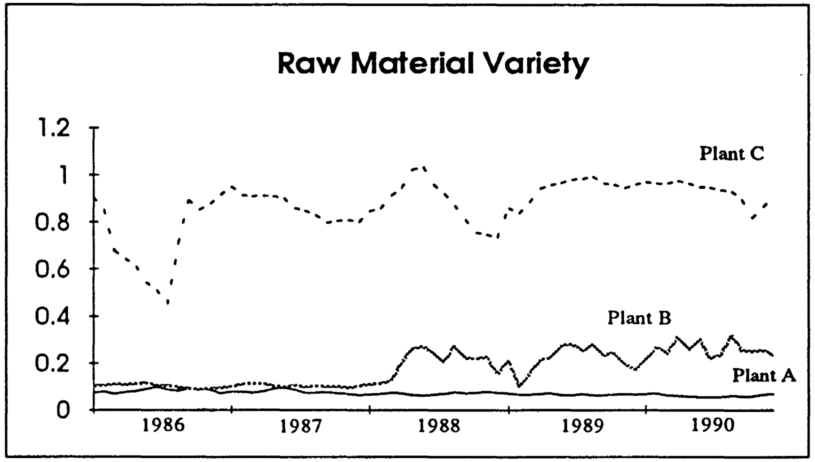

Figure 1.b

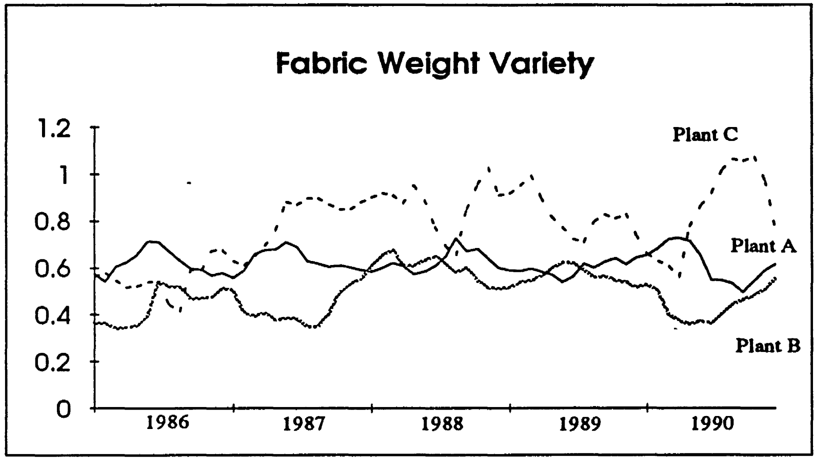

Figure 1.c

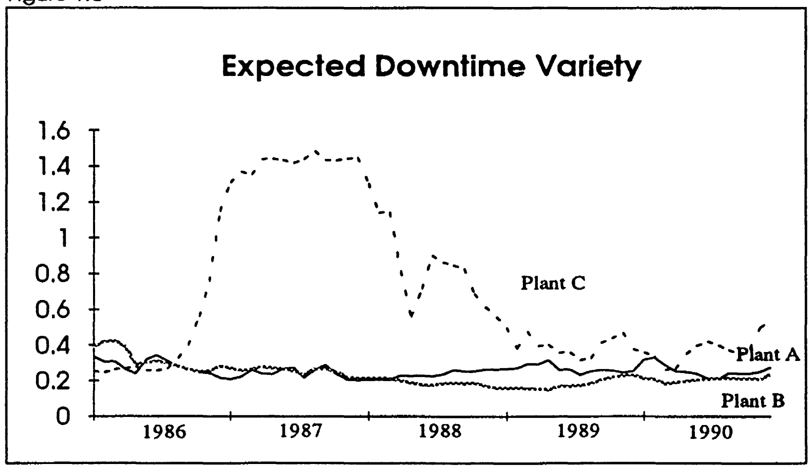

Figure 1.d

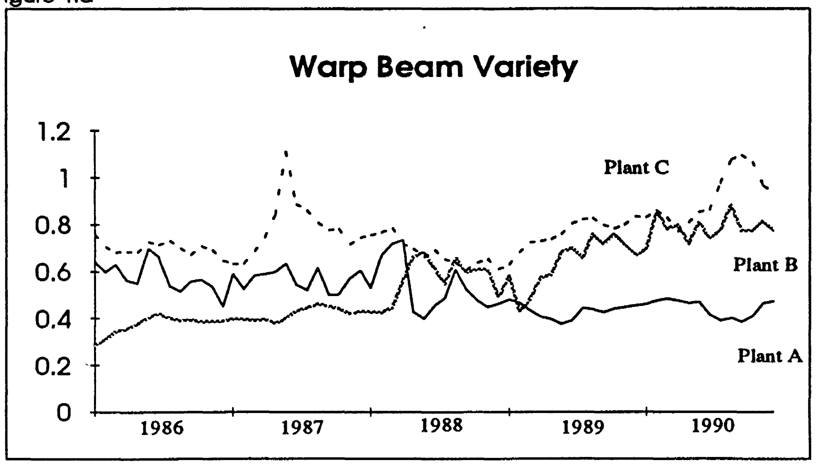

Figure 1 (continued)

Figure 1.e

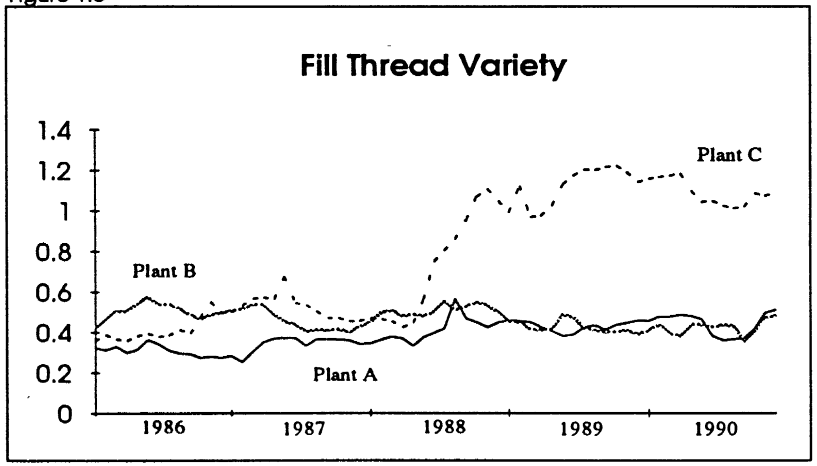

Figure 1.f

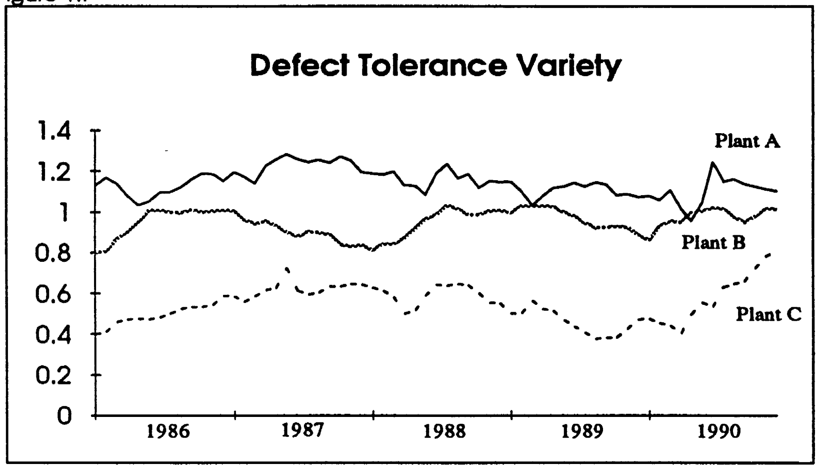

Figure 1.g