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Direct and Indirect Effects of Product Mix Characteristics on Capacity Management Decisions and Operating Performance

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Abstract. Studies of the performance effects of product mix complexity typically treat plant capacity utilization and machine scheduling (for example, setup frequency) as exogenous factors associated with technology choices, economies of scale, and the level of market demand. However, capacity utilization and machine scheduling also reflect tactical operating decisions taken by local managers to maximize short-run performance. If managers rationally anticipate a negative relation between performance and product mix complexity, we expect tactical operating decisions to be used to mitigate performance degradation. Previous empirical studies that ignore this simultaneity provide an incomplete assessment of the performance effects of product mix complexity. This paper uses path analysis to examine the combined impact of product mix on capacity management decisions and operating performance in three textile manufacturing plants. The results support the hypothesis that product mix acts through capacity management decisions to reduce performance from the level implied by direct effects alone. The evidence also supports the behavioral proposition that managers use capacity management decisions strategically—creating production slack when product mix is anticipated to most affect performance. However, although managers use discretionary capacity management intensively when the product mix is composed of complex, heterogeneous products, they are unable or unwilling to use these decisions to fully offset the performance impact of product mix.

Key Words: capacity utilization, complexity, economies of scope, machine setups

1. Introduction

In surveys, U.S. and Japanese manufacturing managers assert that product mix flexibility is the most critical manufacturing capability (Stewart, 1992; DeMeyer, Nakane, Miller, and Ferdows, 1989; Slack, 1987). Product mix flexibility is the 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). Research suggests that flexibility is difficult to achieve—that it is more common for performance to decline with a changing mix of heterogeneous products. The root cause of performance degradation is heterogeneity in production activities that disrupts learning, creates complex material and information flows, and precipitates complex scheduling and capacity management problems (see Skinner, 1974; Panzar and Willig, 1977, 1981; Hayes and Wheelwright, 1984; Hill, 1985; Miller and Vollmann, 1985; Johnson and Kaplan, 1987; Cooper and Kaplan, 1987; Karmarkar and Kekre, 1987; Kekre, 1987; Banker, Datar, and Kekre, 1988; Cooper, 1990; Suarez, Cusumano, and Fine, 1996). This paper focuses on the scheduling and capacity management problems that arise when a complex, changing mix of products is produced.

Specifically, I hypothesize that managers anticipate the negative performance impact of a complex product mix and use discretionary scheduling and capacity management decisions to offset some of these anticipated effects.

The empirical literature on the effects of product mix on performance spans the fields of operations management, management accounting, and corporate strategy and can be separated roughly into two research streams that consider somewhat different research questions. The first research stream examines whether product mix heterogeneity is associated with a performance tradeoff. Early studies yielded mixed results. Hayes and Clark (1985) and Foster and Gupta (1990) present contradictory evidence using plant-level data. Kekre and Srinivasan (1990) and Brush and Karnani (1996) analyze industry-level data and conclude that product mix heterogeneity does not increase costs or reduce productivity. More recent studies that employ refined measures of product mix characteristics, more detailed performance data (for example, cost, quality, productivity, and flexibility), and research sites with common production economics provide more consistent evidence that product mix heterogeneity is negatively related to performance (Banker, Datar, Kekre, and Mukhopadyay, 1990; Banker and Johnston, 1993; Datar, Kekre, Mukhopadhyay, and Srinivasan, 1993; Anderson, 1995; Banker, Potter, and Schroeder, 1995; Cooper, Sinha, and Sullivan, 1995; Ittner and MacDuffie, 1995; MacDuffie, Sethuraman, and Fisher, 1996; Fisher and Ittner, 1999). An exception is Suarez et al. (1996), who find an insignificant univariate correlation between product mix flexibility and either cost or quality for 31 printed circuit board assembly plants. An important caveat in interpreting these results is that it is a cross-sectional study that examines differences between plants rather than performance variation within plants. A possible explanation for why product mix is unrelated to performance is that plants employ somewhat different business processes that are economical for different, correctly anticipated product mixes. In empirical research this is known as a problem of endogeneity (Ittner and MacDuffie, 1995; Fisher and Ittner, 1999).

The likelihood of joint optimization of business processes and product mix motivates a second research stream that examines whether the structure, infrastructure or managerial policies of plants that choose to produce broad, changing mixes of products differ systematically from that of more focused plants. In a study of 54 plants in the paper industry, Upton (1997) finds that management practices and attitudes toward flexibility are significantly related to whether a broad range of products is produced, regardless of technology or infrastructure investments. Similarly, Suarez et al. (1996) find that management practices related to supplier relationships and employee involvement in problem solving are positively related to mix flexibility, while technology investments are negatively related to mix flexibility. The joint selection of business processes and product offerings that these empirical studies document is modeled in papers such as Vander Veen and Jordan (1989), Benjaafar and Gupta (1998), and Gupta and Srinivasan (1998).

A limitation of the second research stream is that the decisions that have been considered as joint—the breadth of the product offering and the organizational structure and infrastructure—are all typically long-term decisions. A question that has not been addressed is how short-term, tactical operating decisions are affected by realized demand for a mix of different products. Specifically, what are the implications of managers anticipating the

negative performance effects of a complex product mix that are documented in the first research stream? In the operations literature, the hierarchy of capacity management decisions includes *strategic* decisions about the size, location, and capabilities of manufacturing plants and *tactical* decisions related to assigning orders to plants and scheduling production on specific machines (Vollmann, Berry, and Whybark, 1992). Strategic capacity management decisions are long-term decisions made by top managers. Tactical capacity management decisions are made by central staff members and local managers. Central schedulers assign orders between plants of similar capability and remaining tactical decisions are delegated to local managers. Thus, strategic and tactical capacity management decisions reflect endogenous choices that are linked integrally to the firm's product offering (Mazzola and Schantz, 1995, 1996). I hypothesize that plant managers who have little control over realized demand and strong motivations to maximize short-run performance (as defined by firm-specific performance measurement systems), use tactical operating decisions to mitigate the performance effects of a complex product mix.

Failure to consider jointly the impact of product mix on tactical operating decisions and performance also highlights a limitation in the first research stream. These studies commonly use measures of plant size, capacity utilization, and product mix composition to control for exogenous factors that influence performance such as economies of scale, market demand, and task difficulty. However, this specification ignores the possibility that these measures also reflect endogenous tactical operating decisions that may be influenced by the same product mix variables that are hypothesized to affect performance. Endogeneity can lead to misinterpretation of statistical results and misstatement of the full effects of product mix on performance. For example, strategic decisions to invest in flexible equipment and organizational structures are based on the firm's anticipated product mix. For firms that make these investments, the costs of producing a complex mix of heterogeneous products are borne before production commences, and as a result, cross-sectional empirical studies find few contemporaneous effects of product mix on performance. It is equally problematic to assume that tactical capacity management decisions are not influenced by product mix in studies using longitudinal data. Indeed, the problem of endogeneity is greater because local managers charged with tactical capacity management decisions are accountable for performance and are motivated to use discretionary decisions to mitigate anticipated performance effects of product mix. Studies that use tactical capacity management variables to control for supposedly exogenous performance effects misstate the total effect of product mix on performance by attributing some of these effects to exogenous factors.

This article uses path analysis to examine: (1) whether product mix heterogeneity and composition are significantly related to capacity utilization and machine setups, together termed "capacity management decisions," as well as performance, and (2) whether the product mix, acting through capacity management decisions, exerts significant indirect effects on performance. Figure 1 depicts the hypothesized structural model. The results support the hypothesis that local managers make tactical capacity management decisions based on product mix characteristics. Specifically, product mix composition and heterogeneity are related significantly to underutilization of capacity and to the frequency and severity of machine setups. The indirect effect of product mix, acting through capacity

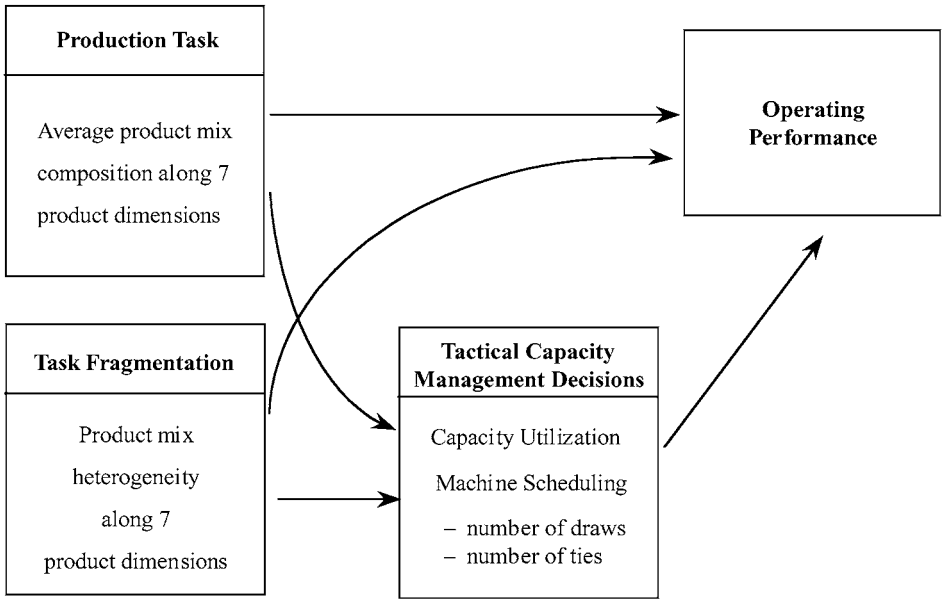


Figure 1. Hypothesized structural model of the relation between product mix characteristics, tactical capacity management decisions and operating performance.

management decisions, is to significantly reduce operating performance; thus estimates of the direct effect of product mix characteristics on performance misstate the total effect of the relationship.

I also examine whether managers use discretionary capacity management decisions strategically. Capacity management decisions allow managers to create organizational slack in anticipation of production problems associated with complex, heterogeneous product mixes. Managers naturally limit the use of capacity management because it requires costly managerial effort and because top managers retain oversight of capacity management decisions. Thus, managers use these decisions judiciously to maximize performance across competing priorities, subject to technological constraints and taking as given the mix of products sold by a separate sales organization. The results indicate that the degree to which product mix characteristics influence the level of underutilized capacity and the frequency and severity of machine setups is inversely related to actual performance. This suggests that managers manage capacity utilization and machine scheduling most intensively when the product mix is anticipated to impair performance, but that they are unable or unwilling to fully compensate for the direct effects of product mix on performance.

The article is organized in five sections. Section 2 describes the research sites and Section 3 develops the variable measures. Section 4 presents the empirical results of testing the hypothesis that short-term tactical operating decisions are influenced by product mix characteristics. Section 5 summarizes the key results, discusses limitations of the study, and identifies directions for future research.

2. Description of the research sites

The combined impact of product mix on capacity management decisions and operating performance is examined using data from three textile manufacturing plants of a single firm. The research sites are those used by Anderson (1995) to examine a specific proposition from the activity-based costing literature; namely, that one category of costs—variable manufacturing overhead costs—are related positively to product mix heterogeneity. Anderson demonstrates that the measure of product mix complexity most commonly used in the empirical literature, the number of product produced, is a poor measure of the heterogeneity that activity-based costing posits to affect cost. Problems with variable measurement may explain the failure of some studies to detect a relation between costs and product mix. Although the product mix heterogeneity variables developed by Anderson (1995) are also used in this study, this paper focuses on performance measures that are used by top managers to evaluate local plants (overhead costs are not *per se* a basis of evaluation) and investigates a different research question—whether capacity management decisions and performance outcomes are co-determined by product mix.

Data on product mix, capacity management, and operating performance were collected from the three weaving plants (referred to as A, B, and C) for the period 1986–1990. Several weeks were spent in each plant over a two-year period collecting data and interviewing managers and production workers. Although the plants produce different products and experience different degrees of product mix heterogeneity, they share common production technologies and plant scale (for example, identical make and vintage equipment), similar workforces (for example, similar mean age, job tenure, absenteeism, and turnover, and all are nonunionized plants), and similar management practices (for example, company workforce policies limit managers' ability to layoff workers during periods of reduced demand). (See Anderson, 1995 for additional description of the research sites.)

Weaving is the process of interlacing lengthwise warp yarns and crosswise fill yarns at right angles. Prior to fabric production, warp yarns are wound onto a metal core, called a warp beam. The warp beam is mounted in a loom and warp threads are threaded through the machine in a process known as drawing. 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 tying. Machine-level production scheduling and the implied frequency with which warp beams are setup through drawing rather than tying are major issues in managing plant capacity utilization. Production schedulers trade-off the ability to deliver a large order quickly (possible if many machines produce the product and warp beams are drawn) against the opportunity to reduce setup time and capacity losses (possible if batches are run in sequence on a single machine with warp beams tied to one another). Finished fabric is wound onto a cloth beam, inspected offline, packed, and shipped to a finishing plant.

Plants A, B, and C specialize in products made of raw material inputs 1, 2, and 3, respectively. Plant C also produces products made of raw material inputs 1 and 2 when doing so helps balance capacity utilization across the plants. Focusing each plant on products made from one raw material input is a strategic capacity management decision aimed at limiting plant-level product mix heterogeneity. Nonetheless, during 1986–1990 the number

Table 1. Descriptive statistics for plant product mix.*

Panel A: Average product mix breadth. The average number of products, defined as unique warp and fill thread combinations, produced in the 13, four-week production periods of 1986–1990.

	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 B: 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 by the average number of products produced in a four-week period.

	Number of products 1986–1990	Average number of products/period	Product mix turnover
Plant A	162	34	4.8
Plant B	237	44	5.4
Plant C	404	53	7.6

*Reprinted from Anderson (1995).

of products produced in each four-week period increased and the stability of the product mix from period to period decreased (Table 1). Throughout the article a production period is four weeks. Each calendar year includes 13 periods and the study encompasses five years, or 65 periods. Growth in the number of products produced over the five years provides a crude approximation of increasing product mix heterogeneity. Controlling for minor differences in plant scale, Panel A of Table 1 provides descriptive statistics on the average number of different fabrics (defined as a unique warp and fill thread combination) produced during the period. Consistent with managers' beliefs, product mix heterogeneity increased in all of the plants. A crude measure of product turnover, computed by dividing the total number of products produced in five years by the average number of different products produced in each four-week period, indicates change in composition of the product mix (Panel B, Table 1). Product mix change occurred in all of the plants; however, consistent with its role in balancing capacity, Plant C was marked by more change than either A or B. Plant C produced 7.6 entirely different product portfolios from 1986 to 1990. In contrast, Plants A and B produced 4.8 and 5.4 product portfolios in the same period.

Although the plants had similar production equipment, capacity utilization differed. Plant A experienced four periods during which utilization dropped below 60% and utilization was erratic over time. Utilization at Plants B and C rarely dropped below 80% and exhibited smooth transitions over time. In part these differences reflect underlying demand for products made of inputs 1, 2, and 3. However, capacity utilization and machine-level production schedules (for example, the number of looms assigned to produce an order, the setup type and the setup frequency) also reflect operating decisions aimed at producing a given set of orders with the highest possible performance. These tactical capacity management decisions are based on knowledge of the quantity and mix of products demanded and on managers' expectations about the impact of product characteristics on manufacturing performance.

A challenge of field-based research is finding sites that differ in the variable being studied but are similar along other dimensions. For the period under consideration, there is little distinction between or within the plants along dimensions known to affect operating performance, including employee skills and work practices, equipment age and type, and plant facilities and infrastructure. In interviews, managers indicated that no plant received resources aimed at equipping it to better cope with complex, heterogeneous products. Despite these similarities, the plants' product mixes differed in complexity and heterogeneity and, in part because of differences in market demand for their products, the plants operated at different levels of utilization. Thus, the sites are suitable for investigating the research questions.

3. Measurement of variables

3.1. Product mix composition and heterogeneity

Measures of product characteristics are developed by Anderson (1995). Briefly, factor analysis is used to reduce 22 engineering parameters that describe warp and fill threads, warp beam and fabric construction, and process settings of the 700+ products produced by the plants during 1986–1990 to seven orthogonal dimensions that uniquely define woven fabrics (Rummel, 1970). The resulting factors are interpreted based on parameters that weigh heavily in the factor solution and process information gathered in field research. The seven dimensions, in order of decreasing eigenvalues (all > 1.0), are as follows:

Raw material content. The factor that explains the greatest variation between products reflects raw material content (input 1, 2, or 3). Consistent with the factory focus strategy, products produced in Plants A and B are clustered in different segments of the raw material scale while products produced in Plant C span the scale and include those of Plants A and B.

Fabric weight. This factor is influenced by the weight of a linear yard of fabric, which in turn is correlated to 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.

Expected machine downtime. This factor distinguishes products based on engineering specifications for process settings, including the rated machine efficiency and expected machine stop level. A critical source of downtime is warp thread breakage. The expected machine stop level, expressed as breaks per 100,000 picks, reflects the expected rate of thread breakage for a given loom speed. Thread breakage can be reduced by treating warp threads with chemicals or by slowing the loom. Consequently, thread thickness, chemical treatment, and process speed are related to this factor.

Warp beam construction. This factor reflects construction of the warp beam from warp threads. Thread length, machine speed, and fabric density determine the throughput time for a typical production run. Physical dimensions of the loom limit the diameter of a full warp beam. Given the permissible beam diameter, thread lengths are determined by

thread thickness and the number of threads on the beam. Limitations on cloth beam size, in conjunction with warp beam dimensions, determine the frequency with which finished fabric is removed from the loom.

Fill thread construction. This factor reflects thickness, twist, and finishes applied to fill threads.

Defect intolerance. This factor reflects customer quality standards (major and minor flaws per unit length of fabric). A high factor score indicates high quality standards, or defect intolerance.

Warp thread construction. This factor reflects thickness, twist, and finishes applied to warp threads.

Using factor scores for the 700+ products, two measures are derived for each of the seven dimensions: (1) measures of task difficulty that reflect the average composition of the product mix; and (2) measures of task fragmentation that reflect heterogeneity of the product mix. Product mix composition is defined as the weighted average of the factor scores of products produced in the four-week production period. Product mix heterogeneity is defined as the standard deviation of factor scores of products produced in the period, weighted by the machine hours that the product consumed.

3.2. Capacity management decisions

Plant managers at the research sites make two types of tactical capacity management decisions: plant-level equipment utilization and machine-level scheduling. Three variable measures capture these decisions. The first variable is a plant-wide measure of underutilized equipment (EXCESS CAPACITY), calculated as one minus the expected machine utilization. Expected utilization is the sum of standard machine hours required to produce a given product mix (including machine setup time) divided by the total machine hours available. Available machine hours are the number of looms in the plant multiplied by the hours in the four-week production period (typically 24 hours $\times$ 28 days). During the study period, the mean underutilization was 14%. A limitation of the underutilization measure is the focus on production equipment. Underutilization of other inputs may also reduce the impact of product mix on operating performance; however, existing plant records provide no means of measuring utilization of other inputs.

The second and third capacity management variables, which measure machine-level scheduling decisions about the frequency and severity of setups, are the number of draws (MAJOR SETUPS) and ties (MINOR SETUPS) performed during the production period. Ties generate small utilization and material losses; however, they require that looms be dedicated to products made from a single warp beam. Draws create large utilization and material losses, but are necessary if a loom is to make products from different warp beams. The number of draws performed in a four-week production period ranges from 20 to 114 with a mean of 59. The number of ties performed in a period ranges from 178 to 938 with a mean of 422.

Although utilization and scheduling are influenced by market conditions (for example, it is not possible to fully utilize equipment when there is no demand for products), we

have no separate measure of market demand. As a result, while we hypothesize that product mix characteristics influence capacity management decisions, we do not expect these variables to fully explain capacity utilization or machine setups. While market demand is an omitted variable, it is not anticipated to create biased or inefficient coefficient estimates because the level of market demand is not obviously correlated with product mix characteristics.

3.3. Operating performance

Previous studies examine the impact of product mix on a variety of performance measures, including cost, labor productivity, product quality, and process reliability. Most studies examine only one measure of performance, with a few recent studies examining several aspects of performance. Even in these cases, separate analysis of the relation between product mix and each performance measure is performed. The likelihood of correlated performance measures makes it difficult to determine whether a significant relation between a product mix characteristic and two different performance measures reflects a common effect. Similar to Suarez, Cusumano, and Fine's (1996) approach for defining measures of flexibility, this paper uses principal component analysis to reduce the set of related performance measures to two independent performance dimensions (Rummel, 1970).

Because we hypothesize that the motivation to manage capacity utilization and machine setups stems from efforts to maximize short-term performance measures that are used in managerial evaluation, we focus on performance measures that are used in this manner. In the research firm, top management conducts monthly reviews of plant performance, during which plant managers present data on product quality, production efficiency, cost control, capacity utilization, machine setups, and human resource management (for example, absenteeism, turnover, and safety). (Measures of order lead times and completion timeliness are not among the firm's performance measures and thus are not examined as performance measures that managers would overtly seek to manage. Clearly these could be important performance measures in a different research setting. Even in this setting performance timeliness may be related to product mix characteristics; however, no data on this aspect of performance are available.) It is important to note that top management retains oversight of the tactical capacity management decisions that we investigate (for example, utilization and setups). Thus although I hypothesize that managers use these decisions to manage performance, I am not suggesting that local managers "fool" top management or that these are "bad" decisions. Indeed, within limits, the wisdom of using capacity management decisions to mitigate the impact of product mix on performance is considered good management. For the period of study, the data on human resource management do not differ among the plants; consequently, these performance data are not considered. The remaining performance data are described below.

3.3.1. Product quality. The firm calculates two related measures of product quality: (1) the percent of off-quality fabric based on square yards of flawed output compared to total square yards produced (PCTOQYDS); and, (2) the percent of off-quality fabric based on the standard cost of flawed output compared to the standard cost of all output (PCTOQVAL).

The first measure reflects the volume of output that is unfit for sale at full price and the second measure reflects the cost of output that is unfit for sale at full price. These measures differ because fabrics produced at lower machine speeds or made of thinner threads generate few yards of output but typically have high standard costs of production.

3.3.2. Production efficiency. Production efficiency measures the degree to which the plant operates according to expectations, as defined by engineering standards. Plant engineers calculate expected output per machine hour, or "rated efficiency," for each product. Production efficiency (PCTEFFIC) is calculated as the actual machine hours consumed in a period divided by the standard allowable machine hours for the product mix. Machine downtime associated with setups is excluded from machine hours consumed in production, but downtime caused by equipment failures, thread breakage, or routine machine cleaning is included. Capacity utilization is also excluded because production efficiency is calculated only for machines scheduled for operation. Machines idled by reduced demand or scheduling decisions do not affect the efficiency measure.

3.3.3. Productivity indices. Productivity is a measure of the effectiveness with which inputs are transformed to outputs. Previous studies have considered the impact of product mix on direct labor productivity (MacDuffie et al., 1996; Fisher and Ittner, 1999). Direct labor is only one input to the production process and is often a small share of production costs. I consider four inputs, capital, energy, labor (direct and indirect), and direct materials, that together account for more than 95% of production costs. Partial productivity indices for each (CPROD, EPROD, LPROD, MPROD) are calculated as the sum of period output, valued at standard cost, divided by the input quantity, valued at the 1990 standard price (or wage). Input quantities are weighted by 1990 standard price to facilitate comparison between the four productivity indices and to allow interpretation of the indices as a crude measure of the inverse of the factor's share of total value added. Partial productivity indices are used rather than a single, aggregate measure of total factor productivity because inputs may exhibit different relations to quality and efficiency and because the partial productivity measures suffer to a different degree from measurement error.

Data for constructing the indices are from archival accounting and production 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:

Labor. The sum of direct and indirect hourly labor and salaried labor measured as

(i) *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.
(ii) *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.

Materials are typically issued to production in advance of realized output in processes with lengthy throughput times. In constructing the material productivity index, the average material throughput rate for each of three categories of raw materials is used to correct this temporal mismatch between material inputs and output.

Energy. Kilowatts of electricity and gallons of water consumed multiplied by the average 1990 price. A characteristic of the process technology is that the energy to operate a loom does not differ greatly from the energy to maintain an idle (but not unpowered) state. The only reason that looms are disconnected from the power source is to perform major repair and maintenance that requires disassembly.

Capital. The period capital stock (determined from the 1990 replacement value of assets and the record of asset acquisitions and disposals from 1986 to 1990) multiplied by the sum of the depreciation rate and the firm's cost of capital (Hall and Jorgenson, 1967). Straight line depreciation methods are applied to engineering estimates of the useful lives of the equipment, building, and infrastructure.

3.4. Summary measures of operating performance

The seven performance measures are all somewhat imperfect, either by construction or as a result of data limitations; however, together they capture with varying degrees of precision elements of operating performance used to evaluate plant managers. They are not independent performance assessments; consequently, as in Suarez et al. (1996), principal component analysis is used to reduce the seven measures of product quality, production efficiency, and cost control to two orthogonal performance dimensions. Principal component analysis is preferred to factor analysis because I want to explain the dimensionality of the total variance exhibited by the measures. Common factor analysis assumes that each variable comprises variance that is common to all variables and variance that is unique to a particular variable and seeks to explain only the dimensionality of the common variance (Rummel, 1970, p. 112). Moreover, principal component analysis does not assume causal structure between observed variables and unobserved latent constructs; it is simply a data reduction method (Hatcher, 1994, pp. 9–10). Table 2 reports the component matrix obtained by performing principal component analysis on the raw performance data, pooled across plants. Two components with eigenvalues greater than one explain 72.4% of the variance in the seven measures. These components, described below, are used in the empirical analysis to assess the joint impact of product mix characteristics on capacity management decisions and operating performance.

The first component is negatively related to both measures of quality and positively related to capital and energy productivity. Correlation between relatively fixed inputs, such as capital and energy, and off-quality output is assured because output (the numerator of the productivity indices) includes only high quality output while capital and energy inputs are expended in the production of both high and low quality output. This relation is not observed with the same intensity for labor productivity because the largest component of off-quality fabric is produced during and immediately following machine setups, which are done by indirect hourly workers. Indirect labor is a relatively small portion of total labor. Standard material costs include allowances for expected losses associated with setups

Table 2. Principal component analysis of operational performance measures.

	Rotated* component matrix	
	Factor 1	Factor 2
Performance measurement variable		
PCTOQVAL	−0.924	0.009
PCTOQYDS	−0.926	0.134
CPROD	0.853	0.183
EPROD	0.936	0.009
LPROD	0.196	0.894
MPROD	0.376	0.239
PCTEFFIC	−0.125	0.794
Initial eigenvalues	3.529	1.54
Percent of variance explained	50.4	22.0
Assigned component name	HIQUALITY	EFFICIENT

PCTOQVAL: Percent of off-quality fabric value based on standard cost of all production.
PCTOQYDS: Percent of off-quality fabric yards based on total yardage produced.
CPROD: Partial productivity of invested capital.
EPROD: Partial productivity of energy expenditures.
LPROD: Partial productivity of labor (direct and indirect hourly workers and salaried workers).
MPROD: Partial productivity of direct material.
PCTEFFIC: Percent of standard output achieved in given production hours.
*Rotation Method = Varimax with Kaiser normalization. Rotation converged in three iterations.

and anticipated downtime; thus, these losses are not penalized in the material productivity measure. The material productivity measure penalizes only unexpected quality losses, while the product quality measures penalize both expected and unexpected quality losses. The material productivity loading (0.376) reflects unexpected quality losses that are common to these measures. The first component is labeled "HIQUALITY," to reflect the relations among the seven performance measures in the component matrix.

The second component is positively related to labor productivity and production efficiency. The other performance measures are not associated significantly (conventionally defined as a component loading >0.40) with the second component. Although total labor costs are largely fixed within the plant, labor is the most mobile input available to managers to counteract adverse performance effects of product mix characteristics. Direct labor works in teams to operate groups of looms. Loom operation does not require constant intervention of a worker, consequently workers devote more or less time to a loom based on severity of operating problems. Indirect labor is deployed from a single labor pool to assist with equipment problems. In short, the second component, labeled "EFFICIENT," captures the degree to which labor inputs are effectively deployed to ensure that engineering performance standards are met.

4. Empirical results

4.1. Univariate time series properties of dependent and independent variables

Nonstationarity and persistence in time series data can cause spurious correlations to be documented in empirical analyses (Harvey, 1981; McCleary and Hay, 1981). Operating performance and product mix are likely to be nonstationary because production experience and product mix heterogeneity increase over time. Operating performance, capacity management variables, and product mix variables are likely to exhibit persistence because production of a single batch typically spans two production periods. To counter these problems, for each plant the variables are subjected to univariate time series modeling to remove variation that is predictable given the historical pattern of the variable itself. Most of the variables are first-order autoregressive processes and the Box–Jenkins Q-statistics of the residuals of the specified ARIMA models are statistically insignificant, indicating that variation arising from predictable patterns in the variable itself is removed. The resulting residuals of the ARIMA models are pooled for the three plants, yielding 159 observations. The subsequent path analysis assumes that observations are serially independent and analysis of the cross correlations indicates that this is a reasonable assumption.

4.2. Method of analysis

As in Ittner and MacDuffie (1995), path analysis is used to examine the fit of the proposed structural model (Figure 1). The model parameters are estimated using maximum likelihood methods. Empirical standard errors are obtained for the path coefficients and for the total effects of product mix composition and heterogeneity on operating performance using bootstrap methods which do not require distributional assumptions about the data. The model is estimated for 500 random samples (with replacement) of 159 observations each, and the resulting distributions are used to compute bias-corrected confidence intervals for each path coefficient (Stine, 1989).

The full model requires estimating 59 path coefficients, 105 covariances—between each pair of the 14 exogenous variables, and error terms for the four endogenous variables—a total of 168 parameters. The number of data observations ($N = 159$) precludes estimating the full model for each performance measured in a single step. Consequently, as in Suarez et al. (1996) the model is estimated in stages for each of the summary performance measures. In the first stage the model is estimated in two parts to identify paths and covariances between exogenous variables that can be constrained to be zero without loss of information in the second stage of analysis. The first part examines structural relationships between product mix composition, capacity management decisions, and operating performance, excluding product mix heterogeneity. The second part examines structural relationships between product mix heterogeneity, capacity management decisions, and operating performance, excluding product mix composition.

In the first stage, the following are constrained to be zero: (1) one product mix heterogeneity variable (fill thread heterogeneity); (2) five covariances between product mix

characteristics; (3) paths between all but one of the product mix composition variables (fill thread) and the number of major setups; and (4) the path between a measure of product mix composition (fill thread) and underutilized capacity. In total, these modifications reduce the number of estimated parameters to 155. Relaxing these constraints separately does not alter the results of the second stage of the analysis.

4.3. Relation between product mix and tactical capacity management decisions

Tables 3 and 4 present the results of estimating the model for the performance measures, HIQUALITY and EFFICENT, respectively. Overall model fit is good, as demonstrated by a CFI of 0.99 for both models and an adequate root mean standard error of approximation (0.12 and 0.11 for the models presented; 0.10 and 0.08 when clearly insignificant paths are removed and the model is reestimated) (Browne and Cudeck, 1993). The results are discussed in three sections. This section discusses the direct effects of product mix on capacity management decisions. These results are common to both models and are presented separately to avoid repetition. Subsequent sections present evidence on direct and indirect effects of product mix and capacity management decisions on performance.

The first three columns of Tables 3 and 4 present maximum likelihood estimates of the direct effects of product mix composition and heterogeneity on tactical capacity management decisions. Product mix variables explain a significant portion of the variance of underutilized capacity, major setups, and minor setups, as reflected in squared multiple correlations of 0.41, 0.59, and 0.90, respectively. Capacity utilization, which is most affected by market forces outside of managers' control, is least well explained by product mix characteristics. Machine-level setup frequency and type, which are controlled more fully by plant managers, are better explained by product mix variables. These results provide support for the proposition that managers make tactical capacity management decisions with an awareness of the likely performance impact of the realized product mix. We have no hypotheses about the significance or insignificance of particular product mix characteristics. Nonetheless, significant individual coefficients are internally consistent with the broad result that product mix characteristics influence capacity management decisions. The most significant coefficients are discussed below as a means of explaining and providing institutional detail for the broad conclusion, rather than in the spirit of hypothesis testing.

Increases in the average raw material factor score are associated with fewer minor setups. Increases in raw material heterogeneity are associated with increased setups of both types. In its role as the swing plant in the factory focus strategy, Plant C is the only plant that switches between raw materials. As a result, it is likely that observations from Plant C weigh heavily in the estimation of these coefficients; however, this cannot be explored empirically because of data limitations. Raw material is the only product dimension for which changes in composition or heterogeneity are disproportionately present in a single plant. The raw material results are consistent with the distinction between major and minor setups and the mission of Plant C. By definition, changes in raw materials preclude use of the minor form of setup. Consequently, large changes in the average raw material factor

Table 3. Path analysis of the influence of product mix characteristics on capacity management decisions and product quality.

	Maximum likelihood estimates of regression coefficients ($N = 159$) (t-statistic calculated using bootstrap standard errors)				
	Excess capacity	Major setups	Minor setups	Quality performance	*Total effect on quality performance*
Capacity management decisions					
Excess capacity				−2.33 (4.95)***	−2.33 (4.95)***
Major setups				−0.01 (3.00)***	−0.01 (3.00)***
Minor setups				0.00 (1.00)	0.00 (1.00)
Average characteristics of product mix					
Raw material	0.06 (1.29)		−129.3 (2.30)**	−0.32 (1.16)	−0.56 (1.93)*
Fabric weight	−0.21 (3.61)***		228.8 (2.99)***	1.16 (2.80)***	1.85 (4.45)***
Expected downtime	0.16 (1.54)		191.6 (2.09)**	0.92 (1.51)	0.71 (1.14)
Warp beam	0.25 (3.24)***		−6.83 (0.11)	1.98 (4.73)***	1.38 (3.74)***
Fill thread		−8.46 (1.71)*	−189.5 (5.33)***	−0.00 (0.01)	−0.08 (0.40)
Customer defect intolerance	−0.08 (1.32)		−99.1 (2.03)**	−0.47 (2.16)**	−0.37 (1.33)
Warp thread	0.15 (1.10)		−242.1 (2.61)***	0.63 (1.25)	0.09 (0.14)
Heterogeneity of characteristics of product mix					
Raw material	−0.13 (1.30)	45.6 (3.94)***	168.6 (2.28)**	0.03 (0.07)	0.04 (0.08)
Fabric weight	0.19 (1.85)*	17.1 (1.31)	−281.0 (2.56)***	1.12 (2.22)**	0.28 (0.45)
Expected downtime	−0.12 (1.58)	−11.3 (2.72)***	−251.3 (2.93)***	−0.57 (1.04)	−0.41 (0.76)
Warp beam	−0.11 (1.28)	21.3 (1.55)	14.1 (0.22)	−1.16 (2.70)***	−1.08 (1.97)**
Fill thread					
Customer defect intolerance	0.15 (1.19)	32.8 (2.50)**	−71.4 (0.93)	−0.62 (1.33)	−1.33 (2.32)**
Warp thread	0.18 (1.68)*	−7.53 (0.59)	205.3 (2.24)**	0.77 (1.30)	0.61 (1.07)
Squared multiple correlations	0.408	0.590	0.904	0.899	

Note: Darkly shaded cells denote nonexistent paths between endogenous capacity management variables. Lightly shaded cells denote paths between exogenous product mix variables that were determined to be insignificant in unreported partial analyses. To ensure full identification of the model with the given set of data observations ($N = 159$), these paths are not reestimated.

***,**,* Two-tailed probability level, $p < 0.01, 0.05, 0.10$, respectively.

Table 4. Path analysis of the influence of product mix characteristics on capacity management decisions and production efficiency.

	Maximum likelihood estimates of regression coefficients ($N = 159$) (t-statistic calculated using bootstrap standard errors)				
	Excess capacity	Major setups	Minor setups	Efficiency performance	*Total effect on efficiency performance*
Capacity management decisions					
Excess capacity				−4.66 (4.87)***	−4.66 (5.55)***
Major setups				−0.00 (0.50)	−0.00 (0.50)
Minor setups				0.00 (0.10)	0.00 (0.10)
Average characteristics of product mix					
Raw material	0.058 (1.29)		−129.3 (2.31)**	−0.304 (0.51)	−0.71 (1.39)
Fabric weight	−0.213 (3.61)***		228.8 (3.00)***	1.54 (1.92)*	2.77 (3.57)***
Expected downtime	0.157 (1.55)		191.6 (2.10)**	−3.19 (2.54)**	−3.72 (2.89)***
Warp beam	0.253 (3.24)***		−6.83 (0.10)	2.38 (3.32)***	1.19 (1.56)
Fill thread		−8.46 (1.70)*	−189.5 (5.32)***	−0.177 (0.51)	−0.35 (1.12)
Customer defect tolerance	−0.079 (1.32)		−99.1 (2.04)**	0.659 (1.41)	0.924 (1.99)**
Warp thread	0.146 (1.10)		−242.1 (2.61)***	−1.12 (0.87)	−2.05 (1.71)*
Heterogeneity of characteristics of product mix					
Raw material	−0.13 (1.30)	45.6 (3.94)***	168.6 (2.28)**	1.59 (1.71)*	2.25 (2.20)**
Fabric weight	0.19 (1.85)*	17.1 (1.31)	−281.0 (2.56)**	3.06 (3.86)***	1.85 (1.88)*
Expected downtime	−0.12 (1.58)	−11.3 (2.70)***	−251.3 (2.94)***	1.48 (1.29)	1.78 (1.61)
Warp beam	−0.11 (1.28)	21.3 (1.55)	14.1 (0.23)	−2.68 (3.02)***	−2.19 (2.02)**
Fill thread					
Customer defect tolerance	0.15 (0.83)	32.8 (2.50)**	−71.4 (0.94)	0.78 (0.87)	−0.06 (0.06)
Warp thread	0.18 (1.69)*	−7.53 (0.59)	205.3 (2.25)**	−1.66 (1.65)	−2.25 (2.24)**
Squared multiple correlations	0.408	0.590	0.904	0.635	

Note. Darkly shaded cells denote nonexistent paths between endogenous capacity management variables. Lightly shaded cells denote paths between exogenous product mix variables that were determined to be insignificant in unreported partial analyses. To ensure full identification of the model with the given set of data observations ($N = 159$), these paths are not reestimated.

***, **, * Two-tailed probability level, $p < 0.01, 0.05, 0.10$, respectively.

score are associated with fewer minor setups. In summary, the effects of raw material on setups reflect a mix of technological limitations and strategic decisions that reflect the firm's factory focus strategy.

The product characteristic, fabric weight, is related to capacity utilization and to setups. As average fabric weight increases, the frequency of minor setups increases and capacity utilization increases. However, as fabric weight heterogeneity increases, the frequency of minor setups decreases and capacity utilization declines. Unlike fabrics made of thin threads, heavier fabrics give managers the option of using major or minor setups. The results reflect decisions to take advantage of economies made possible by the ability to perform minor setups on heavier fabrics. Minor setups make fewer demands on fixed indirect resources. As a result, a higher level of plant-wide capacity utilization is possible without incurring downtime associated with indirect labor services. Increases in fabric weight heterogeneity decrease the likelihood that the minor form of setup may be employed because tying requires sequential production of identical warp beams, and thus increases the underutilized capacity needed to sustain performance.

Increased expected downtime is associated with increased minor setups. Fabrics with significant expected downtime are made of warp and fill threads that break easily under tension. Threads are coated with chemicals to inhibit thread breakage and the looms are slowed to reduce abrasion. The coating builds up on the loom, which necessitates cleaning the loom before another product is produced. This extra operation adds to the economic incentives that managers have to dedicate a few looms to coated products and to use a series of minor setups to complete large orders. However, it increases order fulfillment time and may not be tenable if customers demand fast deliveries. Heterogeneity of expected downtime for the product mix decreases setup frequency. This result seems to suggest that heterogeneity of expected downtime is associated with unexpected downtime. Unexpected downtime may put the plant behind schedule, and as a result may delay switching to new products, and reduce the number of setups.

Product mixes that are composed of products made from warp beams with heavier, thicker warp threads are associated with higher levels of underutilized capacity. Thick warp threads are typically combined with thick fill threads with the result that finished fabric accumulates more rapidly than it would otherwise. Limitations on the diameter of the beam of finished fabric necessitate frequent beam switching, an operation that requires worker intervention but does not interrupt weaving. If workers must intervene more frequently and the workforce is fixed in size, managers may select a lower level of capacity utilization to ensure an acceptable level of performance.

As the thickness of fill and warp threads decreases, setup frequency decreases. This reflects the basic relationship between machine speed and thread thickness; for a given machine speed, thin threads produce a linear yard of fabric more slowly than thick threads. A disproportionate decline in minor setups reflects technological limitations of the automatic tying process, which cannot be used on thin threads. Fill thread heterogeneity was eliminated in an earlier stage of analysis when it was found to have no relation to the endogenous variables. This absence is not surprising, since replacing an exhausted bobbin of fill thread or switching the fill thread that is woven with a given warp thread is an operation that takes minutes, compared to hours required to switch between warp beams. In contrast,

increased heterogeneity in warp thread thickness is associated with increased minor setups and decreased capacity utilization.

The overall pattern of significant product mix characteristics supports a conclusion that product mix characteristics influence tactical capacity management decisions. Some relationships reflect constraints imposed on machine level scheduling decisions by technology (e.g., thin warp threads cannot use the minor setup approach), while others reflect managerial discretion. The discretionary choices may reflect a manager's desire to maintain an acceptable level of performance given a set of production orders. The next section investigates whether tactical capacity management decisions offset the hypothesized negative performance effects of a complex product mix.

4.4. Relation between product mix, capacity management, and product quality

The fourth column of Table 3 contains estimated coefficients of the direct effects of capacity management decisions and product mix characteristics on quality performance. As indicated by the squared multiple correlation of 0.90, the capacity management and product mix variables explain most of the variation in quality performance. The fifth column contains estimates of the total effects of these variables on quality performance. For the product mix variables, the total effects reflect direct effects on performance as well as the indirect effects of these variables acting through capacity management decisions. I discuss the direct effects of capacity management decisions, and then discuss the direct and indirect effects of product mix on quality performance.

The upper portion of the table indicates that increases in major setups and underutilized capacity are associated with reductions in quality performance. The impact of major setups on quality output is predictable. In a major setup many yards of off-quality fabric are produced during the transition between different products because new machine settings are required. In contrast as few as 12 inches of off-quality fabric may be produced after a minor setup. The effect of underutilized capacity is at first counterintuitive. Underutilization of capacity would seem to offer workers the opportunity to be more attentive to quality. However, the underutilization measure is derived data that assumes that products are produced to process engineering standards. If managers suspect that a product mix will not permit attainment of standard output rates, they are likely to schedule a lower level of capacity utilization because excess labor resources will be needed to maintain adequate performance. If the decrease in capacity utilization is insufficient to maintain performance, then a negative relation between underutilization and quality performance emerges. The documented negative relation suggests that managers limit the use of capacity utilization to offset performance effects of complex, heterogeneous product mixes. This is consistent with the institutional setting in which top managers maintain oversight of capacity management decisions and review these decisions in conjunction with data on performance outcomes. It is also consistent with underutilization having different effects on different performance measures, a possibility that is revisited in the discussion of efficiency results.

Explicit hypotheses about which aspects of product mix composition and heterogeneity influence quality performance are not developed. Consequently, the remaining discussion

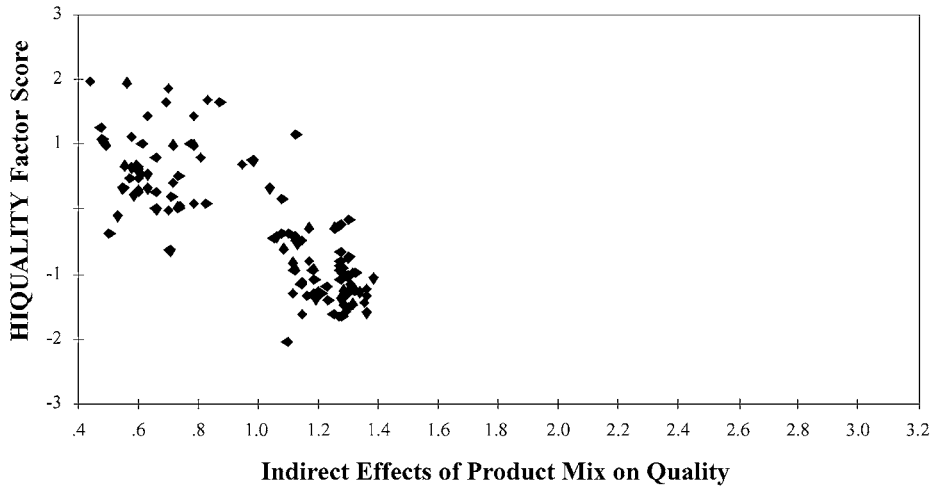
focuses on whether direct effects of product mix systematically misstate the total impact of product mix on performance and whether the data are consistent with a behavioral model of managers using discretionary capacity management tools to balance competing performance priorities. A brief discussion of individually significant coefficients provides insight to performance outcomes and quality management practices.

Previous research estimates direct effects of product mix on manufacturing performance. The degree to which the direct effects of product mix systematically misstate the total effect of product mix on quality performance is measured by the difference between the estimated quality factor score obtained from applying the coefficient estimates in columns 4 and 5 of Table 3 to actual product mix variables. The direct effect of product mix characteristics on quality ranges from -2.30 to $+0.30$ (mean $= -1.20$, standard deviation $= 0.69$). The total effect of product mix characteristics on quality ranges from -3.55 to -0.44 (mean $= -2.10$, standard deviation $= 0.93$) and the indirect effects uniformly reduce quality performance (range of -1.38 to -0.44, mean $= -0.90$, standard deviation $= 0.30$). In sum, the results support the hypothesis that considering only direct effects leads to a systematic misstatement of the total effect of product mix characteristics on quality.

The absolute value of the sum of all indirect effects of product mix characteristics on performance is a measure of the degree to which managers engage in tactical capacity management in response to product mix characteristics. If managers make capacity management decisions without regard to performance expectations, indirect effects would be uniformly distributed across performance outcomes. In contrast, in the proposed behavioral model, if these decisions are made with the recognition that top managers evaluate performance and monitor capacity management decisions, then plant managers will use capacity decisions strategically to maintain adequate performance levels. Figure 2, Panel A, plots the absolute value of indirect effects of product mix on quality performance (calculated for each observation as the sum across all product mix characteristics of the difference between total and direct effects for realized values of the product mix characteristics) against the HIQUALITY factor scores. The initial impression given by the negative relation between performance and the absolute value of indirect effects is that the more managers allow capacity management decisions to be influenced by product mix, the lower the performance. However, this interpretation ignores the fact that we have no way of knowing what performance would have been in the absence of capacity management. If we assume that capacity management requires costly managerial effort, that there are acceptable limits for underutilized capacity, and that quality is only one aspect of performance for which managers are held accountable, then minimal capacity management (small indirect effects) may reflect periods when managers can achieve performance objectives without reducing capacity utilization. In contrast, large indirect effects reflect periods when managers use capacity management intensively to sustain performance. However, implicit constraints, personal costs of managerial effort, or conflicting effects on other performance measures limit the use of these tools and the degradation of quality associated with product mix characteristics is not fully offset.

Considering the direct and indirect effects of product characteristics, three aspects of product mix composition influence quality: fabric weight, warp beam construction, and customer defect intolerance. Of these, only fabric weight and warp beam construction

Panel A: Quality



Panel B: Efficiency

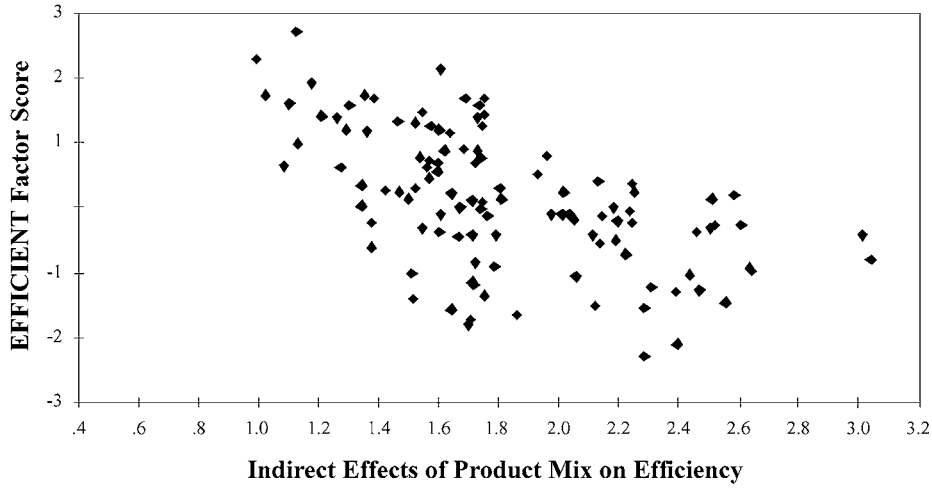


Figure 2. The absolute magnitude of indirect effects of product mix on operating performance plotted against level of performance.

exhibit significant total effects on quality. Heterogeneity along two of these dimensions, fabric weight and warp beam construction, influences quality; however of these, only warp beam construction is associated with significant total effects. Two variables that do not exert significant direct effects have large enough indirect effects to yield significant total effects: average raw material composition and heterogeneity in customer tolerances.

The disappearance of average customer defect intolerance and fabric weight heterogeneity, which exert significant direct effects but insignificant indirect effects on quality, suggests that capacity management decisions counter the performance impact of these variables. The negative direct relation between customer's intolerance of flaws and off-quality output suggests that the firm contracts for levels of quality that it cannot systematically produce. As a result, tighter quality tolerances generate increased off-quality output. This indicates that the firm is engaging in inspection and quality sorting—selling only fabric that is at the high end of the quality distribution to these customers, rather than systematically producing to higher quality standards for these customers.

4.5. Relation between product mix, capacity management, and production efficiency

As in Table 3, the fourth column of Table 4 contains estimated coefficients of the direct effects of capacity management decisions and product mix characteristics on operating efficiency and the fifth column reflects the total effects of product mix characteristics on efficiency. Capacity management variables and product mix characteristics explain a smaller portion of the variance in EFFICIENT (squared multiple correlation of 0.64) than they did for HIQUALITY (squared multiple correlation of 0.90); nonetheless, the estimated model is quite satisfactory.

Considering first the direct effects of capacity management decisions on efficiency, the results indicate that underutilization reduces efficiency. Similar to quality, one interpretation is that managers decrease capacity utilization in an effort to offset debilitating effects of product mix on labor efficiency, but are unable or unwilling to fully compensate for these effects. There are two reasons why managers may be unwilling to decrease utilization to fully offset performance losses. First, top managers explicitly monitor capacity utilization and may discount quality or efficiency performance that is achieved at too high a cost. Second, while some aspects of performance may increase with organizational slack, other performance dimensions may decrease with underutilization of capacity. Product mix explains 41% of the variation in underutilization of capacity. Other causes of underutilization, such as depressed market conditions, reduce labor productivity because labor is a relatively fixed cost of production. The significantly larger negative direct effect of underutilization on efficiency in comparison to quality reflects this. The coefficient estimates of Tables 3 and 4 are directly comparable because the principle components, HIQUALITY and EFFICIENT, are scaled identically. What is not possible is translation of performance scores into managerial preferences for quality versus efficiency performance.

Machine setups have no impact on efficiency. Production efficiency, a measure that figures prominently in this principle component, excludes setups and underutilized capacity. Labor productivity, the other measure in this factor is heavily influenced by direct labor, which is not involved with machine setups. Thus, measurement conventions explain the absence of a relation between setups and EFFICIENT.

The general results on the magnitude and sign of indirect effects of product mix on efficiency are similar to those in the analysis of quality performance. The degree to which the direct effects of product mix systematically misstate the total effect of product mix on efficient performance is measured by the difference between the estimated value of

EFFICIENT obtained from applying the coefficient estimates in columns 4 and 5 of Table 4 to actual product mix variables. The direct effects of product mix on efficiency range from +2.90 to +4.88 with a mean of +3.99 and a standard deviation of 0.46. The total effects of product mix on efficiency range from +0.52 to +3.83 with a mean of +2.20 and a standard deviation of 0.72. As in the case of quality performance, indirect effects uniformly reduce efficiency performance (range of −0.99 to −3.04, mean of −1.89 and standard deviation of 0.45), consequently direct effects systematically misstate the impact of product mix on EFFICIENT. Figure 2, Panel B illustrates the relation between the absolute magnitude of indirect effects—a measure of the intensity with which capacity management is employed in response to product mix characteristics—and efficiency outcomes. As before, capacity management is used most intensively during periods of lower performance.

A difference between the quality and the efficiency results is that the mean marginal effect of product mix on efficiency is positive, while the mean marginal effect on quality is negative. This suggests that on average, product mix characteristics, including heterogeneity, *increase* efficiency. The result also holds when the two aspects of product mix, average composition and product mix heterogeneity, are examined separately. This runs counter to expectations that changes in product mix composition and increased heterogeneity reduce performance; however, it is consistent with arguments that different measures reflect different aspects of performance. Several performance measures may be needed to obtain a full evaluation of manufacturing performance.

By construction the principle components HIQUALITY and EFFICIENT measure different aspects of performance. If labor productivity and production efficiency were paramount, manufacturing managers would be less inclined to make capacity management decisions that lower efficiency even if doing so would improve quality performance. The results suggest that quality performance is more important to managers than efficiency performance, a conclusion that is consistent with qualitative data from management interviews. When asked to describe performance measures for which plant managers are accountable and to list their performance priorities, each person identified quality as the first priority, and cost control and production efficiencies as secondary priorities. If managers place a greater priority on quality than on efficiency performance, it is reasonable to expect them to take actions to reduce the impact of product mix on quality even if this reduces performance along other, less valued dimensions. The results are suggestive, but incomplete. They indicate that future research should attempt a more complete, simultaneous modeling of relations between performance measures. For example, if a larger database was available, it would be natural to model the results of Tables 3 and 4 as simultaneous effects of product mix and capacity management decisions on multiple performance dimensions and to infer from the results the equilibrium weights that rational managers assign to each performance dimension.

5. Summary and conclusions

Previous research examines the impact of product mix characteristics on performance, treating capacity utilization as an exogenous control variable. This paper argues that tactical capacity management decisions are endogenous choices of manufacturing managers

that reflect managers' attempts to maintain adequate performance in the face of complex production tasks. During periods of increased product mix heterogeneity, managers use discretionary tactical capacity management decisions to create organizational slack that offsets the negative performance impact of product mix characteristics. The proposition that product mix characteristics exert a direct influence on capacity management decisions, which in turn directly influence operating performance is tested using data from three textile plants of one firm.

The results support the proposition that managers make capacity management decisions to offset the anticipated negative performance effects of product mix characteristics. In contrast to previous studies, which assume that variation in capacity utilization reflects *only* external market demand, product mix characteristics are found to explain 41% of the variation in capacity utilization and 60 to 90% of the variation in machine setups. In sum, estimating only direct effects of product mix characteristics on performance in environments in which managers have discretion over capacity management decisions systematically misstates the relation between product mix and performance. Previous studies that overlook the possibility that performance and capacity utilization are co-determined by product mix characteristics present an incomplete picture of the impact of product mix on performance.

The evidence also supports the underlying behavioral model in which managers use discretionary capacity management decisions to maintain performance in the face of difficult production assignments. The degree to which product mix indirectly influences performance through capacity management is inversely related to observed performance. Although it is not possible to know what performance would have been had capacity utilization not been overtly managed, the evidence indicates that managers engage in capacity management most intensively when product mix characteristics are anticipated to reduce performance. Nonetheless, managers are unable or unwilling to use capacity management decisions to fully offset negative direct effects of product mix characteristics on some aspects of performance. This descriptive result fits with a model of competing performance priorities that are related differently to capacity management choices and with the institutional setting in which top management reviews capacity management decisions in conjunction with performance data.

A final descriptive result that is suggestive, but inconclusive, indicates that the marginal direct effect of product mix characteristics is negative for quality performance but positive for efficiency performance. By construction, the performance measures are independent. Interviews indicate that the managers uniformly place quality performance as the highest priority in monthly performance reviews and the national reputation of the firm for producing high quality products is consistent with this claim. The results seem to indicate that quality and efficiency performance are competing priorities and that managers must execute a complex capacity utilization strategy to generate good quality and efficiency performance while producing a complex product mix. The evidence is suggestive rather than conclusive because data limitations preclude simultaneous estimation of the impact of product mix characteristics on capacity management decisions and all dimensions of performance. An important avenue for future research is modeling the joint optimization of multiple performance measures taking as given certain environmental variables and allowing managers discretion over other variables. It also suggests an important extension

for empirical studies; namely, simultaneous estimation of these models and assessment of implicit weights that managers place on different performance measures given the pattern of discretionary decisions taken and performance outcomes observed.

While specific measures of product mix characteristics and relevant performance measures will differ with different research settings, the conceptual foundation of this study is quite general. The hypothesis that managers use discretionary operating decisions to influence performance given the set of production tasks that they face is not revolutionary. Indeed, it is a major reason that operations management is considered an important component of business management education. The contribution of this study is to formally introduce this hypothesis to the research literature and to provide evidence that its omission has limited our understanding of the full impact of product mix characteristics on operating performance.

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