行政院國家科學委員會補助專題研究計畫成果報告
台灣產業生產與營運效率、產品成本、及顧客獲利力影響因素之整體性研究－－多重研究方法之運用
The Impact Factors of Production and Operation Efficiency, Product Cost, and Customer Profitability--Multiple Research Methods

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一、中文摘要

本研究主要探討製造業產能利用率、生產力、產品成本及產品利潤之整體性相關議題，首先吾人分析製造業中有多少的生產力是運用於有附加價值之工作中，另外有多少是浪費在無附加價值之活動或閒置之活動中。我們以台灣印刷業之一家個案公司之實証資料，來從事資料分析之工作。根據相關之文獻，吾人首先形成實証假設，然後分析工作複雜性與工作變異程度如何地影響產能之利用率；又產能之利用率、工作瓶頸、及工作複雜性與工作變異性又如何地影響製造之生產力。又產能利用率、產品複雜性、及產品變異性，如何地影響產品之成本及利潤。根據一連串之實証研究，吾人發現：當產能的利用率越高，瓶頸越大，工作複雜性及變異性越高時，會降低製造之生產力。又當產品複雜性越高，產品之變異性越大時，則產品之成本越高，而產品之利潤就越小。

關鍵詞：生產力、工作瓶頸、產品複雜度，產品變異性、產品成本及利潤。

Abstract

This study documents how capacity is used within manufacturing organizations. We document how much of the capacity is used for productive tasks and how much is wasted on non-productive activities and idle time. Using field data from a Taiwanese printing firm, we examine how job complexity and variations affect capacity utilization, and how capacity utilization, work pressure and task complexity affect manufacturing productivity. And, how capacity utilization, job complexity, and job variability affect job cost and profitability. The results of our study find that less than 35% of the capacity is utilized for actual production output with the remaining lost on setups, maintenance, wait, idle time, balancing or shutdown. We also find that manufacturing productivity reduces at

higher levels of capacity utilization, bottlenecks, job complexity, and job variability. Job complexity and job variability have great impact on job cost and job profitability.

Keywords: Productivity, job complexity, job variability, task bottleneck, product cost and profitability.

1. Introduction and Motivation

Contemporary attitudes towards management of production capacity are largely derived from a basic theory of how the use of capacity affects the unit cost of production. As depicted in Figure 1, this theory suggests that as capacity utilization increases the fixed costs of capacity may be amortized over more units of production reducing unit cost. However, as capacity increases the variable costs of production increase at an increasing rate. The convexity of the variable cost curve is induced by increased congestion and confusion associated with a production system reaching capacity limits (Buffa 1983, Stevenson 1996, Adam and Ebert 1989). This relation is demonstrated formally by showing that the wait time per job at a queue increases as a system reaches capacity constraints (see for examples Fry and Blackstone 1988, Banker et. al. 1988, Buss et. al. 1994). The theory suggests that a cost minimizing firm will find optimal capacity utilization at a level less than 100%.

Notwithstanding considerable theoretical study of capacity dynamics, recent field studies assert that we lack a practical/empirical understanding of capacity. Capacity utilization is often equated with "keeping busy" without a clear understanding of "doing what" and "why" resulting in the claim that misuse of capacity has become a serious detriment to company productivity and profitability (McNair and Vangermeersch, Klammer 1990). For example, McNair et. al. (2001) find that 46% of non-idle capacity is used non-productively at an electronics assembly plant. [1] Klammer (1996) reports that 56% of non-idle capacity in an accounting department is used non-productively. With estimates of total capacity costs ranging from 30 to 60 percent of total company cost structure (Miller and Vollman 1998; Banker, Potter and Schroeder 1995), these figures combine to imply that as much as 33 percent of company costs are used non-productively. However beyond insights provided by these field studies, little empirical exploration of capacity use and capacity theory exists (Balakrishnan and Soderstrom 2000).[2]

Using machine level and job level data from a printing plant, we

[1] NcNair et.al. 2001 define non-productive use of capacity is defined as any use not associated with the direct production of a product. This includes set-up time, breakdowns, quality problems and machine slowdowns.

[2] In most empirical research, capacity utilization is used as a control variable rather than the variable of primary study. See Anderson (1995) and Fisher and Ittner (1999) as examples.

empirically explore a series of questions that enhances extant field research and that informs theoretical research in the following ways. First, we attempt to enhance the practical understanding of capacity dynamics by describing and documenting factors that drive productive and non-productive utilization of capacity within a plant. Second, we attempt to validate the basic theoretical mechanism underpinning the positive, non-linear relation between variable costs and capacity utilization (see Figure 1), namely that wait time per job increases as capacity utilization increases. We then expand our analysis to investigate other aspects of manufacturing performance that may deteriorate as the system reaches capacity constraints. Third, given the theoretical importance of functional form in analytical capacity models, we examine the shape of the performance curve to provide some support for the functional forms used in current models. Fourth, we provide economic documentation of the impact of congestion on profitability at the firm. Unlike theoretical models that focus on the cost impact of congestion, we jointly examine the cost and revenue reactions of the firm.

We identify the quantity produced, number of jobs produced, job difficulty and changeover complexity as significant drivers of capacity utilization. We find that increased job waiting time is highly correlated with increases in capacity utilization. Further performance degradation is also found in increased operating loss, unexpected production delays, increased set-up time, and increased spoilage all present at high levels of capacity utilization. We note that the performance deterioration occurs in a linear fashion rather than non-linearly as contemporary theory might suggest. Our job level analyses show that a cost minimizing level of utilization exists within the plant. However, at this firm, revenues associated with the incremental capacity utilization also increase leading to an overall profit increase for the firm suggesting the firm behaves optimally by operating at high levels of capacity utilization which exceed levels of utilization suggested by a cost minimizing perspective.

The paper will proceed as follows. In section 2, we review relevant literature. In section 3, we describe the research site. In section 4, we examine the behavior of capacity utilization. In section 5, we use capacity utilization as a proxy for congestion and show how congestion affects five different performance measures at the plant. In section 6, we examine the profitability of jobs performed at different levels of capacity utilization. Finally in section 7, we summarize our results and contributions.

2. Literature Review

Defining Capacity

In a production environment, the

term capacity refers to "an upper limit or ceiling on the load that an operating unit can handle (Stevenson 1996)." Capacity is either measured in output per unit of time or, when the product mix is heterogeneous, in the percentage of time a constrained resource is used. For example, an automotive assembly line might produce 1000 cars per day or if the mix of cars on the assembly line varies widely one might say the line is 80 percent utilized. For purposes of capacity management, firms often distinguish between theoretical capacity - capacity for which the system was theoretically designed to produce, and practical capacity - the capacity which may be utilized under normal operating conditions (Buffa 1983). Throughout this paper we define and calculate capacity utilization in terms of practical limits.

How is capacity used?

The capacity model shown in figure 1 suggests that the cost-minimizing firm will manipulate volume to control capacity utilization. However, attaining the volume to reach optimal capacity may be reached following very different production strategies that will result in different uses of capacity. For example, a firm might reach optimal capacity with one large order or with multiple orders. If multiple orders are used, each order might differ in complexity. Capacity for the firm with one large order will be used in production time, while capacity for the firm with a wider mix of jobs will be used in set-up time as well as production time. More difficult jobs may require longer set-ups and slower processing speeds which increase capacity utilization.

Recognizing these different strategies for capacity utilization, recent frameworks addressing capacity management recommend that total utilization be broken into three broad categories: (a) productive (value-added) usage, (b) non-productive (non-value-added) usage, and (c) planned or scheduled idle time (McNair et. al. 2001, McNair and Vangemeersch 1998, Klammer 1996). The frameworks narrowly define productive usage as capacity used to produce output at practical speeds. Non-productive capacity then includes, set-up time, unexplained idle time, time spent producing poor quality product and routine maintenance. Planned idle time include holidays and down time due to slow sales (McNair, Hertenstein and Polutnik 2001). These frameworks assert that basic capacity drivers will have a differential effect on non-productive capacity usage versus productive capacity usage. While productive capacity usage increases with volume, non-productive capacity usage will increase with job diversity and job complexity.

Relation between Utilization, Congestion and Manufacturing Performance

The theory depicted in Figure 1 suggests that when a production system reaches a high level of utilization system performance degenerates due increased congestion on the shop floor. These arguments assume an explicit positive association between capacity utilization and congestion. Operations texts include increased work in process inventory, decreased service rates, decreased quality, and slower work pace among the performance measures that deteriorate with increased congestion (Buffa 1983, Stevenson 1996). Of these potential performance effects, increased inventory costs receive most research attention. Analytical models consistently demonstrate through queuing models that the average wait time per job increases as capacity utilization increases leading to an increase in inventory costs per unit (see Hopp and Spearman 1996 for a comprehensive review of queuing models and capacity utilization). In a single server queue, Bitran and Tirupati (1989) illustrate that as capacity decreases with respect to workload, average work in process inventories and lead-times increase. Banker et. al. 1988 demonstrate that average cycle times for products will increase in capacity utilization, an effect exacerbated by increased product variety. Sakasegawa (1977) extended the same utilization-cycle time relationship from single server queues to multiple server queues. Much less attention is paid to the impact of congestion on quality and pace of work being performed. One exception is Balakrishnan and Soderstrom (2000) who document that healthcare quality decreases only for certain classes of individuals in a service system rather than decreasing for the system as a whole. Despite the lack of research, operations texts emphasize that congestion present at high levels of capacity utilization will affect all aspects of the plant including slower work pace and quality of output (xxxx). Our analyses provide the first comprehensive examination all these detrimental performance effects in one setting. We expect unexpected wait time, job processing time, spoilage and set-up times to increase as the system reaches its capacity constraint. Like theoretical models, we explicitly assume that capacity is positively associated with congestion and use capacity as a proxy for congestion effects.

Since much attention is paid to the functional form of capacity utilization models, we also examine the form of the relationship between capacity utilization and performance. Most frequently, the relation between capacity utilization and performance deterioration occurs in a non-linear fashion – increasing at an increasing rate. In listing fundamental laws of a factory, Hopp and Spearman state:

“If a system increases utilization without making any other changes, average cycle times will increase in a highly nonlinear fashion” Factory Physics p. 287.”

We also expect the association between capacity utilization and performance deterioration to be highly non-linear.

Economic Impact of Capacity Utilization

Figure 1 suggests that a cost minimizing firm will operate at a level of capacity utilization below 100 percent. This theory implies that the firm will either add capacity to reach the cost minimizing level (Bitran and Tiruputi 19xx) or shift production from periods of high utilization to lower utilization or even reject orders to avoid the cost penalties associated with high utilization. In practice, the utilization decision must also consider the revenue benefits associated with the incremental volume. Several cases exist when the profit maximizing level of capacity utilization will differ from the cost minimizing level of utilization. For example, capacity management models which include revenue suggest a customers willingness to pay more during periods of high capacity utilization might cause a firm to operate at a level higher than the cost minimizing level (need cites). On the other hand, if orders are scarce, the incremental revenue from additional orders may exceed the cost causing the firm to reject orders before reaching the cost minimizing level. Thus the level of capacity utilization at a firm may differ from the cost minimizing level depending upon the revenue curve faced by the firm. We examine job level profitability data to determine the cost minimizing utilization level as well as the profit minimizing utilization level for the firm.

3. Research Site and Data Description

To examine our questions surrounding capacity dynamics we use 6 months of machine level and over 700 job level observations from a printing company located in Taiwan (Printing Co.) We chose Printing Co. for several reasons. First, the company appears to be well managed. Over the past years it has attained ISO 9002 and ISO 14001 certifications as well as won a national award for quality. Second, we noted most analytical models used to derive expectations about variability, capacity and manufacturing performance are grounded in job shop environments. Printing Co. utilizes 7 different machines that operate much like an M/M/n queue.

The Taiwanese printing industry is quite competitive with few large and many small printing companies. Employing over 200 personnel, Printing Co. is one of the larger publicly traded printing companies in Taiwan. The company products range from books and magazines to posters and calendars. Production at the company is organized into two basic processes: pre-printing and printing. The sales teams work aggressively to win job contracts.

Almost all printing job orders are customized. The production on the new job order starts in the pre-printing process where original client work is prepared for printing. Due to a lack of capacity in the pre-printing department, a considerable number of plates are received from third party providers. For a typical job, employees merge client-supplied artwork, graphics and text electronically to produce a print plate. A single color page requires four plates, one for each primary color - magenta, blue, yellow, and black. Color contrasts are created by overlaying primary color plates. Once completed, employees manually construct job proofs for client approval. Upon approval, the plates are sent to the printing department.

During the time of our study, the printing department operated seven sheet fed printing machines. As their name implies, sheet fed machines require an individual sheet of paper be inserted for each page of the job. Sheet fed machines are distinguished by the number of primary colors they print. Color capacity ranges from two to five colors. A typical sheet fed machine has a maximum print speed of just over 200 pages per minute. Printing can be done on wide variety and sizes of papers. A job is routed from pre-printing to one of the sheet fed machines for printing. Large jobs may be split between several machines but jobs are not routed from one machine to another. Due to the independent workflow assigned to each machine, in our machine level data we treat each machine day as an individual observation. When a job is assigned to a machine, the plate is transferred to the printing department. The set-up involves fixing the plate to the machine and adjusting the machine for five different job attributes: paper type, paper size, job type (e.g. book, magazine, calendar), print method (double or single sided), and color (number of color shades). After set-up the print job is processed on the machine. Process speed is considered to be a function of job characteristics (five job attributes). The more difficult a job characteristic the slower the print speed. Minor set-ups may occur during the printing process as ink is refilled or paper is re-stocked in the machine. Following completion of a print job, workers clean the machine and prepare for the next job. When not in use for setup or printing, a machine may be idle due to unexpected wait, lack of work, or scheduled maintenance. Unexpected wait at a machine may occur for a variety of reasons including, delays in pre-printing department, machine break downs, administrative delays, and customer forced delays such as due to last minute changes in a job-specification. Between two and six workers manage the print jobs on each machine. Workers are paid on an hourly basis with overtime paid after eight hours of labor. Print machine workers are also responsible for inspecting the work and discarding any defective printed material.

We collected daily capacity utilization and product output, spoilage, and complexity data for each of the seven sheet fed machines at Printing, Inc. for six months from February 2000 through July 2000. Adjusting for holidays and planned shutdowns, we have about 1178 machine-day observations for the Printing Co. Some data are lost in analysis due to incomplete observations. Four general categories of capacity usage were tracked on a daily basis: production, set-up, unexpected wait, and planned idle. Production usage is essentially a function of output quantity (number of printed pages) and process speed. Output includes both good and defective units. Process (or machine) speed can be affected by many factors including product diversity, process variations, input variations, congestion, and workload. We partition the actual process usage of capacity into three components. First is the *expected operating* usage defined as the process capacity needed to produce the given good output units. Second is the *spoilage* production usage defined as the process capacity needed to produce the defective or rejected output units at the process. Third is the *operating loss* defined as the difference between the actual process usage of capacity minus the capacity needed to produce the total (good and defective) output units. *Set-up* usage is the portion of capacity used to do setups for each job at Printing Co. Unplanned loss of machine capacity (e.g., breakdowns, unexpected idle time waiting for a job, etc.) is defined as *unexpected wait*. Finally, a process may be idle because of lack of demand, planned maintenance, holidays, etc. Such loss of capacity is termed as *planned idle* part of the total capacity. Figure 2 shows the use of capacity at the plant. We compliment the machine level data with job level data including job lead-times, revenues, costs and profitability. Gathering job level data were necessary to examine firm economic behavior with respect to congestion and to test questions concerning job lead-times.

4. Drivers of Capacity Utilization

In our first set of analyses, we examine the drivers of capacity utilization paying specific attention to which drivers affect productive and non-productive utilization. Recall that productive utilization includes any capacity used to produce output at practical speeds. Non-productive capacity then includes, set-up time, unexplained idle time, time spent producing poor quality product and routine maintenance. Under these definitions, Printing Co. uses capacity productively 32.10 percent of the time while using capacity non-productively 67.90 percent of the time (Figure 2). We expect capacity to increase in quantity, the number of jobs and the complexity of the product mix. We use two measures of complexity of the product mix, DIFFICULTY and CHANGEOVER. DIFFICULTY captures the average actual production complexity associated the product mix. We measure DIFFICULTY by asking production workers to rate the difficulty of different product characteristics. CHANGEOVER captures the set-up complexity associated with the product mix. We measure CHANGEOVER by counting the different number of subset-ups associated with the characteristics of a product and averaging those for a given day. There are 7 different subset-ups possible on a given job. Table 1: Panel A shows descriptive statistics for the measures used in our analysis. Total utilization averages 82%, an average of 93,595 pages are produced each day divided into 4.77 jobs. We noted that at certain times of the month the company operates in rush mode. Rush mode includes days where a high number of date sensitive orders are present in the plant. In our models, we include an indicator variable for rush mode days (RUSH DAYS).

Table 2 shows linear regression models analyzing the drivers of capacity utilization. We use a logarithmic specification to be consistent with non-linear assumptions in theoretical models. However, results of linear models are qualitatively consistent with the results of a logarithmic model. P-E tests for functional form do not provide guidance as to which functional form best fits the data (Greene 199x). Table 2 shows results of models on four different dependent variables, overall capacity utilization, productive capacity utilization, non-productive utilization and the ratio of non-productive utilization to productive utilization. Each model is statistically significant and the adjusted R^2 range from 0.37 to 0.71.

We find that overall capacity utilization is positively associated with production QUANTITY, the number of JOBS, the DIFFICULTY and CHANGEOVER of the product mix. We find the productive capacity utilization is positively associated with production QUANTITY and the number of JOBS, but not associated with the DIFFICULTY and CHANGEOVER complexity of the product mix. On the other hand, non-productive capacity utilization decreases as the production QUANTITY increases and increases as JOBS, DIFFICULTY and CHANGEOVER increase. To show the relative rate of change between productive and non-productive capacity, we formulate a model regressing the drivers of capacity utilization on the ratio of non-productive capacity to productive capacity utilization. In a logarithmic specification this is equivalent to taking the difference between the model coefficients of the non-productive and productive utilization regressions. We find that as QUANTITY increases the proportion of non-productive utilization to productive utilization decreases. Conversely, as JOBS and CHANGEOVER increase the proportion of non-productive utilization to productive utilization increases.

These results imply that different strategies for increasing capacity utilization will have a differential effect on productive and non-productive utilization. If the firm can utilize its capacity with fewer orders the capacity will be used more productively than if the firm fills its capacity with many orders. The DIFFICULTY of those orders has little effect on the productive or non-productive use of the capacity. However, a product mix that requires a high level of CHANGEOVER will increase the non-productive use of capacity.

5. Effects of Capacity Utilization on 5 Measures of Manufacturing Performance

Our second series of analyses examine the influence of capacity utilization on manufacturing performance. In these analyses capacity acts as an agent of congestion within the firm. The theoretical arguments presented here suggest that manufacturing performance deteriorates as utilization increases within the plant. We test this hypothesis on five different measures of manufacturing performance: job-lead time, operating loss, spoilage, unexpected wait time and the average set-up time. Job-lead time is measured in days by taking the difference between the job order date and the actual job delivery date. Operating loss is measured in operating loss per page by taking the difference between the actual operating time per page and the expected operating time per page. Spoilage is the percentage of output that does not meet specifications. Unexpected wait is measured in minutes per job and includes any unexpected downtime due to machine breakdowns, management delays or customer related delays. Because each performance measure is stated in a negative tense, performance deterioration is present when each measure increases. Thus we expect capacity utilization to be positively associated with each measure. Note also that job-lead time measured on a job by job basis rather than at the machine level. The measurement level results in a different model specification for job lead time. Table 1 shows the descriptive statistics for each measure. Job lead time averages 9.27 days, operating loss averages 3.10 minutes per 1000 printed pages, spoilage averages 2% per day, unexpected wait time per job averages 30.04 minutes and the average set-up time per job is 96 minutes.

We use an adjusted capacity measure as a proxy for congestion. The adjustment is made by taking actual capacity utilization and subtracting the time associated with the specific performance measure from both the numerator and denominator of utilization. For example, the utilization measure in the operating loss model is calculated by taking the actual hours utilized and subtracting the hours corresponding to operating loss then dividing by the total hours available less the hours corresponding to operating loss. Inherent, endogeneity in the utilization measure requires this adjustment.[3]

To examine our hypotheses, we regress the utilization measure on the performance variables. We include QUANTITY, JOBS, DIFFICULTY, CHANGEOVER and RUSH DAYS as control variables. In addition, we include the number of direct and indirect employees as a control variable. The firm may compensate for performance deterioration by adding additional labor on each machine. The number of direct and indirect employees control for this potential effect.

To be consistent with theory we use a logarithmic specification for each model.[4] Linear specifications yield the same results with respect to the utilization measures, but yield some differences with respect to the control variables. Table 3 shows the results of 2 models run on each performance measure. The first model excludes the utilization measure. All models are statistically significant and adjusted R^2 range from 0.02 to 0.43 in models excluding utilization and from 0.03 to 0.47 in models including the utilization measure.

We report a positive association between capacity utilization and each performance measure indicating that performance deteriorates as the plant reaches full capacity. F tests comparing the nested models indicate that the utilization measure adds significant explanatory power to each model. The results in the job lead time model are consistent with theoretical models that show average wait-time per job increases as capacity utilization increases. The results also suggest that the performance effects of congestion extend beyond wait time to the actual operating performance of the firm. Operating loss, spoilage, unexpected wait time, and set-up times all increase as capacity utilization increases.

QUANTITY is positively associated with job-lead time, but negatively associated with other performance measures suggesting some

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[3] Models using an unadjusted utilization measure are qualitatively similar, but the t statistics on the utilization measure show a marked increase in significance. Note also that no-such adjustment was made for the job lead-time measure as most of job-lead time is spent waiting to be processed rather than being processed. Utilization does not include any job waiting time.

[4] Theoretical our firm can be modeled as an M/M/m queue. Sakasegawa (1977) suggests that the cycle time or job lead -time can by computed exactly with the following specification:

$$\text{Job Lead Time} = t_e \, \text{utilization}^{\left(\sqrt{2(m+1)}-1\right)} \Big/ m\left(1-\text{utilization}\right)$$

where t_e is the mean processing time and m is the number of machines. This relationship is non-linear with respect to utilization.

benefits to larger jobs within the plant. JOB is positively associated with operating loss and spoilage, but negatively associated with unexpected wait and average set-up. Discussion and observation of plant practices indicate that as the number of jobs waiting to be processed increases the degrees of freedom in scheduling increase in the plant. Thus when a job experiences an unexpected delay another job can easily take its place reducing the unexpected wait on a machine. Furthermore, as the number of jobs increase more efficient changeovers may be scheduled reducing the average set-up per job. For example, a series of calendars with the same basic set-up might be scheduled consecutively rather than alternative calendars with magazines. We note that DIFFICULTY is only positively associated with unexpected wait time. Higher CHANGEOVER accompanies higher spoilage and set-up times. RUSH DAYS are positively associated with operating loss, but negatively associated with job-lead time, spoilage and average set-up time. Interestingly, direct employees show a positive association between the measures of manufacturing performance indicating that performance deteriorates as more direct employees are placed on the floor. On the other hand, indirect employees are negatively associated with operating loss, spoilage and average set-up time suggesting performance deterioration is mitigated by scheduling indirect employees. However, unexpected wait time also increases as more indirect employees are placed in the plant.

In table 4, we examine the functional form of the performance deterioration by dividing capacity utilization into quintiles then comparing least square means of each quintile after including control variables. This specification allows the data to take its natural functional form. The results are plotted in figure 3. Of the five performance measures, average wait time per job and average set-up time per job increase most dramatically. Operating loss per 1000 pages increases from quintile 1 to 2 then levels off. Spoilage and average job lead time increase gradually, but the differences between the quintiles are not significantly different. In general, we do not see a non-linear pattern in the performance deterioration.

6. Effects of Job Complexity, Job Variability, and Capacity Utilization on Job Cost and Job Profitability

In this study, we also examine the effects of job complexity, job variability, and capacity utilization on job cost and job profitability. Table 5 show that job complexity and job variability have impact on job cost and job profitability. Figure 4 shows the relationship between capacity utilization and cost, and capacity utilization and profitability.

7. Conclusions

We present results on the nature of

capacity utilization and factors affecting utilization from an analysis of field-data from two manufacturing companies in Taiwan. We also analyze how the level of capacity utilization, jobs diversity, variability and complexity, and bottleneck affect manufacturing efficiency and productivity. Capacity costs and their management present many challenging issues to accounts. Traditionally little attention has been paid in accounting to management of capacity as it is considered a fixed cost that can not be controlled in the short run. We show that even if capacity costs themselves are fixed in the short run, the pattern of utilization of capacity affects productivity and yield of manufacturing activities. These effects are likely to affect manufacturing costs and profitability even in a short run. Increased capacity utilization reduced productivity and efficiency due to congestion and variability it creates. To the best of our knowledge, this is the first empirical study to examine and document effects of capacity utilization in manufacturing. Analytical models of capacity utilization document performance deteriorating effects of congestion via increased wait time. The results from Printing Co. indicate that the detrimental effects of congestion are more widespread than just wait time, and also include increased operating loss, increased set-up time, and increased spoilage costs. In this paper, we also find that capacity utilization, job complexity, and job variability have effect on job cost and job profitability.

There are several limitations to our data, analyses and results. First there are no well established empirical models in this area that can be used in our analyses. We have assumed log-log relations among variables that may not hold true in practice. Our results at this point are based only on a limited six-month time-series data. There are also no standard metrics to evaluate variability and complexity of task and our measures are susceptible to both misspecification and measurement errors.

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Table 1: Descriptive Statistics

Panel A: Daily Machine Level Data

	N	Minimum	Maximum	Mean	Std. Deviation
OPERATING LOSS time per 1000 printed pages	1178	0.00	775.50	3.10	22.50
SET-UP time per job	1177	0.00	435.00	96.00	58.52
UNEXPECTED WAIT time per job	1177	0.00	840.00	30.04	57.30
SPOILAGE %	1178	0.00	1.00	0.02	0.04
UTILIZATION	1178	0.10	1.00	0.82	0.19
QUANTITY	1178	0.00	248,000	93,595	51,468
JOBS	1178	0.00	33.00	4.77	2.85
DIFFICULTY	1178	0.01	5.88	4.60	0.86
CHANGEOVER per job	1178	0.00	7.00	1.40	0.81

Panel B: Job Level Data

	N	Minimum	Maximum	Mean	Std. Deviation
JOB PROFIT	713	-235,065	617,216	13,055.30	48,693.48
JOB REVENUE	713	300	981,588	42,230.61	84,942.99
JOB TOTAL COST	713	460.75	865,423.44	29,175.31	64,951.17
QUANTITY	712	200	1,664,000	42,102.12	145,063.48
DIFFICULTY	713	0.01	5.00	0.43	0.42
CHANGEOVER	713	0.00	2.67	0.80	0.78
LEADTIME	713	0.00	51.00	9.27	6.25
UTILIZATION	713	0.16	1.10	0.78	0.15

Table 2:
Linear Regression Models Showing the Relation between Capacity Utilization and Capacity Drivers
(t-statistics in brackets, n=1160)

Ln(Dependent Variable)	Total Capacity Utilization	Productive Capacity Utilization	Non-Productive Capacity Utilization	Ratio: Non-Productive to Productive Capacity Utilization
Intercept	-3.19*	-9.48***	1.28***	10.76***
	[-33.16]	[-103.73]	[6.23]	[45.99]
ln(QUANTITY)	0.24***	0.75***	-0.27***	-1.01***
	[27.84]	[93.13]	[-14.71]	[-49.30]
Ln(JOBS)	0.12***	0.07***	0.31***	0.24***
	[7.89]	[4.80]	[9.22]	[6.22]
Ln(DIFFICULTY)	0.09***	0.04	0.11*	0.07
	[3.55]	[1.52]	[1.89]	[1.07]
Ln(CHANGEOVER)	0.007**	0.001	0.005***	0.005***
	[1.93]	[0.39]	[7.01]	[6.01]
RUSH DAYS	0.005	0.02	-0.04	-0.05*
	[0.40]	[1.33]	[-1.35]	[-1.71]
F Statistic	225.13***	1851.23***	135.75***	557.92***
Adjusted R^2	0.49	0.89	0.37	0.71

*** Statistically significant at the 0.01 level (two-tailed).
** Statistically significant at the 0.05 level (two-tailed).
* Statistically significant at the 0.10 level (two-tailed).

Table 3:

on Showing the Relation between Manufacturing Performance and Utilization.

ics in brackets, N=712 Lead-time models, N=1157 for all other models)

e	Operating Loss per 1000 pages		% Spoilage		Unexpected Wait per Job		Average Set Up per Job	
***	-2.52***	-1.95***	2.34*	3.18*	7.93***	17.48***	6.48***	8.79***
3]	[-37.22]	[-21.52]	[7.98]	[7.81]	[3.52]	[4.99]	[29.08]	[28.97]
**	-0.17***	-0.21***	-0.63*	-0.68*	-1.03***	-1.70***	-0.14***	-0.31***
2]	[-27.64]	[-28.60]	[-23.28]	[-20.76]	[-4.99]	[-6.09]	[-6.91]	[-12.31]
	0.03*	1.01	0.32*	0.29*	-1.36***	-1.71***	-0.53***	-0.58***
	[2.86]	[1.19]	[6.77]	[6.06]	[-3.06]	[-4.57]	[-6.91]	[-16.77]
4	0.02	0.007	-0.08	-0.11	1.86***	1.65***	0.06	0.04
3]	[1.37]	[0.45]	[-1.04]	[-1.34]	[3.06]	[2.72]	[1.04]	[0.62]
8	-0.0001	-0.0005	0.06*	0.06*	0.13	0.13	0.07***	0.07***
6]	[-0.06]	[-0.23]	[5.36]	[5.30]	[1.58]	[1.48]	[7.79]	[8.00]
**	0.02**	0.02**	-0.09**	-0.09**	0.06	0.10	-0.11***	-0.12***
9]	[2.24]	[2.40]	[-2.45]	[-2.45]	[0.23]	[0.35]	[-3.91]	[-4.18]

	0.05*	0.02*	0.22***	0.18***	0.37	1.04	0.22***	0.15***
	[3.54]	[1.88]	[3.69]	[3.08]	[0.83]	[0.10]	[4.97]	[3.60]
	-0.02**	-0.03**	-0.15***	-0.15***	2.36***	2.37***	-0.10***	-0.13***
	[-2.03]	[-2.50]	[-2.95]	[-3.08]	[6.07]	[6.13]	[-2.65]	[-3.55]
**		0.17***		0.27***		2.43***		0.48***
0]		[9.03]		[2.95]		[3.54]		[10.66]
**	123.88***	126.18***	116.48***	103.71***	16.13***	15.82***	46.18***	58.59***
3	0.43	0.47	0.41	0.42	0.08	0.09	0.22	0.29
**		82.14***		9.91***		12.76***		113.38***

ficant at p<.05 (two tailed test), * significant at p < .10 (two tailed test)

he following adjustment is made to utilization; Ln(utilization') = (Total hours utilized - hours utilized for given model - hours utilized for given model performance measure).

Table 4:

odel (GLM) Estimates of the Association between Portfolios Formed on the Basis of Utilization and Measures of Manufacturing Performance

(N = 712 for Lead-Time Model, N=1157 for other models)

ıtile 1 ilization = 1%	Quintile 2 Mean Utilization = 75%	Quintile 3 Mean Utilization = 88%	Quintile 4 Mean Utilization = 96%	Quintile 5 Mean Utilization = 99%	Model F-Statistic
.08	9.08[1]	9.15[1]	9.95[1]	10.02[1]	4.64***
).3	13.5[1]	12.3	13.3[1]	12.8	2.76***
.73	1.96	2.02	2.20	2.25	6.96***
;.99	30.24	29.23	34.66[1]	32.38[1]	33.60***
:.18	83.55[1]	113.60[1,2]	123.40[1,2,3]	133.82[1,2,3,4]	85.65***

:ailed) respectively.

ormance change in each quartile after controlling for any co-variates in the following GLM models.

ıd-Time = $\alpha + \beta_1$Quantity $+\beta_2$Difficulty $+ \beta_3$Changeover $+ \beta_4$Rush Days $+ \beta_5$Job Type

/ait per Job or Average Set-up per Job = $\alpha + \gamma_1$Quantity $+ \gamma_2$Jobs $+ \gamma_3$Difficulty $+ \gamma_4$Changeover $+ \gamma_5$Rush Days $+ \gamma_6$Direct Employees $+ \gamma_7$Indirect Employees

:es means indicate that the mean is significantly different ($p<0.15$), two-tail than the mean for the indicated quartile (e.g., a antly different than the mean for quartile 1)

e 54%, 71%, 81%, 88% and 95% respectively

Table 5:

Iodel (GLM) Estimates of the Association between Portfolios Formed on the Basis of Utilization

(N = 710)

intile 2	Quintile 3	Quintile 4	Quintile 5	Model F-Statistic
TIL = 71%	Mean UTIL = 81%	Mean UTIL = 88%	Mean UTIL = 95%	
887.56	38,497.67	40,103.70	46,200.65	34.26***
986.35	27,775.27	31,386.87	31,302.53	71.36***
023.70	10,796.79	8,231.98[1]	14,366.51	2.13**

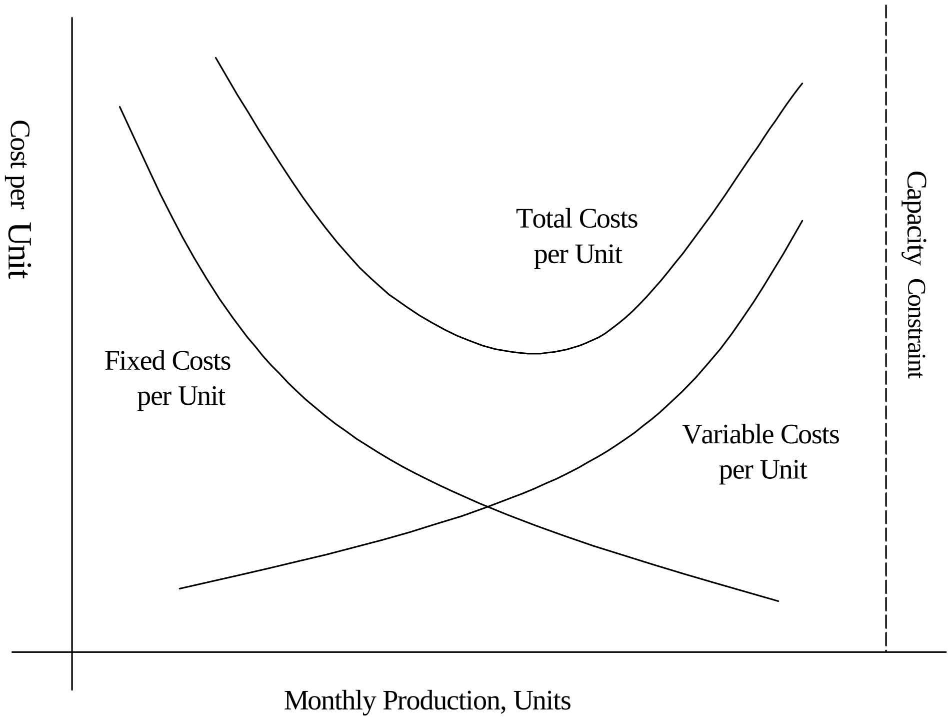
levels (two-tailed) respectively.

ormance change in each quartile after controlling for any covariates in the following GLM models.

: or Profit = $\alpha + \beta_1$Quantity $+\beta_2$Difficulty + β_3Changeover + β_4Rush Days + β_5Job Type

east squares means indicate that the mean is significantly different ($p<0.15$), two-tail than the mean for ›d 1 indicates that the mean is significantly different than the mean for quartile 1)

Figure 1: Model of Capacity Costs



Adapted from Buffa 1983 p. 135.

Figure 2: Uses of Capacity - Printing Co.

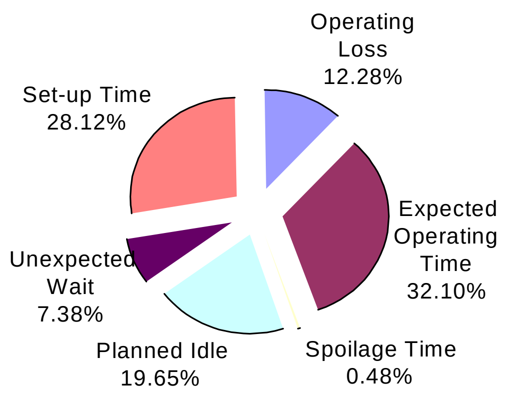


Figure 3: Plot of Least Square Means from General Linear Model Estimates of Association Portfolios Formed on Basis of Utilization and Measures of Manufacturing Performance

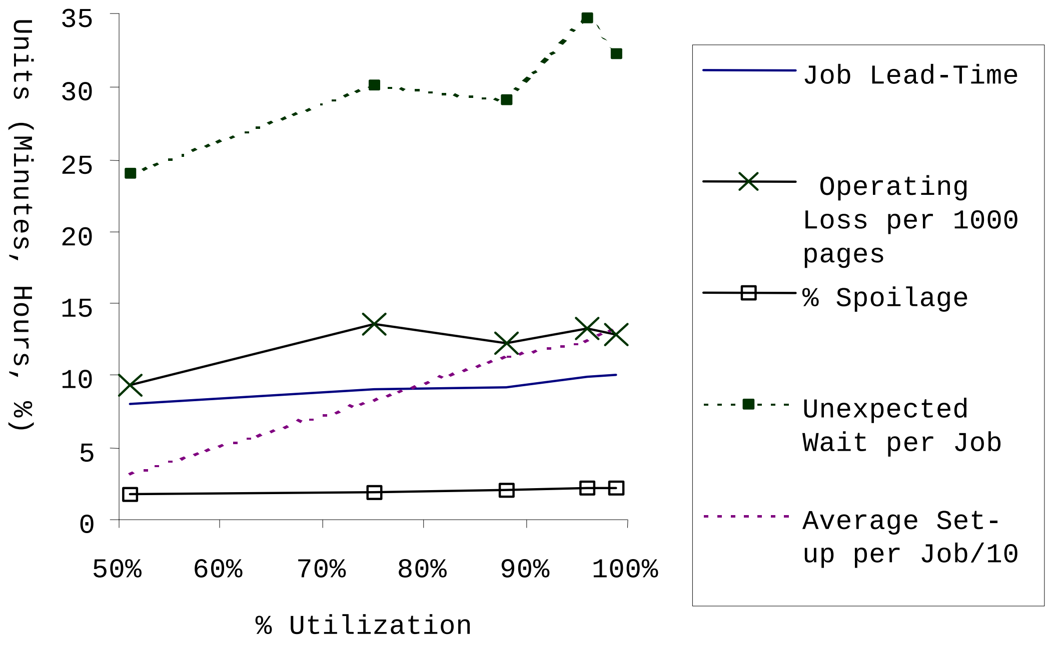


Figure 4: Plot of Least Square Means from Model Estimates of the Association between Formed on the Basis of Utilization and and Total Cost per