Factor Utilization and Margins for Adjusting Output: Evidence from Manufacturing Plants

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This paper describes patterns of factor utilization and output adjustment at the plant level for a wide range of manufacturing industries. We explain why manufacturing plants may differ quite a bit in how they accomplish output adjustments,depending on shutdown cost aspects of technology. Assembly-type operations with low shutdown costs would primarily vary the work period of the plant, whereas continuous processing plants with large shutdown costs would adjust instantaneous flow rates of production. For larger output increases, a lengthening of the work period by assemblers would entail employment changes, whereas continuous processors would be more apt to relax physical capital constraints. We use micro survey data on the organization of actual and capacity plant operations to describe the observed patterns of adjustment in individual manufacturing industries and find substantial heterogeneity across industries. For manufacturing as a whole, the workweek appears to be a significant margin of adjustment.

Recent literature suggests that the relationships between marginal costs and output levels of manufacturers are complicated by the presence of multiple ways to achieve output changes and of one-time costs to adjusting some factors of production. The shape of marginal costs depends on which factors of production are adjusted, and different factors should be adjusted in differing circumstances, depending on whether it is desirable to incur the one-time adjustment costs. Such a view implies that marginal costs may be downward-sloping in some relevant ranges of output fluctuations and upward-sloping in other relevant ranges, with substantial discontinuities at the points where different patterns of factor adjustment come into play.

If such non-convexities in marginal cost curves are commonplace, this fact should be incorporated in economic models of price determination, which generally assume that prices are set at marginal cost. Furthermore, the recent arguments for the existence of non-convexities in marginal costs generally emphasize interactions between costs and how manufacturing plant work periods are configured in terms of such features as the number of operating shifts and days of operation. A related literature also emphasizes the need to account for changes in the workperiod of capital in studying the cyclicality of productivity growth (Beaulieu and Mattey (1995), Burnside, Eichenbaum, and Rebello (1995), Shapiro (1996), among others). Here, we introduce a way of thinking about these issues which allows for large differences across plants and industries in the extent of fixity of various factors of production and corresponding heterogeneity in patterns of factor adjustment. In particular, we posit that the technologies of individual manufacturing plants could range from "pure assembly" type operations, where shutdown and startup costs are low and all output adjustments are accomplished through varying the plants' work periods, to "pure continuous processing" type operations, where shutdown and startup costs are large and none of the output adjustments are accomplished through varying the plants' within-week work periods.

We investigate the empirical relevance of these issues by studying patterns of factor utilization reported in the Census Bureau's Survey of Plant Capacity (SPC). The evidence from the SPC turns out to be consistent with the presence of this broad range of technology types, but we find that, on average in all of manufacturing, the use of the plant work period margin is relatively common, so the “pure assembly” type characterization is closer to the truth in the aggregate.

Our results also suggest that measuring changes over time in the work period of capital in various manufacturing industries is important to understanding productivity growth. Many economists have puzzled over why estimates of total factor productivity growth tend to be very procyclical. Although shifts in aggregate demand are thought by many to be the prevailing source of business cycle fluctuations, estimates often show that total factor productivity growth picks up when output is expanding, and productivity growth slows in contractions, as if exogenous technological fluctuations were driving the fluctuations in output. A sizable literature on capital utilization—surveyed by Beaulieu and Mattey (1995) and extended further by Shapiro (1996)—emphasizes that the appearance of strongly procyclical productivity could be due to the mismeasurement of changes in capital service flows. Some recent studies of actual plant-level behavior have confirmed the importance of the work period of capital margin of output adjustment, particularly for assembly type operations (Aizcorbe 1994, Bresnahan and Ramey 1994). However, other industry studies have emphasized variation in the momentary flow rates of production at continuous processing operations (e.g., Bertin, Bresnahan, and Raff 1996), which are not dependent on changes in the work period. We review the evidence for all manufacturing industries and describe the extent to which the duration of capital use can or cannot be taken as fixed.

I. Costs and Adjustment Margins

Production Volume, Flow, and Costs

Assume for now that there are two short-run fixed factors of production, the stocks of capital (K) and labor (N). However, the flows of services from these stocks are not fixed. Plant managers decide each quarter (t) how intensively to use the stocks in each moment (m) of the quarter.

The relationships between service flows and stocks depend both on the duration of use of the factors—how long they are employed during the period—and on the intensity of use at each moment when the factors are employed. For labor, we assume that the intensity of use at a moment (m) can be indexed by the number of employees actually at work in that plant (j), which we denote $L_{jt}(m)$. The capital stock might or might not be divisible in this sense of being able to operate some units and not others. Given that we cannot separately observe usage of components of the capital stock, we will focus on whether or not any part of the plant is operating; the indicator variable, $\varphi_{jt}(m)$, equals 1 if the plant is open at moment m and equals 0 otherwise. When capital is operating, we define the aggregate intensity with which the plant’s capital stock is worked at moment m, its “speed” $s_{jt}(m)$, to be the ratio of the flow of services from the capital stock, $K^s_{jt}(m)$, to the level of the capital stock, $K_{jt}(m)$. The “speed” of the aggregate plant capital stock can be varied either by using each piece of capital at a higher operating rate or by increasing the number of pieces of capital operating. Putting this notation together, the capital service flow at moment m is given by

$$(1) \qquad K^s_{jt}(m) = \varphi_{jt}(m)s_{jt}(m)K_{jt}(m).$$

In addition to the primary factors of production, labor and capital, manufacturing plants also use intermediate inputs, such as raw materials, components manufactured by others, electricity, and purchased business services. For generality, we assume that the plant’s instantaneous production function, $f_{jt}(\,)$, also depends on the flow rate of these materials and other intermediates, $R_{jt}(m)$. Letting discrete time (t) be a quarterly interval between moments m_{t-1} and m_t, note that the volume of production over the quarter Q is the sum (integral) of instantaneous output:

$$(2) \qquad Q_{jt} = \int_{m_{t-1}}^{m_t} f_{jt}\left(L_{jt}(m), K^s_{jt}(m), R_{jt}(m); K_{jt}, N_{jt}\right) dm.$$

Furthermore, because momentary output is non-zero only if the plant is open ($\varphi_{jt}(m) = 1$), the volume of output also can be written as:

$$(3) \quad Q_{jt} = \int_{m_{t-1}}^{m_t} \varphi_{jt}(m)\, f_{jt}\left(L_{jt}(m), K^s_{jt}(m), R_{jt}(m); K_{jt}, N_{jt}\right) dm.$$

Alchian (1959) is among those who early on emphasized the distinction between flow rates of production f and volumes of production Q for understanding production costs. The key insight is that in some production situations the flow rate of production can be altered easily, and in other situations large costs are incurred if the flow differs much from a norm. If shutdown and startup costs are small enough, intermittent production will be optimal for those producers with relatively fixed flow rates. The cost-minimization decision problem of the firm can separate into the twofold choice of how long to leave the plant open during the period, a decision about $\varphi_{jt}(m)$, and how intensely to operate any time the plant is open, a decision about f_{jt} (Maloney and McCormick 1983). On the other hand, if shutdown or startup costs are large enough, the plant will be operated continuously, and all of the variation in output will come from changes in the instantaneous flow rate of production, f_{jt}.

The decisions about the duration of operations are complicated by the fact that there is much discreteness in the labor input of individual members of the workforce. Employees are scheduled to work for particular portions of days (shifts) and generally have days or weeks away from the job. Plant operation schedules generally reflect similar calendar effects. For the quarterly intervals we consider here, the overall workperiod of the plant

$$H_{jt}^{K} = \int_{m_{t-1}}^{m_t} \varphi_{jt}(m)\,dm$$

can be decomposed into the product of four observables, weeks-per-quarter (*WEEKS*), days-per-week (*DAYS*), shifts-per-day (*SHIFTS*), and shift-length in hours-per-shift (*LENGTH*):

$$(4) \qquad H_{jt}^{K} = WEEKS_{jt} DAYS_{jt} SHIFTS_{jt} LENGTH_{jt}.$$

Plant managers can alter the plant work period by changing any of these duration variables.

Costs and Hierarchies of Adjustment Margins

For understanding price determination, it is useful to understand marginal costs. In a static model, the marginal cost schedule of a plant indicates how overall costs depend on incremental changes in output, assuming that factors of production are adjusted in a way which minimize the cost of achieving the given output level. Dynamic models also can recognize that speeds of adjustment affect costs. In general, different margins for adjusting output have different static marginal costs and different adjustment costs. We formalize this idea by writing out the following total cost function:

$$(5) \quad C_{jt}\big(Q_{jt}(m)\big) = F_{jt}\big(L_{jt}(m), K_{jt}^{s}(m), R_{jt}(m), Z_{jt}(m)\big) + \alpha_L I(L) + \alpha_{K^s} I\big(K^s\big) + \alpha_R I(R) + \sum_{k=1}^{n_z} \alpha_{Z_k} I\big(Z_k\big).$$

Here, the overall instantaneous costs $C_{jt}(Q_{jt}(m))$depend on a static piece, F_{jt}, that reflects, for example, that if output is adjusted by increasing labor input L_{jt}, then the overall wage bill of the plant will rise. Similarly, variable costs depend on the instantaneous rate of materials usage $R_{jt}(m)$ and possiblyalso on the pace of capital service flows K_{jt}^{s} through such channels as endogenous depreciation. Implicitly, the static costs are dependent on factor prices, including the possible kink in the wage schedule at the point where the firm begins to pay overtime premia. For expository purposes, we have represented in a vector Z all production choice variables other than labor, capital services, and materials; for example, Z includes the state variables describing the configuration of the plant work period in terms of the number of weeks, days, shifts, and shift length. The other terms in the total cost function are adjustment costs; $I(\,)$ is an indicator variable for whether or not the input level of the given factor has changed.

In a world with no uncertainty and decisions that pertain to only one period, the marginal cost function for a manufacturing plant could be readily derived from this total cost function by deriving its "slope" with respect to output. In problems with non-convexities such as those considered here, this essentially is done by calculating how the optimal factor input levels would change as output varies and by evaluating the changes in the cost function between optimally perturbed factor input levels. Multiperiod decisionmaking and uncertainty add realism to the problem but also create the need for more fully specifying a dynamic, stochastic programming problem.

Some of the basic insights of such a formalization have been well described by Bresnahan and Ramey (1994). For example, if the plant would find it optimal to adjust output by changing aspects of the work period which affect the degree of overtime use, then the marginal cost function is unlikely to be smoothly upward sloping as output increases. When overtime premia trigger at 40 hours per week, an expansion of output along the shift length component of the plant work period margin H_{jt}^{K} encounters a discontinuity in marginal costs at this threshold, assuming a fixed stock of workers (N_{jt}) and a fixed number of workers per operating shift. However, this particular expansion path is not necessarily optimal; plant managers can avoid the use of overtime by hiring additional workers, say by adding an additional shift. At the overtime threshold, the increased static marginal costs can be avoided if the shift margin (represented in Z) is used to spread the additional labor hours over a larger number of shifts. However, in this event the hiring adjustment costs must be absorbed. As Bresnahan and Ramey (1994) point out, overtime hours are more likely to be used than shift changes if the output adjustments are small or temporary, whereas large, permanent output adjustments are more likely to result in shift changes.

These complications have important implications for the relationship between output changes and incremental costs. For example, a plant already using a lot of overtime and considering expanding output further by adding an additional shift faces a kink in the marginal cost schedule where the switch to an extra shift occurs. Conditional on a shift change, the overtime premia are eliminated, lowering marginal costs. Furthermore, given an additional shift, the plant may initially enter a region of increasing returns to scale (greater efficiency as output increases) because the productivity of the group work effort may be greatly inhibited by understaffing of the additional shift. This characteristic of labor productivity, that labor must be added in increments of fully staffed shifts, is most characteristic of assembly line operations. Assembly line operations may face increasing marginal costs over some ranges of output variation and declining marginal costs over other ranges of output variation.

Extremes of Technology Types

For illustrative purposes, we discuss two technology types at the opposite extremes in the nature of the adjustment costs and the degree of lumpiness in labor productivity. We will call "pure assemblers" those manufacturing operations which face very low within-day shutdown and startup costs. Pure assemblers also face very large costs of adjusting flow rates of materials or the speed of capital input and exhibit a high degree of lumpiness in labor productivity (i.e., the need for fully staffed shifts). In contrast, "pure continuous processors" face very large shutdown and startup costs and do not use the work period margin except for infrequent, critical maintenance or under very adverse demand conditions, when the plant will be shut down for weeks at a time. Adjustment costs for flow rates of production are low for continuous processors. Furthermore, we assume that beyond some small amount of overhead labor, the labor productivity of individual workers at continuous processors is not highly dependent on the exact number of workers at the plant at that time; in the extreme, pure continuous processors are very capital and materials intensive, and the marginal product of labor is zero above the overhead threshold.

The assumed characteristics of the cost function for pure assemblers imply that the work period margin is the only operative margin of adjustment for such plants. Accordingly, with cost-minimizing factor inputs, the volume production function of pure assemblers can be represented in a simplified form which illustrates that instantaneous production does not vary across moments when the plant is open,

$$Q_{jt} = \int_{m_{t-1}}^{m_t} \varphi_{jt}(m)\,\overline{f_{jt}}\,dm = \overline{f_{jt}} \int_{m_{t-1}}^{m_t} \varphi_{jt}(m)\,dm. \tag{6}$$

In other words, the volume of output is proportional to the plant work period:

$$Q_{jt} = \overline{f_{jt}}\,H_{jt}^{K}. \tag{7}$$

For pure continuous processors, the large shutdown and startup costs make the plant bunch the shutdown times into continuous intervals. For example, if some shutdown time is needed to conduct necessary maintenance that temporarily interrupts production, the plant is likely to try to complete all such needed maintenance in a single downtime. Within-week downtime would not be regularly observed, but the plant might shut down for one or more contiguous weeks each quarter to conduct the maintenance.[1]

At the cost-minimizing input levels, labor intensity would be fixed at the overhead amount L′. If capital services are dependent only on the size of the capital stock and duration, not on "speed" effects, then only variation in the instantaneous flow of materials, R, would be important for explaining instantaneous output flows of pure continuous processors:

$$f_{jt}(m) = f_{jt}\left(R_{jt}(m); s_{jt}, L'_{jt}, K_{jt}, N_{jt}\right). \tag{8}$$

As a first order approximation to this function, we represent the instantaneous output flow of pure continuous processors as proportional to the flow of materials:

$$f_{jt}(m) = R_{jt}(m)\,\overline{g_{jt}}. \tag{9}$$

Accordingly, the volume of production for a pure continuous processor can be written as

$$Q_{jt} = \int_{m_{t-1}}^{m_t} \varphi_{jt}(m) R_{jt}(m)\,\overline{g_{jt}}\,dm = \overline{g_{jt}} \int_{m_{t-1}}^{m_t} \varphi_{jt}(m) R_{jt}(m)\,dm. \tag{10}$$

Furthermore, the volume of production will be proportional to the plant work period:

$$Q_{jt} = R_{jt}^{*}\,\overline{g_{jt}}\,H_{jt}^{k}, \tag{11}$$

with the factor of proportionality depending on the average flow rate of materials R_{jt}^{*} when the plant is open during the quarter. Given our assumption that continuous processors vary quarterly work periods only in weekly increments, and the number of days per week, shifts per day, and hours per shift are fixed at a continuous operating configuration (24 hours per day for 7 days, or 168 hours per week), this implies

$$Q_{jt} = WEEKS_{jt}\,R_{jt}^{*}\,\overline{g_{jt}}\,168. \tag{12}$$

II. EVIDENCE FROM THE SPC

Why Study the SPC Data?

To learn about the relative prevalence of these technology types, a direct estimate of the cost function (5), which really contains the parameters of interest, is preferable. However, developing empirical evidence on this matter is difficult both because the needed data on output levels, factor in-

1. In the face of very adverse demand conditions, shutdowns of continuous processors are likely to extend for periods that exceed a few weeks. The high shutdown and startup costs imply that when such control of finished goods inventory through downtime is exerted, this will be accomplished, insofar as possible, by extending the duration of maintenance shutdowns.

puts, and factor prices are not fully available, and because there are some important econometric issues which are difficult to address properly in such cost function estimation. For example, ordinary least squares estimation of the cost function parameters via equation (5) is unlikely to provide precise, consistent estimates: as time evolves, favorable shocks to technology or to factor prices can cause marginal costs to decline as output increases, even if diminishing short-run returns to scale are important in the absence of such shocks. Appropriate (relevant and exogenous) demand-side instruments are difficult to find.

We can overcome some of these difficulties by working with the data from the Census Survey of Plant Capacity (SPC). The SPC microdata report information on individual manufacturing plants' output and factor input levels, including the configuration of their work periods. Thus, for example, we can investigate whether the special forms of the volume production functions for either pure assemblers or continuous processors (equations (7) and (12)) fit the data well.

The SPC data also contain information on capacity (output) utilization and factor utilization relative to hypothetical levels of factor inputs at capacity. As we will explain in more detail below, the normalizations implicit in the construction of these utilization measures help us control for the effect of supply (technology) shocks, leading us to focus not just on how output and factor inputs have changed over time, but also on how much output and factor inputs differ from their configurations at capacity.

Information on Actual Operations

The SPC questionnaires were sent to a (probability based) subsample of the manufacturing plants which participated in the Census Bureau's Annual Survey of Manufactures (ASM). In terms of industry composition, representation is quite broad. We study the results of the surveys from the ten years between 1979 and 1988, a period when respondents were asked about the variables of interest. After the end of each year in this period, about 8,000 to 9,000 manufacturing establishments were asked to report on various characteristics of their actual and capacity fourth quarter operations in the preceding year. Some panel members failed to respond to all of the questions. We use only the 16,812 observations from those plants that fully responded to the questions of interest in each year they were a member of the sample. See Mattey and Strongin (1995) for a fuller description of when panel members were dropped for non-response and other data problems.

Respondents were asked about the work period of the plant, in actuality and at capacity, in terms of how many hours per day (*HOURS*), days per week (*DAYS*), and weeks per quarter (*WEEKS*) the plant was or would be in operation. Thus, the work period of the plant, H_{jt}^{K} can be measured for the fourth quarter as a whole as the product of *HOURS*, *DAYS*, and *WEEKS*. Information on the number of shifts per day (*SHIFTS*) also was collected; we compute hours per shift (*LENGTH*) by dividing hours per day by the number of shifts per day.

Tabulations of the responses show that in manufacturing as a whole about 65 percent of the plants were open every week of the quarter (Table 1).[2] Another 25 percent of the plants shut down for only one week of the quarter. Shutdowns of manufacturing plants for more than one week per quarter were relatively rare. However, within-week shutdowns were relatively common. About 58 percent of the plants were open only five days per week. Another 12 percent of the plants shut down exactly one day per week. Within-day shutdowns also were relatively common. About 19 percent of the plants operated only one shift per day. Furthermore, among the 29 percent of the plants that operated two shifts per day, less than 13 percent lengthened these shifts to the 12-hour shift-length which would be needed to keep the plant open 24 hours per day. This simple descriptive evidence that within-week and within-day shutdowns were relatively common suggests that the large shutdown and startup costs which characterize the "pure continuous processor" technology type were not very pervasive in the manufacturing sector as a whole.

Further analysis, however, shows that the roughly 25 percent of plants that ran 24 hours per day, seven days per week were clustered in a relatively few industries. In other words, there was considerably more homogeneity of workweek practices within industries (defined in terms of four-digit SIC classifications) than of workweek practices within manufacturing as a whole.

To show this higher degree of homogeneity within industries, we have classified each four-digit SIC industry into industry groups on the basis of the characteristics of the (capacity or actual) work period of the SPC-reporting plants from that industry. As explained in more detail in Appendix 2 of Mattey and Strongin (1995), continuous processing industries were identified by computing the average work period at capacity, H^{Kc}, for each industry and calling "continuous processors" those industries which would extend operations to virtually every hour of the quarter at capacity. The remaining industries were split into roughly two groups, depending on whether the actual plant work periods in those industries had high coefficients of

2. In about 2 percent of the cases, plants report actual operations of 14 weeks, likely reflecting reference to accounting system calendars which consider this to be the number of weeks in some of the quarters.

variation over time. Those industries with plants with the highest variation in work periods are called "variable work period" industries. The resulting taxonomy is consistent with some of the stylized facts in the economics literature; for example, the blast furnace industry studied by Bertin, Bresnahan, and Raff (1996) is classified as a continuous processing industry, and the auto assembler industry studied by Bresnahan and Ramey (1994) and others is classified as a variable work period industry. See Mattey and Strongin (1995) for a complete listing of this classification of four-digit SIC industries.

The final three columns of Table 1 show that there was considerably more homogeneity of work period practices within these industry groups than within total manufacturing. About 90 percent of the 4,311 plant observations in the continuous processing industries showed operations extending for three eight-hour shifts per day, and about 7 percent run around the clock by having two twelve-hour shifts. Among plants in continuous processing industries, within-week shutdowns also were rare but were somewhat more common than within-day shutdowns; although only about 3 percent shut down overnight during the main workweek, about 16 percent of the plants shut down for one or two days per week.

In contrast, more than 78 percent of the plants in the variable work period industries were open five days and shut down exactly two days per week. Within-day shutdowns also were more common in this group than for continuous processors; about two-thirds of the plants ran only one or two shifts per day, with most shifts being no more than eight hours. Only a small fraction of plants in this group operated 24 hours per day.

This simple descriptive evidence that within-week and within-day shutdowns were relatively uncommon in continuous processing industries suggests that the "pure continuous processor" type of cost and production function might be applicable to these industries.[3]

Similarly, the "pure assembler" type of cost and production function might be applicable in the variable work period industries. However, additional evidence is needed to discern whether the observed workweek behaviors of plants in these industry groups really do reflect technological differences or instead reflect differences in the demand profiles for the products of these industries.

One alternative possibility to a technological explanation for the observed workweek differences is that all industries face similarly low shutdown and startup adjustment costs, but those industries we have classified as continuous processors experienced stronger demand than other industries in this sample period. To be more precise, it is possible that plants in all industries had similar (less than

TABLE 1

Organization of the Work Period in Manufacturing (percent of observations in group)

	Industry Group			
	Total Mfg.	Continuous Processing	Variable Work Period	Other Industries
Weeks per Quarter (*WEEKS*)				
<8	0.3	0.4	0.3	0.1
8–11	9.4	4.8	13.7	7.4
12	25.1	11.4	36.2	21.3
13	63.1	81.0	48.2	69.0
>13	2.0	2.4	1.7	2.2
Days per Week (*DAYS*)				
<5	2.0	0.4	2.6	2.5
5	57.9	11.0	78.4	68.3
6	12.0	4.9	14.5	14.4
7	28.0	83.6	4.5	14.8
Shifts per Day (*SHIFTS*)				
1	19.0	1.0	27.3	22.4
2	28.8	8.8	40.4	29.1
3	52.2	90.1	32.3	48.5
Hours per Shift (*LENGTH*)				
<8	6.3	1.3	9.1	6.8
8	80.7	91.3	74.9	79.8
>8	13.0	7.4	16.0	13.4
Number of Observations	16,812	4,311	7,215	5,286

Source: Calculations by the authors from the Survey of Plant Capacity microdata.

Note: This frequency distribution pertains to observations from the 1979–1983 and 1984–1988 ASM waves.

3. The fact that within-week and within-day shutdowns were relatively uncommon in continuous processing industries is not a tautological implication of the taxonomy which defined continuous processing industries; the continuous, non-continuous distinction was drawn on the basis of the characteristics of plants at capacity, not on the actual operating patterns of the plants.

continuous) target workweeks, but the industries we have called continuous processors underinvested in physical capacity and ended up having to lengthen actual plant workweeks substantially in order to meet higher than expected demand.

As we will discuss below, we can rule out this possibility by examining the survey data on capacity (output) utilization and factor utilization and the reported levels of factor inputs at capacity. However, to follow such a discussion requires an understanding of how the survey concept of capacity relates to the notions of technology and costs we discussed above.

Capacity Utilization and Factor Utilization

The capacity utilization concept focuses on how much feasible production capability is left, given a manufacturer's current, actual rate of output. Notationally, we let δ denote an operator that creates a utilization rate, the difference between a variable at the actual output level and that variable at the capacity output level. Also, we use lower-case variables to denote logarithmic form. Thus, for example, the (logarithmic) output utilization rate for plant j at time t is

$$\delta q_{jt} = q_{jt} - q_{jt}^{c}, \tag{13}$$

where q_{jt} is the logarithm of actual output during the period, and q_{jt}^{c} is the logarithm of capacity output during the period. Similarly, δh_{jt}^{k} and δl_{jt} are the factor utilization rates for the work period and for labor intensity.

There are many possible theoretical definitions of capacity. We restrict our discussion to the capacity concept used in the Census SPC and Federal Reserve Board estimates of capacity utilization. We interpret the full-production capacity concept described in the survey questionnaires as basically equivalent to one of the capacity concepts defined by Klein (1960): capacity output is a full-input point on a production function.[4] That is, capacity is a level of output attainable by "fully employing" the variable factors of production, given the current technology and keeping fixed factors at their current levels. Notationally, this could be written as:

$$Q_{jt}^{c} = \int_{m_{t-1}}^{m_t} f_{jt}\left(L_{jt}^{c}(m), K_{jt}^{cs}(m), R_{jt}^{c}(m); K_{jt}^{c}, N_{jt}^{c}\right) dm, \tag{14}$$

where the c superscripts denote the capacity values of the variables. For the definition of capacity to be complete, the full-employment level of the variable factor inputs needs to be defined, and the distinction between variable and fixed factors needs to be precise.

In the Census SPC, respondents are explicitly told to consider the plant's stock of capital machinery and equipment, K_{jt}, to be a fixed factor, so $K_{jt}^{c} = K_{jt}$. More generally, if the short-run costs of adjusting a factor of production are sufficiently high, that factor is considered to be fixed at current levels for the purposes of determining capacity. For example, respondents are instructed to assume that at capacity the work period is constrained to "the number of shifts and hours of plant operation that can be reasonably attained by your plant in your community." We interpret this as a statement that if adding a third shift to a two-shift operation would entail relocating workers from other communities and paying correspondingly large hiring costs, such as moving expenses and housing supplements, then the configuration of the plant work period at capacity is two shifts. However, if the local labor market already has sufficient qualified workers to keep short-run recruitment and hiring costs for shift expansion low, then the capacity number of shifts can exceed the current number of shifts.

The survey instructions tell respondents not to consider overtime pay and added costs for materials to be limiting factors in estimating capacity. We interpret this as indicating that in assessing the level of factor inputs at capacity, respondents should not focus on the fact that static marginal costs (F_{jt} of equation (5)) can increase with the duration of the work period or volume of materials use, but rather should identify when sharply diminishing returns or high adjustment costs effectively place limits on factor inputs.

For example, for pure assemblers, changes to the linespeed (R_{jt}) and to labor intensity (L_{jt}) are postulated to trigger large adjustment costs. Hence, we would expect the capacity values of line speed and labor intensity to match their actual values. This would imply that when a pure assembly plant is open, the momentary output will be the same in actuality and at capacity, $\overline{f_{jt}} = \overline{f_{jt}^{c}}$. For such plants, the volume of capacity output would be proportional to the plant work period at capacity:

$$Q_{jt}^{c} = \overline{f_{jt}^{c}} H_{jt}^{Kc}, \tag{15}$$

and all of the output utilization gap would be explained by differences between the actual and capacity configurations of the work periods:

$$\delta q_{jt} = \delta h_{jt}^{k}. \tag{16}$$

For pure continuous processors, changes to the flow rate of materials (R_{jt}) are postulated to have low adjustment costs, but changes to labor intensity (L_{jt}) and to any aspects of the work period (H_{jt}^{K}) are postulated to trigger large adjustment costs. Hence, we would expect the capacity values of the flow rate of labor intensity and the work period

4. The term "full production capacity" was introduced in the Census SPC for 1990 and represents only a slight modification of the capacity definition previously called the maximum "practical" level of output.

to match their actual values. The volume of production at capacity would be proportional to the plant work period at capacity:

$$Q^c_{jt} = R^{c*}_{jt}\,\overline{g^{\,c}_{jt}}\,H^{kc}_{jt}, \tag{17}$$

with the factor of proportionality depending on the average flow rate of materials at capacity R^{c*}_{jt} and another term $\overline{g^{\,c}_{jt}}$ which depends only on factors such as labor intensity and the capital stock which are equivalent across actual and capacity configurations. Hence, for pure continuous processors, all of the output utilization gap would be explained by differences between the actual and capacity configurations of the instantaneous flow rate:

$$\delta q_{jt} = \delta r^*_{jt}\,. \tag{18}$$

Any evidence from the SPC which corroborates these strong implications of the postulated technological differences between continuous processors and variable work period industries serves to undermine the alternative explanation that technologies are identical but ex post differences in demand realizations have caused observed work period patterns to diverge across industries. As we will now discuss, some of these strong implications hold up relatively well.

In addition to capacity (output) utilization, the work period and labor intensity factor utilization rates are observable. To obtain individual output utilization rates from the microdata, we start with the observations on the volume of production V_{jt}, which is reported at current prices, P_{jt}:

$$V_{jt} \equiv P_{jt}Q_{jt}\,. \tag{19}$$

Respondents are asked to use these same plant-specific prices in reporting the value of the volume of output at capacity, V^c_{jt}. Hence, the ratio of the reported variables on volume, V_{jt}/V^c_{jt}, also equals output utilization in real terms, Q_{jt}/Q^c_{jt}.

The SPC reports the number of production workers employed at the plant, N_{jt}, and also provides a corresponding measure of quarterly production worker labor hours, H^L_{jt}. Labor intensity, L_{jt}, is computed as the ratio of labor hours, H^L_{jt}, to the work period, H^K_{jt}. Respondents also report the capacity level of employment, N^c_{jt}, labor hours, H^{Lc}_{jt}, and components of the work period of capital H^{Kc}_{jt}. Accordingly, we can derive the utilization rates for the work period of the plants, δh^k_{jt}, and labor (intensity), δl_{jt}, from reported data. We do not observe materials flow intensity, δr_{jt}.

Factor Inputs at Capacity by Industry Group

The capacity configuration of the work period factor inputs differs markedly by industry group (Table 2). Reflecting the initial criterion in our taxonomy, 91 percent of the plants in the continuous processing industries would run seven days per week at capacity. In contrast, only 11 percent of the plants in the variable work period group would operate every day of the week at capacity. Similarly, about 93 percent of the plants in continuous processing industries would run three eight-hour shifts per day at capacity, whereas only about 53 percent of the plants in variable work period industries would adopt this around-the-clock configuration for the capacity work period. Such differences in capacity configurations of the work period across

TABLE 2

ORGANIZATION OF THE WORK PERIOD AT CAPACITY (PERCENT OF OBSERVATIONS IN GROUP)

	Industry Group			
	Total Mfg.	Continuous Processing	Variable Work Period	Other Industries
Weeks per Quarter (*WEEKS*^{c})				
<8	0.0	0.0	0.0	0.1
8–11	3.4	0.6	5.3	3.0
12	19.9	7.1	30.3	16.3
13	74.3	89.9	62.5	77.6
>13	2.4	2.3	1.9	3.0
Days per Week (*DAYS*^{c})				
<5	0.3	0.0	0.4	0.4
5	41.1	3.1	57.8	49.3
6	23.7	6.0	30.7	28.8
7	34.9	91.0	11.2	21.4
Shifts per Day (*SHIFTS*^{c})				
1	9.8	0.3	10.9	16.0
2	24.8	6.8	36.1	24.0
3	65.4	92.9	53.0	60.0
Hours per Shift (*LENGTH*^{c})				
<8	6.8	0.8	10.4	6.8
8	81.2	92.8	74.8	80.6
>8	12.0	6.4	14.8	12.6
Number of Observations	16,812	4,311	7,215	5,286

See notes to Table 1.

industry groups would be difficult to explain in terms of ex post differences in demand realizations.

Utilization by Industry Group

Patterns of factor utilization also differ markedly by industry group. First, it is clear that plants in the continuous processing industries almost always show no deviation from their capacity to run 24 hours a day, each day the plant is open (Table 3); only 3.1 percent of the continuous processing plants deviate from the capacity number of shifts per day, and 2.3 percent of the plants deviate from the capacity number of hours per shift. In contrast, about one-third of the plants in the variable work period group had the actual number of shifts deviating from the capacity number of shifts, and actual shift length also was out of line with capacity shift length about 22 percent of the time. Similarly, among plants in the continuous processing industries, actual operations were cut back one or more days from the capacity threshold for days only 11 percent of the time, but about 29 percent of plants in the variable work period group used this days-per-week margin for holding excess capacity.

For plants in the variable work period group, each of the *WEEKS*, *DAYS*, *SHIFTS*, and *LENGTH* margins is used with roughly equal frequency, between one-fifth and one-third of the time. At a given instantaneous flow rate of production, one would expect the magnitude of the effects on output utilization of using different work period margins to be roughly proportional to their effects on the work period itself. For example, for plants with thirteen weeks at capacity, we expect that shutting down for a week (losing one-thirteenth of the work period) would decrease actual output relative to capacity output by about one-thirteenth. Dropping a day from a six-day capacity workweek would decrease total hours one-sixth, other things equal, whereas decreasing the number of shifts from three to two shifts would reduce the work period by one-third. Given a modal shift length of eight hours, the impact on total hours of one-hour increments to shift length tend to be somewhat smaller than those of adjusting the work period by a day but larger than those of adjusting the quarterly work period by a week. Given these differential impacts of adjusting the various work period margins but relatively equal frequencies of use, we should expect shift utilization patterns to explain a lot of the variance in output utilization for plants in variable work period industries.

To pursue this idea, as well as to determine whether or not other aspects of equation (16) and equation (18) fit the data well, we turn to regression evidence. Table 4 displays the results of regressions that explain the plant-specific output utilization rates, δq_{jt}, as a function of the utilization

TABLE 3

FREQUENCY OF USE OF DIFFERENT MARGINS FOR ADJUSTING WORK PERIODS IN MANUFACTURING (PERCENT OF OBSERVATIONS WITH NONZERO DEVIATIONS FROM CAPACITY)

	Industry Group			
	Total Mfg.	Continuous Processing	Variable Work Period	Other Industries
Weeks per Quarter ($\delta weeks \neq 0$)	15.2	10.3	20.2	12.3
Days per Week ($\delta days \neq 0$)	23.2	11.1	28.7	25.6
Shifts per Day ($\delta shifts \neq 0$)	20.2	3.1	32.8	16.9
Hours per Shift ($\delta length \neq 0$)	14.5	2.3	22.5	13.5
Number of Observations	16,812	4,311	7,215	5,286

See notes to Table 1.

rates for labor intensity and the work period of the plant, either as a whole or with components of the work period entered separately. The orthogonal portion of the intensity of the flow rate of materials, δr_{jt}, is left to the residual. Regressions omitting selected explanatory variables also were computed. We present the pattern of regression results as a decomposition of the variance in the dependent variable.

For total manufacturing, the regression results suggest that neither the pure assembler technology (equation (16)) nor the pure continuous processor technology (equation (18)) are adequate representations; variations in utilization of plant workperiods explain some, but not all, of the variance in output utilization. Also, changes in actual labor intensity relative to labor intensity at capacity explain about 25 percent of the variance in capacity utilization.

The results are more consistent with the implications of the pure technology types within the corresponding industry groups than within manufacturing as a whole. For plants in the continuous processing group, the residual unexplained variation is 63 percent, quite a bit larger than for the variable work period or other industries groups. This large residual variance suggests that orthogonal variations in the flow rate of materials and components are more important for continuous processors than for other manufacturers, as we expected. For continuous processors, most of the predictive power of the work period variable, δh^k, is

TABLE 4

CONTRIBUTIONS TO VARIANCE IN OUTPUT UTILIZATION
(PERCENT OF VARIANCE)

	Contributions of Explanatory Variables[a]								
			Components of δh^k						
Industry Group	δl	δh^k	$\delta weeks$	$\delta days$	$\delta shifts$	$\delta length$	Total Explained[b]	Unexplained
Total Manufacturing	25	37	4	6	27	3	62	38
Continuous Processing	15	22	5	9	7	1	37	63
Variable Work Period	27	41	5	5	32	1	68	32
Other Industries	26	31	2	5	26	2	57	43

SOURCE: Calculations by the authors from the Survey of Plant Capacity microdata.

NOTES: a. The entries are calculated from the R^2 of regressions of output utilization δq on the explanatory variables. Each entry is the average of two estimates of the contributions of the regressors; one estimate is the difference between the R^2 of the full multivariate regression and a regression deleting only the explanatory variable shown at the head of the column, and the other estimate is the R^2 of a bivariate regression of output utilization on the explanatory variable. This process was repeated with δh^k treated as a single variable and with only the components of δh^k in the regressions. Note that this variance decomposition method does not constrain the sum of contributions to equal the total explanatory power.

b. These regressions use observations from the 1979–1983 and 1984–1988 ASM waves. There are 16,812 observations for total manufacturing, 4,311 for continuous processors, 7,215 for plants in variable work period industries, and 5,286 observations for plants in other industries.

through use of the weeks and days margins, whereas within-day deviations from the (generally round-the-clock) configuration of operations at capacity are rare. The tendency to use shutdowns of days or weeks at a time instead of overnight suggests that the shutdown and startup costs are larger at continuous processors than in other industries.

Patterns of factor utilization among plants in the variable work period group look more similar to those implied by the pure assembler technology than to those implied by the pure continuous processor technology, but the pure assembler technology equation (16) does not fully describe the behavior of these plants. Variations in the work period of the plants are more important than variations in labor intensity and more important than residual flows for explaining short-run output adjustments among plants in the variable work period industries. Also, among the components of the work period, shift deviations have the largest explanatory power, likely reflecting the fact that plants in this group face relatively low overnight shutdown and startup costs. However, in contradiction to the implications of equation (16), actual labor intensity does not always equal labor intensity at capacity for these plants, and also the residual flow is able to explain about 32 percent of the variance in capacity utilization.

In all three industry groups, manufacturing plants exhibit some positive correlation between output and utilization of each of three factors, the work period H^K, labor intensity L, and materials flow intensity R. One likely shortcoming of the stark dichotomy of technology types relates to aggregation. Individual components of the manufacturing process, such as a furnace or an individual assembly line, might be well-described by either the continuous processing or assembly model, but a manufacturing establishment can consist of many such components. For example, Bertin, Bresnahan, and Raff (1996) find that basic iron and steel production was well-described by a continuous processing model at the level of individual blast furnaces, but many plants had more than one blast furnace on site. By shutting down or starting up individual furnaces, an establishment that was a collection of continuous processing units could vary plant-level output without changing the flow rates of individual components or the work period of the plant as a whole. Similarly, some assembly operations are organized into "work stations" rather than assembly lines. If each work station has low shutdown and startup costs, and the work stations can function independently of each other, then partial shutdowns can be used to vary output. This happens, for example, in apparel establishments that are merely a collection of sewing machines doing the same job. In both the case of an aggregation of continuous processing units and the case of an aggregation of assembly stations, the plant work period is a noisy measure of the actual work period of capital, and materials flow and labor intensity are likely to be positively correlated with the measurement error.

Changes over Time

Measurement error and omitted variables become even more important issues for analyzing changes in output and factor inputs over time using the SPC data. One major difficulty with estimating the volume production functions for either pure assemblers or continuous processors (equations (7) and (12)) is that the actual constant-dollar volumes of output Q_{jt} are not observed; we observe output volumes only in nominal terms, V_{jt}. Thus, we must focus on the revenue functions for pure assemblers and pure continuous processors, which are:

$$V_{jt} = \overline{f_{jt}}\, H^K_{jt} P_{jt} \ , \tag{20}$$

$$V_{jt} = WEEKS_{jt}\, R^*_{jt}\, \overline{g_{jt}}\, 168 P_{jt} \ . \tag{21}$$

Unfortunately, plant-specific prices, P_{jt}, are not observed for each plant. Also, the proportionality factors ($\overline{f_{jt}}$ for assemblers and $\overline{g_{jt}}$ for continuous processors) which we would like to estimate as fixed parameters actually may differ across plants and over time. For example, technological improvements at a given assembly plant which shift its momentary production function, f_{jt}, would lead to an increased nominal volume of output even with an unchanged work period and prices.

We proceed, with the above duly noted caveat, under the simplifying assumption that, for a given plant, these proportionality factors do not change over time. Then, we focus on the logarithmic time difference forms of these equations to eliminate the proportionality factors:

$$\Delta v_{jt} = \Delta h^K_{jt} + \Delta p_{jt} \ , \tag{22}$$

$$\Delta v_{jt} = \Delta WEEKS_{jt} + \Delta p_{jt} + \Delta r^*_{jt} \ . \tag{23}$$

Table 5 displays the results of regressions which nest these specifications by explaining the plant-specific nominal output changes, Δv_{jt}, as a function of changes in labor intensity and in the work period of the plant, either as a whole or with components of the work period entered separately. Also, an industry-level proxy for the plant-specific price changes is included in each regression. Again, we present the pattern of regression results as a decomposition of the variance in the dependent variable.

The most striking feature of these regression results is the low explanatory power. The total explained variance for manufacturing as a whole is 17 percent. Subsample results for the variable work period group reveal only a little bit more explanatory power, 22 percent. We suspect that the poor goodness-of-fit largely owes to the inadequacy of changes in industry average prices to capture changes in plant-specific prices. Many manufacturing plants have a heterogeneous product mix which includes secondary products characteristic of other industries in addition to those products primary to the industry to which the plant is classified (Mattey and ten Raa 1997), and this heterogeneity diminishes the relevance of industry-based deflators. Also, even for individual products, dispersion of prices across plants can be quite large (Beaulieu and Mattey 1994). Another possible explanation for the low explanatory power of these regressions is that plant-specific technological changes tend to be quite large.

Given these caveats, it still is interesting to note that some of the basic implications of equations (22) and (23) show through in the subsample results for industry groups. With regard to continuous processors, equation (23) implies that the residual variation may be large, reflecting the presence of the additional term Δr^*_{jt} in the residual, and all of the explained variance should be accounted for by the contributions of changes in prices and in weeks of operation. In fact, the residual variance is large, and virtually all of the explained variance is accounted for by the contributions of changes in prices and in weeks of operation. With regard to the variable work period group, equation (22) implies that all of the explained variance should be accounted for by the contributions of changes in prices and in all components of the work period, possibly including major roles for within-week margins of work period adjustment. In fact, changes in the number of days-per-week, shifts, and shift-length do account for about one-half of the overall explanatory power. Among these, changes in the number of shifts are the most important. However, in contradiction to the pure assembler technology type, changes in labor intensity also account for about one-half of the overall explanatory power.

Next, we address the issue of whether there are major differences in how plants achieve capacity output adjustments over time which tend to corroborate or refute the hypothesis that plants in the continuous processor group face relatively large shutdown costs and plants in the variable work period group face relatively small shutdown costs. In addition to the work period of the plant at capacity, h^{kc}_{jt}, there are several other sources of potential variation in capacity output suggested by its definition and our emphasis. These include changes over time in the stock of capital, K_{jt}, the flow rate of materials at capacity, r^c_{jt}, and the intensity of labor at capacity, l^c_{jt}. Substantial changes in either the work period at capacity, h^{kc}_{jt}, or the intensity of labor, l^c_{jt}, are likely to entail changes in the capacity level of employment, N^c_{jt}.

To summarize the extent to which capacity changes over time are due to changes in plant hours at capacity, h^{kc}_{jt}, versus changes in the capital stock, K_{jt}, labor intensity at capacity, l^c_{jt}, or the flow rate of materials at capacity, r^c_{jt}, we again look at contributions to the fit of regressions. Each regression has the form:

$$(24)\quad \Delta v^c_{jt} = \beta_0 + \beta_1 \Delta h^{kc}_{jt} + \beta_2 \Delta l^c_{jt} + \beta_3' \Delta \hat{k}_{jt} + \Delta p_t + \Delta \varepsilon_{jt} .$$

The dependent variable is the change over time in the plant's (logarithmic) level of nominal capacity output. The vector $\Delta \hat{k}_{jt}$ contains four qualitative response variables indicating whether changes in the capital stock have changed capacity and four quantitative measures of changes in the capital stock. Changes in prices, Δp_t, are measured at the industry level. The flow rate of materials at capacity r^c_{jt} is not observable, and the orthogonal portion of r^c_{jt} and plant-specific price changes which differ from industry averages likely dominate the residual in the equation, ε_{jt}.

The proxies for changes in the capital stock included in the vector $\Delta \hat{k}_{jt}$ are based on two types of measures. First, the capacity survey contains separate questions on why a respondent is reporting a change in capacity over time, including specific questions on changes in the capital stock. The variables on this portion of the survey are qualitative. Respondents can check one or more boxes indicating whether capacity has changed because of four types of changes in the capital stock, which cover expenditures and retirements of buildings and machinery separately.[5] About 2.6 percent of the respondents indicate that building capital expenditures have led to capacity expansion, and 9 percent indicate substantial expenditures on machinery. Retirements occur much less frequently, at a 0.4 percent rate for build-

5. In addition to the four capital-related reasons for changing capacity, respondents also can indicate that capacity changes are from factors such as changes in the method of operation, product mix, or composition of material inputs. About 3 percent of respondents indicate capacity changes arise from changes in method of operation, and 2 percent cite material inputs. Product mix changes are widely cited, with about

TABLE 5

CONTRIBUTIONS TO VARIANCE IN CHANGES IN ACTUAL OUTPUT (PERCENT OF VARIANCE)

	Contributions of Explanatory Variables[a]								
			Components of δh^k						
Industry Group	Δl	Δh^k	$\Delta weeks$	$\Delta days$	$\Delta shifts$	$\Delta length$	Δp	Total Explained[b]	Unexplained
Total Manufacturing	7	7	2	2	4	0	3	17	83
Continuous Processing	0	3	3	0	0	0	15	19	81
Variable Work Period	11	10	2	3	6	1	0	22	78
Other Industries	8	6	2	1	2	1	0	14	86

SOURCE: Calculations by the authors from the Survey of Plant Capacity microdata.

NOTES: a. The entries are calculated from the R^2 of regressions of logarithmic changes in nominal output Δv on the explanatory variables. Each entry is the average of two estimates of the contributions of the regressors; one estimate is the difference between the R^2 of the full multivariate regression and a regression deleting only the explanatory variable shown at the head of the column, and the other estimate is the R^2 of a bivariate regression of output changes on the explanatory variable. This process was repeated with Δh^k treated as a single variable and with only the components of Δh^k the regressions. Note that this variance decomposition method does not constrain the sum of contributions to equal the total explanatory power.

b. These regressions use observations from the 1979–1983 and 1984–1988 ASM waves. There are 5,707 observations for total manufacturing, 1,597 for continuous processors, 2,282 for plants in variable work period industries, and 1,828 observations for plants in other industries.

ings and a 1.8 percent rate for machinery. Overall, changes in the capital stock of at least one of these four types are reported as reasons for capacity changes for only about 11 percent of the observations.

Our second type of measure of changes in the capital stock is compiled by matching the SPC microdata with the microdata from the ASM. The latter survey includes quantitative estimates of new investment and retirements of machinery and buildings. We express these flow variables as a proportion of the book value of the corresponding type of capital (machinery or buildings) and let them serve as additional predictors of capacity changes.

The regression results are again summarized in terms of contributions to explaining the variance in the dependent variable, which in this case is changes in capacity output (Table 6).

These regressions also have low explanatory power, again likely due to the inadequacies of the price deflators or to a dominant role for technological change. Nevertheless, the subsample results show that for continuous processors, changes in the capital stock were the most important observable margin for adjusting capacity output (in real terms). Changes in the capacity labor intensity and work period explained almost none of the variation in capacity output. For plants in the variable work period group, changes in the capital stock also accounted for a noticeable fraction of capacity output changes. However, for plants in this group, changes in the capacity work period and labor intensity also were important.

The results on changes in capacity over time are interesting when viewed in conjunction with data on capacity utilization rates. Among plants in the continuous processor group, the mean capacity (output) utilization rate over the full sample period was 88 percent, which implies that such plants tend not to carry much excess capacity. In contrast, the mean capacity utilization rate for plants in the variable work period group was about 59 percent, which indicates that they tended to have a lot of room for upward expansion of output. Thus, in order to achieve large upward adjustments of actual output, continuous processors need to increase capacity, but plants in the variable work period group

13 percent of respondents indicating this as a source of capacity change. Because the direction of the impact on capacity of the changes indicated by these additional qualitative response variables is ambiguous, we have not included them in the analysis.

TABLE 6

CONTRIBUTIONS TO VARIANCE IN CHANGES IN CAPACITY OUTPUT (PERCENT OF VARIANCE)

	CONTRIBUTIONS OF EXPLANATORY VARIABLES[a]					
INDUSTRY GROUP	Δl^c	Δh^{kc}	$\Delta \hat{k}$	Δp	TOTAL EXPLAINED[b]	UNEXPLAINED
TOTAL MANUFACTURING	2.4	1.0	2.4	4.1	10.1	89.1
CONTINUOUS PROCESSING	0.5	0.0	3.6	14.1	18.2	81.8
VARIABLE WORK PERIOD	4.2	1.6	2.0	0.8	9.1	90.9
OTHER INDUSTRIES	2.0	2.1	2.7	1.5	8.5	91.5

SOURCE: Calculations by the authors from the Survey of Plant Capacity microdata.

NOTES: a. The entries are calculated from the R^2 of regressions of logarithmic changes in nominal capacity output Δv on the explanatory variables measuring changes in labor intensity at capacity, Δl^c, changes in the work period at capacity, Δh^{kc}, proxies for changes in the capital stock, $\Delta \hat{k}$, and changes in industry-level prices, Δp. Each entry is the average of two estimates of the contributions of the regressors; one estimate is the difference between the R^2 of the full multivariate regression and a regression deleting only the explanatory variables shown at the head of the column, and the other estimate is the R^2 of a regression of output utilization on the explanatory variables at the head of the column. Note that this variance decomposition method does not constrain the sum of contributions to equal the total explanatory power.

b. These regressions use observations from the 1979–1983 and 1984–1988 ASM waves. There are 8,795 observations for total manufacturing, 2,378 for continuous processors, 3,671 for plants in variable work period industries, and 2,739 observations for plants in other industries.

generally do not need to increase capacity. Thus, the capacity change regression results suggest that plants in the continuous processor group basically only have two margins for large expansions of output, engaging in physical investment in plant and equipment or improving technology. However, many plants in the variable work period group have additional margins, such as adding a shift and hiring additional employees to staff it.

III. How This Helps Resolve Puzzles

So far in this paper, we have presented theoretical examples of how technological differences among manufacturing plants could give rise to varying patterns of factor utilization which affect the relationships between costs and output changes. We also have shown that empirical evidence is consistent with the existence of some actual manufacturing plants with technologies resembling each of the theoretical extremes, "pure continuous processors" and "pure assemblers," but the use of workweek margins as in the assembler type appears to have more relevance than continuous processing in the aggregate. The recognition of these patterns helps resolves some puzzles in the economics literature.

Capacity Utilization, Marginal Costs, and Prices

Other things equal, an increase in capacity utilization at a manufacturing plant is likely to be associated with an increase in its output price, given that capacity is invariant in the short-run, and assuming that output is increasing because the demand curve has shifted outward along an upward-sloping supply (marginal cost) curve. Alternatively, economic theory admits the possibility of a negative correlation between capacity utilization and price changes if the output increase is along a downward-sloping portion of the marginal cost curve. In terms of empirical evidence, capacity utilization is useful as an aggregate indicator of inflationary pressures (Corrado and Mattey 1997), but Shapiro (1989) is among those who have noted that the data do not universally support the simple notion that output utilization increases signal outward movements along upward-sloping marginal cost curves. Given also Shea's (1993) findings, the balance of evidence seems to support relatively sharply upward-sloping marginal cost curves in continuous processing industries, but there is greater uncertainty about the slope of marginal cost curves in variable work period industries.

Our findings in this paper that there appear to be large differences between continuous processing industries and variable work period industries in how output adjustments are achieved provide a consistent framework for understanding this pattern of empirical results on capacity utilization and price changes. To the extent that plants in variable work period industries have technologies which represent the "pure assembler" archetype, they face decreasing marginal costs over some ranges of output changes and increasing marginal costs over other ranges of output changes. In particular, a plant which adds a shift incurs an adjustment cost but also triggers decreasing marginal costs over the range of output where the shift would be quite understaffed. This non-convexity in marginal cost curves is not present in continuous processors because the shift margin is not available to them.

Workweek of Capital and Productivity Growth Accounting

Many economists have puzzled over why estimates of total factor productivity growth tend to be very procyclical. Although shifts in aggregate demand are thought by many to be the prevailing source of business cycle fluctuations, estimates often show that total factor productivity growth picks up when output is expanding, and productivity growth slows in contractions, as if exogenous technological fluctuations were driving the fluctuations in output.

Recent contributions to the literature on capital utilization note that the appearance of strongly procyclical productivity could owe to the mismeasurement of changes in capital service flows. In periods of high capital utilization, the flow of services from the capital stock is likely to be underestimated, and total factor productivity overestimated, if capital service flows are assumed to be proportional to capital stocks. Data on capital utilization could help one overcome this measurement difficulty.

The problem is that capital utilization per se is not observable. Materials and energy usage have been used as proxies for capital utilization by some authors (e.g., Basu 1996 and Burnside, Eichenbaum, and Rebelo 1995), whereas the workweek of capital has been emphasized as the best capital utilization proxy by others (Shapiro 1986, 1993, 1996, Beaulieu and Mattey 1995).

The models and empirical evidence discussed in this paper help us discriminate between these alternative choices for capital utilization indicators. In particular, the workweek of capital is a perfect indicator of capital utilization for any plant with a pure assembler technology type (equation 7). In contrast, pure continuous processors do not use the workweek margin, so the workweek should not be used as an indicator of capital utilization for such plants. In our heuristic derivation of a simplified production function for continuous processors (equation 12), we also have assumed that the instantaneous speed of capital, the $s_{jt}(m)$ of equation (1), is invariant. However, more generally continuous processors could exhibit variations in the speed of capital, likely in proportion to the momentary flow rate of materials and other intermediates $R_{jt}(m)$. In this case, the average flow of materials R^*_{jt} during the quarter would be a perfect proxy for capital utilization at continuous processors. Our empirical evidence suggests that although one cannot perfectly segregate actual manufacturing industries into such pure technology groups, the data do support some bifurcation along these lines.

Shapiro (1996) has studied the workweek data from the SPC as aggregated from the plant to industry level by Beaulieu and Mattey (1995). Shapiro found that in terms of reducing the appearance of procyclicality in total factor productivity growth, the plant workweek data are superior to materials and energy usage proxies for noncontinuous processor industries. For continuous processor industries, the materials and energy proxies are superior to the workweek as a measure of capital utilization. Shapiro's (1996) findings are consistent with the theoretical models of technology types presented here and with our demonstration that the classification of actual industries into such technology groups is not strongly rejected by the data.

IV. CONCLUSION

Recent literature suggests that the relationships between marginal costs and output levels of manufacturers are complicated by the presence of multiple ways to achieve output changes and of one-time costs to adjusting some factors of production. A related literature also emphasizes the need to account for changes in the work period of capital in studying the cyclicality of productivity growth. This paper explains the basic issues in these literatures and develops new evidence on the relevance of their concerns about heterogeneity in patterns of factor utilization, drawing from previously unstudied individual responses to a survey of manufacturing plant capacity and factor utilization. We find that the concerns about the heterogeneity in patterns of factor adjustment are well-founded. Plants in some industries appear to face sizeable shutdown and startup costs which prevent them from using within-week plant work period changes as a margin of adjustment. Plants in many other industries exhibit substantial variations in plant workweeks over time. For manufacturing as a whole, the workweek appears to be a significant margin of adjustment.

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