Capacity constraint and seasonal productivity variations at the plant level

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This paper examines seasonal productivity variations by using monthly plant-level physical output and capacity data. The regression results confirm that seasonal output elasticity is substantially larger than non-seasonal elasticity not only at the industry level, but also at the plant level. The productivity becomes low in demand-peak season particularly at plants with capacity highly utilized, as consistent with the capacity constraint interpretation. The effect of capacity constraint on productivity fluctuations, however, is modest compared with that of seasonal demand variations.

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I. INTRODUCTION

Seasonal fluctuations of production have been intensively explored. Previous studies have found important interactions between seasonality and business cycles by focusing on the critical role of capacity constraint. For example, to explain their finding of a positive correlation between seasonal and cyclical variations, Beaulieu et al. (1992) suggested the truncation of high season output by the capacity constraint. Based on the intuition that firms tend to allocate larger fraction of annual production to off-peak season as capacity is more severely constrained, Cecchetti et al. (1997) compared seasonal fluctuations during a boom with those during a recession.

Seasonal variations, however, should not be ignored in other economic variables as well. Among important variables, the productivity exhibits large seasonal variability. It is implausible to attribute the strong seasonality in productivity to non-seasonal technology shocks. Braun and Evans (1998) showed that a single seasonal demand peak due to Christmas is sufficient, under labor hoarding and increasing returns, to explain the whole seasonal variations in U.S. Solow residuals. No previous work, as far as the author knows, however, has considered the capacity constraint in analyzing seasonal productivity fluctuations.

This paper examines the effect of capacity constraint on seasonal productivity variations. The biding capacity constraint due to the seasonal demand peak is likely to reduce the productivity in high season and thus to attenuate seasonal variations of productivity. This paper attempts to quantitatively evaluate this effect on productivity fluctuations, by applying the instrumental variables method proposed by Miron and Beaulieu (1996). Since the capacity utilization rate varies considerably from plant to plant even within the same industry, this paper exploits plant-level data.[1] To preview the results, our estimates show that the productivity becomes low in demand-peak season particularly at plants with capacity highly utilized, although the effect of capacity constraint on productivity fluctuations is found markedly minor compared with the substantial role of seasonal demand variations.

The rest of the paper is organized as follows. Section II explains methods for estimating productivity. Section III describes our plant-level data and reports empirical results. Section IV concludes.

II. ESTIMATION METHODS

This section describes our estimation methods. First, consider the standard framework used in the productivity analysis as follows. Taking logarithm and totally differentiating the production function for plant i at time t, we obtain

$$dy_{it} = \beta dz_{it} + \varepsilon_{it} \qquad (1)$$

,where y, z, ε and β are output, input, Solow residuals, and elasticity, respectively.[2] Since errors are in general correlated with inputs, the equation (1) cannot be estimated by OLS. As Miron and Beaulieu (1996) proposed, however, seasonal dummy variables can be served as valid instrument variables (IV) because they are likely to be uncorrelated with errors but correlated with inputs under the usual assumption that technology shifts are non-seasonal while demand varies seasonally. Let label $\hat{\beta}^{S}$ the IV estimate of elasticity from regression of (1) using all the monthly dummies as the only instruments.

Second, to obtain the non-seasonal elasticity estimate $\hat{\beta}^{NS}$, this paper estimates the following OLS regression (2) with monthly dummies DUM_j (j=1,2,…,12) additionally included in the regression.[3]

$$dy = \beta^{NS} dz + \sum_j \gamma_j DUM_j + \varepsilon \qquad (2)$$

Seasonal output is likely to be more elastic than non-seasonal output, for example, under labor hoarding because firms tend to avoid costly labor adjustment facing seasonal fluctuations, which are usually transitory and anticipated ($\hat{\beta}^{NS} < \hat{\beta}^{S}$).[4]

Finally, to assess the effect of capacity constraint, we must reexamine whether the assumption of errors uncorrelated with seasonality holds in all months. Consider the illustrative case where the cost function is inverted-L shaped, as in Beaulieu et al. (1992). If the capacity constraint is binding in high season, the technology in the capacity-constrained months can be interpreted as different from that in normal months because of its low marginal labor productivity. Thus, the orthogonality condition fails in those demand-peak months since technology shifts in this case are induced seasonally. "A simple remedy is to pare the list of instruments to those months where the orthogonality condition is likely to hold." (Miron and Beaulieu (1996) p.56)[5] Let denote $\hat{\beta}_C^S$ the IV estimate from the following (3), where monthly dummies except the dummy for the highest capacity utilization month, *h*, are used as instruments for inputs.[6]

$$dy = \beta_c^S dz + \delta DUM_h + \varepsilon \qquad (3)$$

The seasonal output elasticity from which the seasonal component of output in the peak month is eliminated must be larger than the usual seasonal elasticity ($\hat{\beta}^S < \hat{\beta}_C^S$). The comparison of the two IV estimates ($\hat{\beta}^S$, $\hat{\beta}_C^S$) enables us to infer the effect of capacity constraint on seasonal productivity variations.

III. DATA AND EMPIRICAL RESULTS

As an example of production with strong seasonality, this paper chooses the production of air conditioners in Japan. The monthly data of physical unit output and capacity are derived from *Current Survey of Production* (Seisan Dotai Tokei in Japanese).[7] As evident from Table 1, the seasonal variation is much larger than non-seasonal variation in this industry.[8] The large cross-section standard deviation suggests that plants are considerably heterogeneous in terms of productivity as well as of capacity utilization.[9]

Table 2 presents principal regression results.[10] The noteworthy findings are as follows. First, the result in the "AGGREGATE" row confirms the previous finding by Miron and Beaulieu (1996) that the seasonal variation in output is highly elastic to the seasonal variation in labor input at the industry level. The seasonal variation is nearly three times as large as non-seasonal variation.[11] The strong contrast between seasonal and non-seasonal variability appears consistent with the labor hoarding.[12]

Second, as reported in the "PLANT" rows in Table 2, the results from 21 individual plants overwhelmingly demonstrate that the industry-level finding of seasonal elasticity larger than non-seasonal elasticity is not the artifact of aggregation.[13] Hence, consistent with the existing evidence from U.S. plant-level data reported by Baily et al. (2001), previously observed variability of aggregate productivity is a within-plant phenomenon rather than a reflection of composition reallocations across plants.[14]

Finally, as the $\hat{\beta}_C^S / \hat{\beta}^S$ column shows, in 16 out of 21 plants, the seasonal output is noticeably more elastic with respect to seasonal labor input in normal eleven months, compared with that in the highest capacity utilization month.[15] The output elasticity β is estimated to be higher by around six percent (average of estimates for individual plants) to nine percent (aggregate estimate) if we merely exclude the only one capacity-constrained month from the instruments. Consequently, the effect of capacity constraint should be viewed as rather sizable, although it is modest compared with the enormous contrast between seasonal variations and non-seasonal variations.

Besides, Table 3 shows that this effect of the extreme month on productivity is evident particularly at those plants whose capacity utilization rate is distinctively high (0.459>0.308). Thus, the inter-plant comparison of average capacity utilization levels provides evidence that our regression results are consistent with the capacity constraint interpretation.

Therefore, our finding is in line with the previous results from Beaulieu et al. (1992) and Cecchetti et al. (1997) in confirming the significant effect of capacity constraint on seasonal variability, but is also consistent with the conclusion by Braun and Evans (1998) in discovering that seasonal demand variations play a dominant role in productivity fluctuations.

IV. CONCLUDING REMARKS

The effect of capacity constraint on plant-level productivity variations has been investigated. This paper has found that the capacity constraint affects productivity although its effect is minor compared with that of seasonal demand variations. Since the effect of capacity constraint depends on the degree to which capacity can be adjusted, tasks remained for future works include the comparison of industries facing different adjustment costs of capacity.

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Table 1. *Summary Statistics*

	Output	Productivity	Capacity Utilization
AGGREGATE			
Average	667,825	2.047	0.614
S.D. (*seasonal*)	181,556	0.419	0.169
(*non-seasonal*)	108,631	0.276	0.098
PLANT-LEVEL			
Average	32,318	2.450	0.413
S.D. (cross-section)	31,899	2.194	0.139

Note: "AGGREGATE" corresponds to the sum over all plants in our sample. "S.D. (*seasonal*)" is defined as standard deviation among each month's average ($\overline{X}^M \equiv \frac{1}{8}\sum_{Y=1988}^{1995} X_Y^M$, where M and Y denote month (M=1,…,12) and the calendar year (Y=1988,…,1995).), while "S.D. (*non-seasonal*)" is standard deviation among each year's average ($\overline{X}_Y \equiv \frac{1}{12}\sum_{M=1}^{12} X_Y^M$). "S.D. (cross-section)" is the standard deviation among each plant's average.

Table 2. *Comparison of estimates*

	$\hat{\beta}^{NS}$	$\hat{\beta}^{S}$	$\hat{\beta}^{S}_{C}$	$\hat{\beta}^{S} / \hat{\beta}^{NS}$	$\hat{\beta}^{S}_{C} / \hat{\beta}^{S}$
Aggregate	0.742 (0.216)	2.071 (0.157)	2.254 (0.166)	2.791	1.088
Average	0.692	2.274	2.409	3.286	1.059
Plant No.1	4.656 (0.676)	4.083 (0.773)	4.548 (0.875)	0.877	1.114
2	2.536 (1.398)	1.684 (0.740)	1.812 (0.776)	0.664	1.076
3	1.732 (1.364)	2.176 (1.360)	2.167 (1.385)	1.256	0.996
4	1.518 (0.129)	1.372 (0.143)	1.473 (0.163)	0.904	1.074
5	1.246 (0.358)	1.011 (0.171)	1.025 (0.177)	0.812	1.014
6	1.082 (0.363)	1.627 (0.302)	1.495 (0.356)	1.503	0.919
7	0.947 (0.192)	0.863 (0.251)	0.945 (0.267)	0.911	1.095
8	0.788 (0.376)	1.221 (0.184)	1.199 (0.199)	1.550	0.982
9	0.749 (0.164)	1.664 (0.284)	1.806 (0.316)	2.222	1.085
10	0.638 (0.149)	0.676 (0.227)	0.688 (0.401)	1.061	1.017
11	0.567 (0.100)	0.657 (0.194)	0.747 (0.242)	1.158	1.137
12	0.562 (0.123)	1.126 (0.157)	1.292 (0.186)	2.002	1.148
13	0.497 (0.168)	1.480 (0.148)	1.572 (0.156)	2.980	1.062
14	0.406 (0.077)	1.106 (0.128)	1.170 (0.148)	2.728	1.057
15	0.395 (0.338)	2.135 (0.473)	1.995 (0.533)	5.408	0.934
16	0.262 (0.147)	1.732 (0.249)	1.750 (0.261)	6.611	1.010
17	0.140 (0.111)	0.886 (0.233)	1.081 (0.303)	6.309	1.220
18	0.021 (0.047)	1.004 (0.264)	0.993 (0.263)	48.637	0.990
19	-0.030 (0.117)	1.550 (0.449)	2.832 (0.938)	-51.673	1.827
20	-0.441 (0.260)	0.576 (0.209)	0.642 (0.198)	-1.304	1.116
21	-3.735 (2.276)	19.134 (6.687)	19.350 (6.866)	-5.124	1.011

Note: Estimated standard errors for β are in parentheses. "Average" is unweighted average of all plants. Plants are renumbered in the descending order of average capacity utilization.

Table 3. *Average capacity utilization rates of plants*

	$\hat{\beta}_C^S / \hat{\beta}^S > 1$	$\hat{\beta}_C^S / \hat{\beta}^S \leq 1$
$\hat{\beta}^S / \hat{\beta}^{NS} > 1$	0.45924	0.30844
$\hat{\beta}^S / \hat{\beta}^{NS} \leq 1$	0.33229	--------

Note: The figures are unweighted averages of each plant's average capacity utilization. The four plants with negative elasticity estimates or with outlier value (No.18-21 in Table 2) are excluded from calculation.

Notes

[1] The microdata are valuable in this context. For example, Tomiura (2002) examined industry-level findings of Cecchetti et al. (1997) by the plant-level data. The terms “plant” and “establishment” are used interchangeably in this paper.
[2] The error term is assumed to satisfy standard properties. The production function is assumed to take the Cobb-Douglas form, without loss of generality.
[3] As noted by Miron and Beaulieu (1996), this specification (2) corresponds to regressing non-seasonal component of output on non-seasonal component of input, while (1) produces the same coefficient estimates as regressing seasonal component of output on seasonal component of input but with correct standard errors.
[4] On the other hand, under the increasing returns, we have no reason to believe that seasonal and non-seasonal elasticity estimates to differ. Related with the distinction between anticipated and unanticipated changes, Baily et al. (2001) analyzed the impact of long-term expectations on labor productivity at the plant-level.
[5] Miron and Beaulieu (1996) proposed the exclusion of extreme months in this context, but this paper is the first attempt to empirically apply this method.
[6] The third estimate from (3) corresponds to seasonal output elasticity from which seasonal component in the extreme month is removed. The excluded month varies depending on the plant. Although having the highest level of capacity utilization rate in the year does not mean that the capacity of the plant is constrained in that month, our approach is a reasonable one because we cannot directly observe whether the capacity constraint of each plant is binding or not.
[7] The classification code is No.2180 in the Refrigerating Machines (No.18). The confidentiality requirement imposed by the Statistics Law prohibits us from releasing data of individual plant. Anyone can, however, have access to the same microdata as long as the person obtains individual permission from the government in advance. The production quantity in this paper is defined as the number of outside units of air conditioners. Compared with deflated value data, the physical unit quantity data is preferable since we explicitly discuss capacity constraint. The sample period is from January 1988 to December 1995, to facilitate comparison with Tomiura (2002).
[8] “Seasonal” and “Non-seasonal” in Table 1 are not the orthogonal decomposition of all variations.
[9] “AGGREGATE” is the sum over all 21 plants in our sample. Excluded from the original government data are six plants operated for less than two years because they are not suitable for seasonality analysis. The labor input data is derived from “actual total number of personnel worked during the month” in terms of man-days. Since *Current Survey of Production* collects no data on working hours and since no employment statistics contain data on production quantity and capacity, this series is the most suited one for our purpose. This choice does not affect our comparison of IV with OLS estimates. The capacity utilization rate is the ratio of production quantity over production capacity, both measured in physical units.
[10] The right-hand side variable in the regressions is the labor input because monthly data on capital is available in no statistics. However, many previous studies, including Bernanke and Parkinson (1991), have confirmed that omitting capital does not essentially alter the results. Since no related data are available in the same statistics, we do not control for variations in labor effort intensity and in material input use. All the variables are in the first-differenced logarithm form.
[11] The magnitude of our estimated elasticity is also in a comparable range with those by Miron and Beaulieu (1996) from U.S. industries. Their estimates are 0.689 for seasonal and 1.736 for non-seasonal. Among industries examined by them, the estimates from electric machinery, which must include the air conditioner, are also relatively similar to those in this paper, as the seasonal elasticity is 3.600 and the non-seasonal elasticity is 0.372.
[12] Since some elasticity estimates exceed one, the increasing returns seem to play a non-negligible role probably in combination with labor hoarding. Besides, since we do not control for it due to data limitation, variable intensity of labor efforts and of intermediate input uses may also matter. We should not interpret our results as discriminating among alternative hypotheses.
[13] Even if we exclude those plants with zero output during low season, the seasonal elasticity is higher than non-seasonal elasticity in 13 out of 15 plants. The conclusion is still robust even if we

exclude plants with statistically insignificant elasticity estimates.

[14] Since we use physical unit quantity data, we can also reject the hypothesis that observed productivity patterns are driven by varying markups.

[15] The capacity utilization rate in Table 3 is standardized so that the maximal value during the sample period is one. Even if all plants are included or average capacity is calculated in the highest month, the conclusion is robust. The cross-section regression of elasticity ratio on capacity utilization rate also confirms this regularity.