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THE PRODUCTION SMOOTHING MODEL IS ALIVE AND WELL

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ABSTRACT

Monthly data in physical units for seven industries are used to examine the production smoothing hypothesis. The results strongly support this hypothesis. Significant effects of expected future sales on current production are found for four industries, and the estimated decision equations for all seven industries imply production smoothing behavior. The previous negative results regarding the hypothesis appear to be due to the use of poor data, particularly the shipments and inventory data of the Department of Commerce.

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by

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I. Introduction

Recent literature has been concerned with the question of whether production is smoothed relative to sales.[1] Contrary to what one might expect, this does not seem to be the case, and various explanations have been offered as to what might be going on. Most of this work, however, has relied on data of questionable reliability. Miron and Zeldes (1988b), for example, using two-digit industry data, have pointed out that production data derived from the shipments and inventory data reported by the Department of Commerce do not closely match the industrial production data reported by the Board of Governors of the Federal Reserve. This conclusion was reached earlier in Fair (1969, p. 128) for four three-digit industries: Meat Products, Tires, Blast Furnace and Basic Steel Products, and Iron and Steel Foundries.[2] Lack of good data may be a particularly acute problem in testing the production smoothing hypothesis, where one is looking for differences in the paths of two series that are possibly small relative to the average levels of the paths.

There are better data available than those from the Department of Commerce, and this paper uses some of these data. It uses monthly data in physical units for seven three- and four-digit industries, adjusted for the

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[1] See, for example, Blinder (1981), (1986a), (1986b), Blanchard (1983), West (1986), Miron and Zeldes (1988a), and Ramey (1988)

[2] For the Tire industry, the Department of Commerce data were compared to data reported by the Rubber Manufacturers Association. For the other three industries, the Department of Commerce data were compared to the data from the Federal Reserve.

number of working days in the month, to examine this hypothesis. The results rather strongly support the production smoothing hypothesis,[3] and so the previous negative results in this regard may simply be due to the use of bad data.[4]

II. The Time Interval

The question of whether production is smoothed relative to sales or shipments is not independent of the length of the time interval of the data. Consider the production and shipment of a good like a candy bar. If a plant, say, produces 10,000 candy bars an hour when it is operating, then within the interval that the plant is continuously operating, say eight hours a day, production is surely smoothed relative to shipments, which will probably be carried out at most a few times an hour. Only over a longer

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[3]A number of years ago I did a study of production behavior (Fair (1971)) that showed that expected future sales are significant determinants of current production decisions. This study used data on four of the seven industries studied in the present paper (Cigarettes, Cigars, Tires, and Cement). My initial reaction upon reading Blinder's negative results about the production smoothing model was that they seemed completely at odds with my earlier results. This paper shows that this is in fact the case. The equations estimated in Table 2 of this paper for the four industries are very similar to the equations estimated in Table 1 in Fair (1971), and it will be seen that the equations in Table 2 imply production smoothing behavior. To some extent the results in Table 2 for the four industries are simply updates of the results in Table 1 of my earlier study.

[4]A possible exception to this is the study of Blanchard (1983), which uses highly disaggregated data -- data at the automobile division level -- and rejects the production smoothing hypothesis. These data are not, however, as good as one might at first think. Blanchard's production variable Y, which is the sum of U.S. and Canadian production, does not match his sales variable S, which is only sales to U.S. customers. He is forced to deal with the data in this way because there are no data on Canadian inventories. There are thus clearly some errors of measurement in his data. In addition, the automobile industry is characterized by a complicated set of relationships between producers and dealers (who hold most of the inventories), which Blanchard has to approximate by various simplifying assumptions, and it is not clear that the standard production smoothing model captures these relationships very well.

interval is it possible that production per interval will fluctuate more than shipments per that interval. If the interval is a decade, fluctuations of production across decades are likely to be virtually identical to fluctuations of sales.

Most studies use a month as the time interval, and this is also done here. Months, however, have the unfortunate characteristic that they are not all of the same length, and adjustments need to be made for this fact. In computing the industrial production index, the Federal Reserve Board (FRB) estimates the number of working days in each month in each industry and divides the production figures by the number of working days to put them on a daily rate basis. This type of adjustment is also done here for the production and sales data. In addition, as will be seen, for two industries -- Cigarettes and Cigars -- adjustment is made for the fact that many firms in the industries shut down for vacations in July and December.

The question examined in this paper is thus whether the average rate of production per month fluctuates more or less than the average rate of sales per month.

III. A Preliminary Examination of the Data

Let Y_t denote the level of production in month t, let S_t denote the level of sales or shipments in month t, and let V_t denote the stock of inventories at the end of month t. By definition, production equals sales plus the change in inventories:

$$(1) \quad Y_t = S_t + (V_t - V_{t-1}) .$$

Monthly data in physical units on at least two of these three variables are available for the Cigarette, Cigar, Tire, Cement, Copper Refining, Lead

Refining, and Slab Zinc industries in the United States. (Data sources are presented in the Appendix.) For three industries -- Tires, Lead Refining, and Slab Zinc -- data on all three variables are available. None of the data used in this study are seasonally adjusted. It seems to make little sense to seasonally adjust the data when testing the production smoothing hypothesis. The hypothesis is about actual changes in production, sales, and inventories, not seasonally adjusted changes.

Data on the number of working days in the week for each industry are available from the FRB. Given these data and given a calendar for each year, one can compute the number of working days in each month for each industry. D_t will be used to denote the number of working days in month t for the given industry.

For the Cigarette and Cigar industries, data on Y_t and S_t are available, and data on V_t were constructed using equation (1) and a benchmark value for V. For the Cement and Copper Refining industries, data on Y_t and V_t are available, and data on S_t were constructed using equation (1). For the other three industries, where data on all three variables are available, equation (1) does not hold exactly (life is never simple), and so at least one variable is measured with error. For each of these industries, three sets of data were used. For the first set, the data on Y_t and V_t were used to construct data on sales using equation (1). Let SS_t denote this computed sales variable. For the second set, the data on Y_t and S_t were used to construct data on the stock of inventories using equation (1) and an initial benchmark value for the stock of inventories. Let VV_t denote this computed inventory stock variable. For the third set, the data on S_t and V_t were used to construct data on production using equation (1). Let YY_t denote this computed value of production. The following equations thus hold for these three industries:

(1a) $Y_t = SS_t + (V_t - V_{t-1})$,

(1b) $Y_t = S_t + (VV_t - VV_{t-1})$,

(1c) $YY_t = S_t + (V_t - V_{t-1})$.

Adjustments to D_t were made for the Cigarette and Cigar industries for the months of July and December. Plots of the data for Y_t for these two industries show large declines in output in July and December. These declines reflect vacation shutdowns for a week or two by many firms in the industries. Shutdown days are non working days (like Saturdays and Sundays for industries that do not work these days), and they should not be counted in D_t. In order to adjust for shutdowns, estimates are needed of the average number of shutdown days in July and December. These estimates were obtained as follows.

Consider July for the Cigarette industry. Monthly data were collected from 1952 through 1987 (26 years). For each year $Q = (Y_{June}/D_{June} + Y_{Aug.}/D_{Aug.})/2$ was computed. Let $R_{July} = Y_{July}/Q$. R_{July} would be the number of working days in July in the year in question if the rate of production in July were the same as the average rate in June and August. If D_{July} is the number of working days in July not adjusting for vacations (data from the FRB), then $Z_{July} = D_{July} - R_{July}$ is the estimated number of vacation shutdown days in July in the given year. Although it is unrealistic to assume in any one year that the July rate of production is the same as the average rate in June and August, this is probably not an unrealistic assumption across many years. With 26 years worth of data, 26 values of R_{July} and then Z_{July} can be computed. Let $\hat{Z}_{July}$ denote the average of these 26 values. $\hat{Z}_{July}$ was taken to be the estimate of the number of vacation shutdown days in July. Given this value, D_{July} for a given year was taken to be the number of working days in July of that year before adjustment minus $\hat{Z}_{July}$. A similar procedure was followed for December, where Q in this case is $(Y_{Nov.}/D_{Nov.} + Y_{Jan.}/D_{Jan.})/2$. This procedure was also followed for the Cigar industry. For Cigarettes the estimated adjustment for July was 4.07 days, with a standard error of 1.22 days, and the estimated adjustment for December was 5.02 days, with a standard error of 1.71 days. For Cigars the estimated adjustments were 6.03 and 5.92 days respectively, with standard errors of 1.58 and 1.72.[5]

In what follows y_t will be used to denote Y_t/D_t and s_t will be used to denote S_t/D_t. (In this notation, equation (1) is $y_tD_t = s_tD_t + V_t - V_{t-1}$.) The first question to ask of the data is whether the variance of y_t is greater than or less than the variance of s_t. To make the results comparable to those in Blinder (1986a) and Miron and Zeldes (1988b), the variables were detrended first.[6] The results using the detrended data are presented in Table 1 under the heading "Daily Rates." They are quite striking, given the recent results in the literature. Only for the Cigar industry and for one case for the Tire industry is the variance of production greater than the variance of sales. For the other industries the

[5] The estimates were not rounded to the nearest integer because it is not the case that all firms in the industries shut down for the same number of days.

[6] The same procedure was used here as was used in Blinder (1986a) and Miron and Zeldes (1988b). The log of each variable was regressed on a constant and time. The coefficients were estimated by GLS under the assumption of a second order autoregressive process of the error term. The antilogs of the fitted values of this regression were then subtracted from the actual values to create the detrended data. The estimates of the coefficient of the time trend were insignificant for Copper Refining and Lead Refining, and so no detrending was done for these two industries. The estimates for the time trend for Cigars and Slab Zinc were negative (and significant).

TABLE 1

Ratio of the Variance of Detrended Production to the Variance of Detrended Sales

Industry	Sample Period	Data Used	Monthly Levels	Daily Rates
Cigarettes	1952.04-1988.08	(b)	1.020	.758
Cigars	1952.04-1988.08	(b)	1.128	1.067
Tires	1947.04-1987.06	(a)	.872	.892
	"	(b)	1.120	1.151
	"	(c)	.910	.936
Cement	1947.04-1964.12	(a)	.365	.354
Copper Refining	1947.04-1987.12	(a)	.890	.886
Lead Refining	1947.04-1987.12	(a)	.831	.832
	"	(b)	.759	.761
	"	(c)	.942	.939
Slab Zinc	1947.04-1987.12	(a)	.926	.916
	"	(b)	.907	.899
	"	(c)	.950	.947

Notes:

(a) Production and Inventories and Definition for Sales.
(b) Production and Sales and Definition for Inventories.
(c) Sales and Inventories and Definition for Production.

"Monthly Levels" means that data on production and sales were the total amounts produced and sold during the month.

"Daily Rates" means that the data on production and sales were the average amounts produced and sold per working day during the month.

ratio of the variance of production to the variance of sales varies from .354 to .939. Similar results hold for production and sales not divided by D_t (under the heading "Monthly Levels") except for the Cigarette industry, where not adjusting for the July and December shutdowns reverses the result. The overall results thus provide strong support for the production smoothing hypothesis.

For the Slab Zinc industry, where data on all three variables are available, equation (1) almost holds, and so the results for the three different sets of data are very close. For the Tire industry and the Lead Refining industry, on the other hand, the results are somewhat different. For Lead Refining, production is smoothest relative to sales when direct data on both production and sales are used -- case (b) in Table 1. For Tires, on the other hand, the opposite is true, and in fact in this case production is more variable than sales.

It is possible to use the results in Table 1 for the Cigarette and Cigar industries (SIC industries 211 and 212) and the results in Table 3 in Miron and Zeldes (1988b) for the Tobacco industry (SIC industry 21) to gauge the effects of measurement error in the Department of Commerce shipments and inventories data. Cigarettes and cigars account for almost all of the Tobacco industry. The data on production and sales for the Cigarette and Cigar industries used for the results in Table 1 (data from the Internal Revenue Service) are quite good, and the FRB in fact uses the IRS data on production in constructing the industrial production index for the Tobacco industry. The ratios of the variances in Table 1 for Cigarettes and Cigars range from .758 to 1.128, depending on the industry and whether monthly levels or daily rates are used.

The ratios in Table 3 in Miron and Zeldes (1988b) are, however, quite different. When the FRB production index is used in combination with the shipments data from the Department of Commerce, the ratio (for the Tobacco industry) is .54. When the production data computed from the Department of Commerce data on shipments and inventories are used in combination with the shipments data from the Department of Commerce, the ratio is 2.43, about 4.5 times larger. If the IRS data (and thus the FRB production data) contain little measurement error, which is probably a reasonable approximation, then the results in the two tables show that 1) the Department of Commerce shipments data is absolutely much too noisy and 2) the Department of Commerce production data computed from the shipments and inventory data are much too noisy relative to the shipments data. It thus seems rather obvious that the Department of Commerce data are not useful for examining the production smoothing hypothesis.

It is generally the case when using the Department of Commerce data that the variance of production is greater than the variance of sales.[7] This result is what has lead some to question the production smoothing hypothesis. The numbers in Table 1 may help explain this result. For the three industries where data on production, sales, and inventories are available, production is less smooth relative to sales when it is computed from the identity -- row (c) -- than when the level of sales is computed from the identity -- row (a).[8] Measurement errors seem to be such as to add additional noise to the computed variable. Now, when the Department of

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[7]This is true, for example, of the results in Table 3 in Miron and Zeldes (1988b), which match Blinder's (1986a) results very closely.

[8]I don't know why row (b) for Tires, which uses direct data on both production and sales, is at odds with the other two rows for this industry (row (b) having sales smoother than production). In many months the identity is far from being met for this industry, and so there are clearly large measurement errors somewhere.

Commerce data are used, production is the variable computed from the identity. Since the measurement errors seem much larger for the Department of Commerce data, it could easily be that the errors lead to the derived production data being more noisy than the shipments data. Put another way, if the level of shipments were the derived variable, it may very well be that shipments would be noisier than production.[9]

IV. Estimated Decision Equations

In examining the production decision of a representative firm, the standard approach in the literature is assume that a firm chooses production, given sales, to minimize the expected present discounted value of costs,

$$(2)\quad L = E_t \sum_{i=1}^{\infty} \beta^i C_{t+i} ,$$

subject to equation (1), where C_{t+i} is the cost in period t+i and β is the discount factor. E_t is the expectations operator conditional on information available at time t. C_{t+i} is usually taken to be a function of y_{t+i}, y_{t+i-1}, s_{t+i}, and V_{t+i-1}:[10]

$$(3)\quad C_{t+i} = f(y_{t+i}, y_{t+i-1}, s_{t+i}, V_{t+i-1}).$$

Given a specification for f, given y_{t-1} and V_{t-1}, and given the conditional distributions of the current and future values of s, it is possible in

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[9]The results in Ghali (1987), which are based on cement data by district and on data from five other industries, generally support the production smoothing hypothesis. This is added support to the view that the negative results concerning the production smoothing hypothesis are due to the use of poor data; when better data are used, the result is generally reversed.

[10]See, for example, Ramey (1988).

principle to solve for the optimal value of y_t, which will be denoted y_t^0.

It is generally not possible to derive an analytic expression for y_t^0, and other approaches are needed. One approach is to estimate the parameters of the cost function from the first order conditions. While this approach is currently popular, it has the disadvantage of requiring a parametric specification of the cost function. Also, it is usually not possible to back out the decision equations once the first order conditions have been estimated.

An alternative approach, which is followed here, is to estimate approximations to the decision equations. The procedure is as follows. First, the random variables s_{t+i}, $i = 0, 1, \ldots$ are replaced by their expected values, $E_t s_{t+i}$, $i = 0, 1, \ldots$. It is a common procedure in the engineering literature to replace random variables with their expected values to make the problem tractable. In the case of a quadratic objective function and a linear model, this replacement results in no loss because certainty equivalence holds. Otherwise, there is some loss, but many problems may be close enough to the linear-quadratic case for the loss to be fairly small.

Given this replacement in the present context, one can write the decision equation for current-period production as:

$$(4) \quad y_t^0 = f(y_{t-1}, V_{t-1}, E_t s_t, E_t s_{t+1}, E_t s_{t+2}, \ldots, \alpha) ,$$

where α is the vector of parameters of the cost function. Equation (4) states that the optimal value of production for period t is a function of y_{t-1}, V_{t-1}, and expected future sales. The functional form of (4) is generally not known. The aim of the empirical work is to estimate equations that are approximations of (4). One part of the empirical work is to find measures for the expected values, and the other part is to choose the functional form. It is not possible to recover the parameters of the cost function using this approach, but it is possible, as will be seen below, to examine whether the estimated equation implies production smoothing behavior. The estimated residuals from the estimation work can be interpreted as errors approximating the true decision equations and the true expectation formation mechanism.

For the work below equation (4) is assumed to be linear. Two expectational hypotheses are examined. For both hypotheses it is assumed that firms know current sales: $E_t s_t = s_t$. The first hypothesis, hypothesis A, is that firms expect a future month's sales to be the same as the sales in the same month a year ago: $E_t s_{t+i} = s_{t+i-12}$. The second hypothesis, hypothesis B, is that firms form expectations rationally and that there is an observed vector of variables (observed by the econometrician), denoted Z_t, that is used in part by firms in forming their (rational) expectations. The estimation work below does not require for consistent estimates that Z_t include all the variables used by firms in forming their expectations. Z_t was taken to include the constant term, a linear time trend, V_{t-1}, y_{t-1}, and s_{t-i}, i = 0, 1, ... 12. The lead length for both hypotheses was taken to be six months.

Under hypothesis A the equation was estimated by ordinary least squares, and under hypothesis B the equation was estimated using Hansen's (1982) method of moments estimator.[11]

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[11]Hansen's method as used in this paper is the following. The actual future values of sales are used on the right hand side of the equation, and the equation is first estimated by two stage least squares (2SLS). The estimated residuals from this equation are used to create Hansen's M matrix under the assumption of a fifth order moving average of the error term (fifth order because there are leads of six in the equation). Hansen's

As the model has been set up so far, there are no sign or size restrictions on the coefficients. The following specification leads to some restrictions, and it will be useful to examine the coefficient estimates within this framework. Let V_t^* denote the firm's long run desired stock of inventories. V_t^* is assumed to be a function of s_t:

$$(5) \quad V_t^* = \beta_0 + \beta_1 s_t \quad , \beta_1 > 0.$$

Let y_t^* denote the firm's desired rate of production in period t if there were no costs of adjusting production. y_t^* is assumed to be determined as:

$$(6) \quad y_t^* = s_t + \gamma_0(V_t^* - V_{t-1}) + \sum_{i=1}^{n} \gamma_i(E_t s_{t+i} - E_t s_{t+i-1}) ,$$

$$\gamma_i > 0 , \; i = 0, 1, \ldots, n .$$

Equation (6) states that a desired stock of inventories greater than the actual stock leads the firm, other things being equal, to produce more than

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estimator is then

$$(X'ZM^{-1}Z'X)^{-1}X'ZM^{-1}y ,$$

with estimated covariance matrix

$$T(X'ZM^{-1}Z'X)^{-1} ,$$

where X is the matrix of explanatory variables (including the future sales variables), Z is the matrix of first stage regressors, y is the left hand side variable, and T is the number of observations. M is estimated as follows. Let $a_j = (T-j)^{-1}\Sigma_{t=j}^{T} v_t v_{t-j}$ and $B_j = (T-j)^{-1}\Sigma_{t=j}^{T} Z_t Z_{t-j}$, $j = 0,1,\ldots,J$, where v_t is the estimated residual for period t from the 2SLS regression and J is the order of the moving average (five in the present case). The estimate of M is then $(a_0B_0 + a_1B_1 + a_1B_1' + \ldots + a_JB_J + a_JB_J')$. See Hayashi and Sims (1983) for a discussion of this way of estimating M. The more general way of estimating M did not produce sensible results.

it sells (so as to build the stock back up). Also, if sales are expected to increase in the future, this leads the firm, other things being equal, to produce more than it sells (so it can meet some of the increased future sales by selling out of inventories). If the actual stock of inventories is equal to the desired stock and if sales are not expected to change in the future, then desired production is simply equal to current sales.

If there are costs of changing production, actual production may differ from desired production. Actual production is assumed to be:

$$(7) \quad y_t - y_{t-1} = \lambda(y_t^* - y_{t-1}) \quad , \quad 0 < \lambda < 1 .$$

Equation (7) is a standard partial adjustment equation. Combining equations (5), (6), and (7) yields:

$$(8) \quad y_t - y_{t-1} = \lambda\gamma_0\beta_0 + \lambda(s_t - y_{t-1}) + \lambda\gamma_0\beta_1 s_t - \lambda\gamma_0 V_{t-1} + \lambda \sum_{i=1}^{n} \gamma_i (E_t s_{t+i} - E_t s_{t+i-1}) .$$

Estimating equation (8) is the same as estimating an equation with y_t on the left hand side and the constant term, y_{t-1}, V_{t-1}, s_t, and $E_t s_{t+i}$ ($i = 1,\ldots,n$) on the right hand side. (Remember that $E_t s_t = s_t$ by assumption for both expectational hypotheses.) This latter equation is simply the linear version of equation (4) with $E_t s_t = s_t$. Equation (8) thus imposes no restrictions on the linearized version of equation (4). The advantage of estimating the equation in the form of (8) is that the coefficients have some interpretation. This interpretation will, of course, be wrong if equations (5) - (7) are poor approximations, but at least equation (8) provides an initial framework. The key question here is whether the estimated decision equations imply production smoothing behavior, and the examination of this question below is valid even if the interpretation of the coefficients in equation (8) is wrong.

The results of estimating equation (8) for the seven industries and the two expectational hypotheses are presented in Table 2.[12] The results are as follows.

1. The estimates of λ are all significantly less than one (and greater than zero), which supports the partial adjustment equation (7).

2. All the estimates of $\lambda\gamma_0$ (and thus the implied estimates of γ_0) are positive as expected. Some of the implied estimates of γ_0 are, however, unreasonably small. $1/\gamma_0$ is the estimated number of working days required to adjust the actual level of inventories to the desired level, other things being equal. For four of the industries -- Cigars, Copper Refining, Lead Refining, and Slab Zinc -- the values of $1/\gamma_0$ are unreasonably large, as reported at the bottom of Table 2. For the other three industries the values seem quite reasonable.

3. The implied estimate of β_1 is negative for three industries -- Cigarettes, Copper Refining, and Lead Refining. At least for these three industries, equation (5) is rejected, and V_t^* must be a function of other than just the current level of sales.

4. The expected future sales variables are highly significant for Cigarettes, Cigars, Tires, and Cement. For these four industries the two expectational hypotheses lead to roughly the same results, with perhaps a slight edge to hypothesis B. The expected future sales variables are not significant for the other three industries. For these three industries the

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[12]For the three industries in which data on production, sales, and inventories were available, the data on production and inventories were used and the level of sales was computed from the identity -- row (a) in Table 1.

TABLE 2

Equation Estimates

$$y_t - y_{t-1} = \lambda\gamma_0\beta_0 + \lambda(s_t - y_{t-1}) - \lambda\gamma_0 V_{t-1} + \lambda\gamma_0\beta_1 s_t + \lambda \sum_{i=1}^{n} \gamma_i (s^e_{t+i} - s^e_{t+i-1})$$

	Cigarettes		Cigars		Tires		Cement		Copper Refining		Lead Refining		Slab Zinc	
	(A)	(B)	(A)	(B)	(A)	(B)	(A)	(B)	(A)	(B)	(A)	(B)	(A)	(B)
Estimates of:														
$\lambda\gamma_0\beta_0$	645.5	533.7	1.74	-8.64	-6.80	-47.03	-69.5	-138.0	273.7	-193.6	146.4	81.3	-1.61	-2.68
	(4.10)	(4.97)	(0.38)	(1.99)	(0.67)	(3.22)	(3.55)	(4.40)	(2.24)	(0.46)	(3.00)	(0.92)	(0.11)	(0.18)
λ	.817	.852	.553	.882	.441	.672	.556	.499	.597	.584	.350	.433	.204	.227
	(32.57)	(33.97)	(16.73)	(16.03)	(11.00)	(13.24)	(23.23)	(16.62)	(19.46)	(11.79)	(11.03)	(5.54)	(8.91)	(6.47)
$\lambda\gamma_0$	.00376	.00318	.000357	.000078	.00159	.00312	.00282	.00436	.000252	.000209	.000440	.000492	.000163	.000295
	(3.99)	(4.95)	(1.91)	(0.49)	(3.21)	(4.66)	(4.90)	(5.14)	(1.71)	(0.99)	(2.70)	(2.89)	(1.83)	(2.49)
$\lambda\gamma_0\beta_1$	-.030	-.022	.007	.036	.117	.277	.190	.316	-.053	.055	-.078	-.0.31	.005	.011
	(2.65)	(2.88)	(0.50)	(2.72)	(2.68)	(4.58)	(4.82)	(5.24)	(2.01)	(0.58)	(2.69)	(0.54)	(0.68)	(1.35)
$\lambda\gamma_1$	.147	.177	.071	.283	.290	.747	.279	.433	.027	-.013	.021	.132	.033	.059
	(5.56)	(6.57)	(2.72)	(5.06)	(6.52)	(8.75)	(7.50)	(7.78)	(1.07)	(0.07)	(0.63)	(0.79)	(1.65)	(0.69)
$\lambda\gamma_2$	.056	.037	.060	.191	.252	.507	.269	.323	.019	.475	.014	.319	.033	.184
	(1.96)	(1.27)	(1.83)	(3.55)	(5.34)	(6.53)	(7.56)	(5.35)	(0.58)	(2.39)	(0.36)	(1.27)	(1.42)	(2.32)
$\lambda\gamma_3$	-.004	-.056	.037	.121	.175	.446	.128	.113	.033	.226	-.020	.021	.016	.036
	(0.12)	(1.83)	(1.09)	(2.15)	(3.99)	(6.51)	(4.06)	(2.24)	(1.02)	(1.19)	(0.51)	(0.10)	(0.72)	(0.41)
$\lambda\gamma_4$	.079	.079	.098	.221	.211	.398	.181	.283	.025	.215	.031	.545	.034	.053
	(2.74)	(2.64)	(2.86)	(3.79)	(5.18)	(6.46)	(6.69)	(6.93)	(0.81)	(1.22)	(0.85)	(1.88)	(1.61)	(0.60)
$\lambda\gamma_5$	.005	-.013	.132	.217	.127	.257	.147	.166	.006	.312	.031	-.076	.027	-.056
	(0.18)	(0.46)	(4.05)	(4.16)	(3.42)	(4.76)	(5.61)	(3.92)	(0.21)	(1.77)	(0.91)	(0.39)	(1.36)	(0.61)
$\lambda\gamma_6$	-.069	-.118	-.050	-.010	.098	.212	.069	.097	.024	-.032	.002	.041	.015	-.053
	(3.31)	(4.44)	(1.70)	(0.21)	(2.81)	(4.20)	(2.71)	(2.43)	(0.83)	(0.19)	(0.07)	(0.18)	(0.82)	(0.56)
R^2	.780	.798	.503	.516	.267	.301	.855	.822	.487	-.051	.257	-.456	.243	.111
SE	78.3	75.1	18.6	18.3	56.2	54.9	36.8	40.7	442.7	633.4	159.6	223.4	105.6	114.5
DW	2.20	2.28	2.21	2.02	1.61	1.46	1.37	1.51	1.73	2.11	2.00	2.63	1.67	1.70
No. obs.	419	491	419	419	465	465	195	195	471	471	471	471	471	471
WALD	55.27*	39.36*	11.33	20.36*	11.41	7.52	78.11*	81.16*	4.71	4.88	5.44	6.02	19.84*	10.13
F	2.12**	--	7.38**	--	8.25**	--	16.88**	--	0.34	--	0.57	--	0.71	--
Implied Value: $1/\gamma_0$	217	268	1549	8744	277	215	197	114	2332	2794	795	880	1252	769
Implied Production Smoothing	.709	.739	.901	.955	.731	.673	.364	.355	.656	.740	.546	.619	.839	.791

Notes: t-statistics in absolute value are in parentheses.

Column (A) results based on assumption that $s^e_{t+i} = s_{t+i-12}$, $i = 1, 2, \ldots, 6$.

Column (B) results based on assumption that expectations are rational.

WALD = WALD statistic for test of structural stability between the two halves of the sample. * means that the hypothesis of stability is rejected at the 95 percent confidence level.

F = F statistic for test of the hypothesis that $\gamma_1 = \gamma_2 = \gamma_3 = \gamma_4 = \gamma_5 = \gamma_6 = 0$. ** means that the hypothesis is rejected at the 95 percent confidence level.

$1/\gamma_0$ is the estimated number of working days taken for the full adjustment of the actual stock of inventories to the desired stock, other things being equal.

See text for discussion of the implied production smoothing figures.

F test of the hypothesis that all the expected future sales variables have coefficients of zero is not rejected under expectations hypothesis A. Hypothesis B leads to nonsensical results for these three industries.

5. The hypothesis of structural stability between the two halves of the sample was tested for each equation using a Wald test.[13] The hypothesis was rejected for Cigarettes and Cement and for Cigars under hypothesis B and Slab Zinc under hypothesis A.

6. Looking at the overall results for a given industry, the results for Tires are quite good. They provide strong indirect support for equations (5) - (7). Note that expected future sales as far as six months ahead significantly affect current production decisions. The results for Cement are also quite good except for the structural stability test. Results for the Cement industry are based only on 195 observations, which may not be enough to provide a reliable test of structural stability. The results for Cigars are good except for the large value of $1/\gamma_0$. The results for Cigarettes suffer from a negative value for β_1 and failure of the structural stability test. The results for Copper Refining, Lead Refining, and Slab Zinc are the least good. The only good estimate is the estimate of λ. There is not much support for equations (5) and (6) for these three industries, although there is for equation (7) because of the estimates of λ.

V. Implied Production Smoothing Behavior

Do the estimated equations in Table 2 imply production smoothing behavior? This question can be examined in the following manner. Consider

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[13] See Andrews and Fair (1988) for a discussion of this test.

hypothesis A first. Given this hypothesis and given values of y_{t-1}, V_{t-1}, s_t, s_{t-1}, ... s_{t-12}, an estimated equation can be used to solve for y_t. V_t can then be solved for using the formula $V_t = V_{t-1} + y_t D_t - s_t D_t$, where D_t is the number of working days in the month. Given these values and given a value for s_{t+1}, one can solve for y_{t+1} and then V_{t+1}. This process can be repeated throughout the sample period. This is a dynamic simulation of the estimated equation given the actual sales path. The predicted values of y from this simulation are the values that the firm would choose using the estimated decision rule and the given sales path. A similar procedure was followed for hypothesis B. In this case the actual future sales values were used for the expectations.[14]

Having run a dynamic simulation, one can then compare the predicted production path with the actual sales path to see which is smoother. This is done at the bottom of Table 2. The "implied production smoothing" figure in each case is the ratio of the variance of detrended predicted production to the variance of detrended actual sales.[15] In every case the ratio is less than one, and so the estimated decision equations imply production smoothing behavior.

It is important to note that the production smoothing figures at the bottom of Table 2 are not dependent on the specification of equations (5) - (7) being correct. These equations impose no restrictions on the linearized version of equation (4), and so the results in Table 2 are simply estimates

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[14]For this exercise it does not really matter what sales path is used. The exercise is to see what a decision equation predicts production to be for some sales path and then to compare the predicted production path to the particular sales path. The actual sales path is obviously a convenient and informative path to use, but other paths could also be used.

[15]The same detrending procedure was used here as was used for the results in Table 1.

of the linearized version of equation (4).

It is also important to be clear on what the production smoothing figures do and do not show. The predicted values from the equations show what production would be if firms followed the equations exactly. Given sales, firms deterministically determine production. If instead there are production shocks or decision errors on the part of the firms, then actual production will deviate from that predicted by the decision rule. These shocks and errors are likely to lead to actual production being more variable than production predicted from the rule. (For all but Cement, predicted production in Table 2 is smoother relative to sales than is actual production in Table 1.) If the shocks and errors are roughly equal to the estimated errors of the equations, then one is roughly back to comparing actual production to actual sales, which is done in Table 1.

VI. Conclusion

To some extent the results in Table 1 are enough to support the main point of this paper, which is that the data seem quite consistent with the production smoothing hypothesis. The previous results to the contrary are quite likely due simply to the use of poor data, primarily Department of Commerce data on shipments and inventories. The results in Table 2 show that at least for some industries quite strong effects of expected future sales on current production decisions can be picked up. But even for the three industries for which expected future sales are not significant, the estimated decision equations imply production smoothing.

DATA APPENDIX

Cigarettes and Cigars

Data from the Department of Treasury, Bureau of Alcohol, Tobacco, and Firearms. Data collected for the period January 1952 - August 1988. Estimation period: February 1953 - December 1987. Break at December 1969 for the Wald test. Units are in millions for cigarettes and in hundreds of thousands for cigars. Small and large cigars are added together. Data on Y and S collected. Benchmark values used to construct V were 148964 in December 1987 for cigarettes and 7733 in December 1987 for cigars.

Tires

Data from the Rubber Manufacturers' Association. Data collected for the period January 1947 - June 1987. Estimation period: February 1948 - October 1986. Break at December 1966 for the Wald test. Units are thousands of tires -- passenger car plus truck and bus tires. Data on Y, S, and V collected.

Cement

Data from the Bureau of Mines. Data collected for the period January 1947 - December 1964. (The Bureau of Mines ended its publication of these data in 1964.) Estimation period: February 1948 - April 1964. Break at December 1955 for the Wald test. Units are thousands of barrels. Data on Y and V collected.

Copper Refining, Lead Refining, Slab Zinc

Data from past issues of Metal Statistics. Data collected for the period January 1947 - December 1987. Estimation period: February 1948 - April 1987. Break at December 1966 for the Wald test. Units are in tons. Data on Y and V collected for Copper and on Y, S, and V for Lead and Zinc.

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