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Abstract

In recent years there has been a resurgence of interest in the empirical behavior of inventories. A great deal of this research examines some variant of the production smoothing model of finished goods inventories. The overall assessment of this model that exists in the literature is quite negative: there is little evidence that manufacturers hold inventories of finished goods in order to smooth production patterns.

This paper examines whether this negative assessment of the model is due to one or both of two features: costs shocks and seasonal fluctuations. The reason for considering costs shocks is that if firms are buffetted more by cost shocks than demand shocks, production should optimally be more variable than sales. The reasons for considering seasonal fluctuations are that seasonal fluctuations account for a major portion of the variance in production and sales, that seasonal fluctuations are precisely the kinds of fluctuations that producers should most easily smooth, and that seasonally adjusted data is likely to produce spurious rejections of the production smoothing model even when it is correct.

We integrate cost shocks and seasonal fluctuations into the analysis of the production smoothing model in three steps. First, we present a general production smoothing model of inventory investment that is consistent with both seasonal and non-seasonal fluctuations in production, sales, and inventories. The model allows for both observable and unobservable changes in marginal costs. Second, we estimate this model using both seasonally adjusted and seasonally unadjusted data plus seasonal dummies. The goal here is to determine whether the incorrect use of seasonally adjusted data has been responsible for the rejections of the production smoothing model reported in previous studies. The third part of our approach is to explicitly examine the seasonal movements in the data. We test whether the residual from an Euler equation is uncorrelated with the seasonal component of contemporaneous sales. Even if unobservable seasonal cost shocks make the seasonal variation in output greater than that in sales, the timing of the resulting seasonal movements in output should not necessarily match that of sales.

The results of our empirical work provide a strong negative report on the production smoothing model, even when it includes cost shocks and seasonal fluctuations. At both seasonal and non-seasonal frequencies, there appears to be little evidence that firms hold inventories in order to smooth production. A striking piece of evidence is that in most industries the seasonal in production closely matches the seasonal in shipments, even after accounting for the movements in interest rates, input prices, and the weather.

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Section I: Introduction

In recent years there has been a resurgence of interest in the empirical behavior of inventories. A great deal of this research has examined some variant of the production smoothing model of finished goods inventories. Blinder (1986a) emphasizes that, in the absence of cost shocks, the model implies that the variance of production should be less than the variance of sales, an inequality that is violated for manufacturing as a whole and most 2 digit industries. West (1986) has derived a variance bounds test that extends this inequality in a number of ways and also finds that the model is rejected by the data. Both Blinder and West conclude that there is strong evidence against the production smoothing model. Other authors, such as Blanchard (1983), Eichenbaum (1984), and Christiano and Eichenbaum (1986) present evidence that is less unfavorable to the model, but they reject it as well.

This paper examines the extent to which the negative assessment of the model is due to two features: cost shocks and seasonal fluctuations. Blinder (1986a) and West (1986) both note that the presence of cost shocks could explain the rejections that they report, and Blinder (1986b), Maccini and Rossana (1984), Eichenbaum (1984), and Christiano and Eichenbaum (1986) have tested the model in the presence of cost shocks, with partial success. The reason for considering these shocks is simply that if firms are buffetted more by cost shocks than demand shocks, production should optimally be more variable than sales.

Most of the empirical work on the production smoothing model uses data that has been adjusted with the X-11 seasonal adjustment routine. This includes studies by Blinder (1986a, 1986b), Eichenbaum (1984), and Maccini and Rossana (1984). Blanchard (1983), Reagan and Sheehan (1985), and West (1986) begin with the seasonally unadjusted data and discuss the observed seasonal patterns; they then adjust the data with seasonal dummies. Few studies examine whether the seasonal fluctuations themselves are consistent with the model of inventories. Exceptions include West (1986), who includes a section in which he examines a variance bounds test based on both the seasonal and non-seasonal variations in the data, and Ghali (1986), who uses data from the Portland Cement industry and finds that the seasonal adjustment of the data was an important factor in the rejection of the production smoothing model.[1]

There are several reasons to think that using seasonally adjusted data to test inventory models is problematic. To begin with, seasonal fluctuations account for a major portion of the variation in production, shipments, and inventories. Table 1 shows the seasonal, non-seasonal, and total variance of the logarithmic rate of growth of production and shipments, for a set of 2-digit manufacturing industries.[2] For both variables, seasonal variation accounts for more than half of the total variance in most industries. Clearly, any analysis of production/inventory behavior that excludes seasonality has at best explained only part of the story and has failed to exploit much of the variation in the data.

The seasonal fluctuations are likely to be particularly useful in examining the production smoothing model because they are anticipated. Any test of the production smoothing model involves a set of maintained hypotheses, one of which is the rationality hypothesis. Rejections of the model, therefore, are not usually informative as to which aspect of the joint

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[1] Irvine (1981) uses seasonally unadjusted data, with no seasonal dummies, to examine retail inventory behavior and the cost of capital.

[2] This table is similar to Table 2 in Blanchard (1983). As he points out, since the seasonal component is deterministic, it has no variance in the statistical sense. The numbers reported here for the seasonal variances are the average squared deviations of the seasonal dummy coefficients from the

hypothesis has been rejected. When a rational expectations model is applied to seasonal fluctuations, however, it seems reasonable to take the rationality hypothesis as correct, since if anything is correctly anticipated by agents seasonal fluctuations ought to be. Applying the production smoothing model to seasonal fluctuations may help determine in which aspect, if any, the model fails.

One reason to avoid the use of seasonally adjusted data is that, since the true model must apply to the seasonally unadjusted data, the use of adjusted data is likely to lead to rejection of the model even when it is correct.[3] This is especially the case with data adjusted by the Census X-11 method because this technique makes the adjusted data a two-sided moving average of the underlying unadjusted data.[4] Therefore, the key implication of most rational expectations models, that the error term should be uncorrelated with information available at time t, will not hold in the adjusted data.[5] If the data are adjusted by some other method, such as seasonal dummies, then the time series properties of the adjusted data are not altered as radically as they are with X-11.[6]

We integrate cost shocks and seasonal fluctuations into the analysis of the production smoothing model in three steps. First, we present a general production smoothing model of inventory investment that is consistent with

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[3] Summers (1981) emphasizes this point.

[4] X-11 is not literally a two-sided moving average filter. Rather, it can be well approximated by such filters. For more on this point, see Cleveland and Tiao (1976) and Wallis (1974).

[5] See Sargent (1978).

[6] It is still the case, however, that such adjusted data can produce inconsistent estimation results if the model of interest contains fundamental

both seasonal and non-seasonal fluctuations in production, sales, and inventories. The model allows for both observable and unobservable changes in marginal costs ("cost shocks"). The observables include wages, energy prices, raw materials prices, and interest rates, as well as weather variables (temperature and precipitation).[7] We examine a firm's cost minimization problem, so the tests are robust to various assumptions about the competitiveness of the firm's output market. A key implication of the model is that, for any firm that can hold finished goods inventories at finite cost, the marginal cost of producing an additional unit of output today and holding it in inventories until next period must equal the expected marginal cost of producing that unit next period. With standard types of auxiliary assumptions about functional forms and identification, the model leads to an estimable Euler equation relating the rate of growth of production to the rate of growth of input prices, and the level of inventories and the interest rate. We estimate these Euler equations and test the overidentifying restrictions implied by the model, using data on six 2-digit industries.

The second part of our approach is to perform the exact same estimations and tests of the above model using both seasonally adjusted data and unadjusted data.[8] The goal here is to determine whether the incorrect use of seasonally adjusted data is responsible for the rejections of the production smoothing model reported in previous studies.

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[7]Maccini and Rossana (1984) estimate a different style model of inventory accumulation (a general flexible accelerator model) using data on aggregate durables and non-durables inventory accumulation in which they include wages, energy costs, interest rates, and raw materials prices. They found that only raw materials prices had significant effects in their model.

[8]Constant dollar, seasonally unadjusted inventory data were not available, and therefore were constructed. This is discussed further in Section IV.

The third part of our approach is to explicitly examine the seasonal movements in the data. Since the predictable seasonal movement in demand is exactly the variation that should be most easily smoothed, tests of the model at seasonal frequencies are particularly powerful. In this third part, we test whether the residual from the Euler equation is uncorrelated with the seasonal component of contemporaneous sales. Even if unobservable seasonal cost shocks make the seasonal variation in output greater than that of sales, the timing of the resulting seasonal movements in output should not match that of sales. We test this implication of the model below.

The remainder of the paper is organized as follows. Section II presents the basic production smoothing model that we employ throughout the paper and derives the first order condition that we estimate. In Section III, we describe the identifying assumptions, the resulting testable implications, and the econometric techniques used to test those implications. In Section IV, we discuss the data used. Section V presents the basic results with seasonally adjusted and unadjusted data. In Section VI, we examine the seasonal-specific results. Section VII concludes the paper.

Section II: The Model

Consider a profit maximizing firm. Sales by the firm, the price of the firm's output, and the firm's capital stock may be exogenously or endogenously determined. The firm may be a monopolist, a perfect competitor, or something in between. The firm is, however, assumed to be a competitor in the markets for inputs. For any pattern of prices, sales, and the capital stock, the firm acts so as to minimize costs.

The firm's intertemporal cost minimization problem is:

$$\min_{\{y_{t+j}\}} E_t \sum_{j=0}^{\infty} \Gamma_{t,t+j}\, C_{t+j}(y_{t+j}) \tag{1}$$

subject to:

$$n_{t+j} = n_{t+j-1}(1 - s'_{t+j-1}) + y_{t+j} - x_{t+j}$$

$$n_{t+j} \geq 0 \qquad \forall_j .$$

where y_t is production in time t, x_t is sales in period t, and n_t is the stock of inventories at the end of period t, all measured in terms of output goods. C_t is the one period nominal cost function of the firm, to be derived shortly. $\Gamma_{t,t+j}$ is the nominal discount factor, i.e., it is the present value at time t of one period t+j dollar. Thus, $\Gamma_{t,t+j} \equiv \left[\prod_{s=0}^{j-1} \left(\frac{1}{1 + \tilde{R}_{t+s}}\right)\right]$ (and $\Gamma_{t,t} \equiv 1$). $\tilde{R}_{t+s} = (1 - m_{t+s+1})R_{t+s}$. R_t is the pretax cost of capital for the firm, and m_t is the marginal tax rate. E_t indicates expectations conditional on information available at time t.

The term s'_t is the fraction of inventories lost due to storage costs. In the case of linear storage costs, s'_t is simply equal to a constant (call this s_1). Some researchers have modeled storage costs as being convex in the level of inventories. For example, convex inventory costs are the key factor driving Blinder and Fischer's (1981) model of the real business cycle. We capture these types of costs here by writing $s'_t = s_1 + s_2 \cdot n_{t-1}$.[9]

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[9] If storage costs come in the form of depreciating inventories, then the accounting identity definition of output would be $y_t = x_t + \left(n_t - n_{t-1}(1 - s_t)\right)$. In this paper, we construct output in the standard way: $y_t = x_t + (n_t - n_{t-1})$. If storage costs are actually paid out (rather than coming in the form of depreciated stocks) and these costs are proportional to the replacement cost of the goods, then our model and our constructed output

For any cost minimizing firm that carries inventories between two periods, the marginal cost of producing an extra unit of output this period and holding it in inventories until next period must equal the expected marginal cost of producing an extra unit of output next period. This first-order condition can be written as:

$$MC_t = E_t\left[\frac{MC_{t+1}(1 - s_t)}{1 + \tilde{R}_t}\right] \tag{2}$$

or

$$E_t\left[\frac{MC_{t+1}}{MC_t} \cdot \frac{(1 - s_t)}{1 + \tilde{R}_t}\right] = 1 \ . \tag{2a}$$

Rational expectations implies:

$$\frac{MC_{t+1}}{MC_t} \cdot \frac{(1 - s_t)}{1 + \tilde{R}_t} = 1 + \varepsilon_{t+1} \tag{3}$$

where $E_t[\varepsilon_{t+1}] = 0$, i.e. ε_{t+1} is orthogonal to all information available at time t. s_t is the marginal storage cost, equal to $s_1 + 2s_2 \cdot n_{t-1}$.[10]

The Euler equation (3) will not be satisfied if desired inventories are zero, i.e., if stockouts are possible.[11] In the industries that we use to estimate the equation, industrywide inventories are always positive, although this does not, of course, imply that inventories are always positive for every firm in these industries. As we show below, this model tends to imply a

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costs are paid out in dollars, in an amount proportional to the goods stored, our equation is approximately correct. Given the likely small size of storage costs, we do not think these distinctions are empirically relevant.

[10]If average storage costs (s'_t) are equal to $s_1 + s_2 n_{t-1}$, this implies that marginal storage costs (s_t) are equal to $s_1 + 2s_2 n_{t-1}$.

[11]See Abel (1985) and Kahn (1986) for models in which stockouts play a

positive growth rate for output. With no sales growth, this might suggest that firms would like to hold negative inventories in the earlier periods or, given the non-negativity condition (1), zero inventories. However, if sales growth is sufficiently positive, desired inventories will tend to be positive.

At this point, it is worth pointing out the parallel between the production/storage problem of a cost minimizing firm, and the consumption/saving problem of an optimizing consumer. Here, a firm minimizes the expected discounted value of a convex cost function over time, subject to an expected pattern of sales and costs of holding inventories. The consumer's problem is to maximize the expected discounted value of a concave utility function over time, subject to an expected pattern of income and return to holding wealth. Not surprisingly, then, the solution to cost minimization yields a first-order condition analogous to the first-order condition implied by the stochastic version of the permanent income hypothesis (Hall (1978), Mankiw (1981), Hansen and Singleton (1983)) and we can apply the methods of that literature to testing the production smoothing model of inventories and output. Production, sales, inventories, the interest rate, and storage costs are analogous to consumption, income, wealth, the rate of time preference, and the return on wealth, respectively.[12] In the simplest version of this model, the real interest rate, the growth in the capital stock, and productivity growth are all constant over time. In this case, the expected growth in output is constant over time--i.e., real output follows a geometric random

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[12]The non-negativity condition on inventories mentioned above is analogous to a borrowing constraint in the consumption literature. If time series/cross section data on firms were available, an approach similar to that

walk with drift. This is analogous to Hall's (1978) condition that consumption follow a random walk with drift.

To implement the model described above, we need to specify the form of the cost function. We assume a standard Cobb-Douglas production function with m inputs (q_i, i = 1, ..., m). We call the last input (q_m) the capital stock. In each period, the firm thus solves the following (constrained) problem:

$$\underset{\{q_1,q_2,\ldots,q_{m-1}\}}{\text{Min}} \sum_{i=1}^{m} w_i \cdot q_i \tag{4}$$

$$\text{s.t.} \qquad f(q_1,\ldots,q_m) = \mu \prod_{i=1}^{m} q_i^{a_i} = \bar{y}$$

$$q_m = \bar{q}_m$$

where w_i and q_i are the price and quantities respectively of input i, and f is the production function. μ is a productivity measure that may shift over time in deterministic and/or stochastic ways.[13] Define $A = \sum_{i=1}^{m-1} a_i$. The one period (constrained) cost function from this problem is:

$$C(y) = w_m \cdot q_m + K'' \cdot q_m^{\frac{A-1}{A}} \left[\prod_{i=1}^{m-1} w_i^{a_i/A}\right] \cdot \mu^{-\frac{1}{A}} \cdot y^{\frac{1}{A}} \tag{5}$$

[13]Unlike some previous studies, we do not include either costs of adjusting the level of output or costs of being away from a "target" level of inventory. As Maccini and Rossana (1984) point out, the costs of adjusting output presumably arise because of the costs of changing one or more factors of production. These costs may be important, and careful modeling of them is

and the marginal cost function MC(= dC/dy) is:[14]

$$MC = K' \cdot q_m^{\frac{A-1}{A}} \left[\prod_{i=1}^{m-1} w_i^{a_i/A}\right] \cdot \mu^{-\frac{1}{A}} \cdot y^{\frac{1-A}{A}} . \tag{6}$$

Equation (6) can be used to calculate the ratio of marginal costs in t and t+1:

$$\ln\left(\frac{MC_{t+1}}{MC_t}\right) = \left[\sum_{i=1}^{m-1} (a_i/A) \cdot \ln\left(\frac{w_{it+1}}{w_{it}}\right)\right] - \left(\frac{1-A}{A}\right)\ln\left(\frac{q_{mt+1}}{q_{mt}}\right) + \left(\frac{1-A}{A}\right)\ln\left(\frac{y_{t+1}}{y_t}\right) - \frac{1}{A} \ln \frac{\mu_{t+1}}{\mu_t} . \tag{7}$$

The next step is to derive an expression for the growth rate of output. We do so by taking logs of the Euler equation (3), taking a Taylor expansion of $\ln(1 - s_t)$ around $s_t = 0$ and of $\ln(1 + \varepsilon_{t+1})$ around $\varepsilon_{t+1} = 0$, plugging in equation (7), and rearranging. This gives:

$$\begin{aligned} Gy_{t+1} = {} & \left[(A/1-A)s_1 - \tfrac{1}{2}\sigma_\varepsilon^2\right] + \left(\frac{A}{1-A}\right)\left[\ln(1 + \tilde{R}_t) - \sum_{i=1}^{m-1} (a_i/A)Gw_{it+1}\right] \\ & + Gq_{mt+1} + 2s_2\left(\frac{A}{1-A}\right)n_t + \left(\frac{1}{1-A}\right)G\mu_{t+1} + \left(\frac{A}{1-A}\right)\left[\left(\tfrac{1}{2}\sigma_\varepsilon^2 - \tfrac{1}{2}\varepsilon_{t+1}^2\right) + \varepsilon_{t+1}\right] \end{aligned} \tag{8}$$

where for any variable Z, $GZ_{t+1} \equiv \ln(Z_{t+1}/Z_t)$. The last term in brackets in equation (8) has mean zero.

<u>Discussion of the Model</u>

Equation (8) is the basis of all the estimations performed in this paper. It says that the growth rate of output is a function of the real interest rate (where the inflation rate used to calculate the real rate is a weighted average of the rates of inflation of factor prices), the growth in the capital stock, the level of inventories, productivity growth, and a

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surprise term. The key implication that we test in this paper is that no other information known at time t should help predict output growth.

As is well known, an advantage of estimating this Euler equation is that we avoid solving for firms' closed form decision rule for production; this allows us to step outside the linear-quadratic framework and it allows us to estimate our model that includes stochastic input prices and interest rates. An additional advantage of estimating this type of model rather than the linear quadratic version is that we do not need to assume that output is stationary around a deterministic trend. Rather, the model allows for a logarithmic trend in the level of output and it implies that the growth rate of output is stationary, a condition that Nelson and Plosser (1982), for example, find characterizes aggregate output series.

The model allows for seasonal fluctuations in several ways. First, there may be seasonal movements in the observable or unobservable component of the productivity shifter. Second, there may be seasonals in the relevant input prices. Of course, it is not entirely accurate to describe these as determining the seasonal fluctuations in output growth, since in general equilibrium the seasonals in output growth and input prices are determined simultaneously. For an individual firm, however, and even for a two digit industry, the degree of simultaneity is likely to be small.

Rather than assuming that the productivity shifter μ is totally unobservable to the econometrician, we allow it to be a function of some observable seasonal variables and some unobservables. The observable variables are weather related: functions of current temperature and precipitation. It seems quite reasonable a priori that productivity would be affected by the current local weather and therefore we include these variables in the estimation. We write $\mu = e^{Z\gamma+\eta}$, where Z is a matrix of observable weather variables and η is the unobservable productivity shifter.

In the absence of changes in costs, the model presented is a simple production smoothing model. For a given time path for the capital stock, the derived cost function is convex, inducing firms to try to spread production evenly over time.[15] When we introduce changing costs into the analysis, the result is no longer a pure production smoothing model. Although our model is consistent with the variance of production exceeding the variance of sales, the convexity of the cost function remains and we continue to refer to the model as a type of production smoothing model.

Blinder (1986) states that introducing (unobservable) cost shocks into the analysis makes the variance bounds inequality untestable, because one could explain an arbitrarily large variance of production relative to sales by assuming unobservable cost shocks with appropriately large variance. The approach that we have just described gets around this problem in two ways. First, we include measurements of a number of factors that might influence the marginal cost of production, and account for these in the analysis. Second, we test another implication of the model, that is valid even with unobservable cost shocks: once a number of cost variables are accounted for, the movements in output should be uncorrelated with predictable movements in sales. In other words, even if production moves around a lot due to cost shocks, these movements should not be related to predictable movements in sales. This will be an especially insightful test when applied to predictable seasonal movements in sales.

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[15]This smoothing that arises from a convex cost function is different than the smoothing induced by introducing costs of adjusting output (as in,

Section III: Identification and Testing

A. The General Approach

Equation 8, augmented to include the weather variables, can be written as:

$$Gy_{t+1} = (A/1-A)s_1 - \tfrac{1}{2}\sigma_\varepsilon^2 + \left(\frac{A}{1-A}\right)\left[\ln(1+\tilde{R}_t) - \sum_{i=1}^{m-1}(a_i/A)Gw_{it+1}\right] + Gq_{mt+1}$$
$$+ 2s_2\left(\frac{A}{1-A}\right)n_t + \left(\frac{1}{1-A}\right)GZ_t\cdot\gamma + \left(\frac{1}{1-A}\right)G\eta_{t+1} + \left(\frac{A}{1-A}\right)\left[\left(\tfrac{1}{2}\sigma_\varepsilon^2 - \tfrac{1}{2}\varepsilon_{t+1}^2\right) + \varepsilon_{t+1}\right] \qquad (9)$$

We cannot estimate this equation by OLS, because the right-hand side variables are in general correlated with the expectations error. We therefore use an instrumental variables procedure to estimate the equation. To do so, we must choose instruments that are correlated with the included variables, but not with the error term. Recall that the error term includes two components: the expectations error and the growth in the unobserved productivity shifter. Any variable that is known at time t will, by rational expectations, be orthogonal to ε_{t+1}.[16] However, rationality of expectations does not imply that $G\eta_{t+1}$ is orthogonal to time t information--it is perfectly possible that there are predictable movements in productivity growth. Note that a reasonable possibility is that the productivity measure follows a geometric random walk,

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[16]We assume that production decisions for the month are made after information about demand and other economic variables is revealed, i.e., period t output decisions are made contingent on period t economic variables. An alternative assumption would be that production decisions are made before demand for the month is known. This creates a stockout motive for holding inventories (see Kahn, 1986). In section V, we also present results based on the alternative assumption that output must be chosen before demand

in which case the growth in productivity will be i.i.d. and therefore orthogonal to lagged information.[17]

Garber and King (1984) point out that a number of studies that estimate Euler equations assume that there are no shocks in the sector that they are estimating--effectively ignoring the identification issue. In this paper, we allow some measurable shocks to this sector, and we make the following identifying assumptions about the relationship between the unobserved cost shifter and the included instruments. (1) The unobserved productivity shifter (η) is uncorrelated with lagged values of sales and with the part of current sales that was predictable based on lagged information. (2) The growth of the productivity shifter is uncorrelated with lagged growth rates of input prices, lagged growth rates of output, and lagged interest rates.

We thus consider the following variables to be orthogonal to the error term in the regression: lagged growth in sales, lagged growth in output, lagged interest rate, lagged growth in factor prices, and lagged inventories.[18] To test the model, we first estimate equation (9) with instrumental variables, including as instruments the variables in the above list. Since there are more instruments than right-hand side variables, the equation is overidentified. We then test the overidentifying restrictions by regressing the estimated residuals on all of the included instruments (including the predetermined right-hand side variables). T times the R^2 from this regression is distributed χ^2_k, where T is the number of observations and k is the number of overidentifying restrictions. One possible alternative hypothesis to our null is that firms simply set current output in line with

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[17]This is the assumption made by Prescott (1986).

[18]In some sets of results we relax the assumption that the lagged growth

current sales. In this case, we would expect the lagged growth rate of sales to enter significantly in our test of the overidentifying restrictions.

B. Seasonality and Identification

It is possible that there are seasonal movements in productivity that are not captured by the weather variables. One possible way to capture these would be to allow the productivity measure to be an arbitrary function of seasonal dummies. We do this in our first set of results by including seasonal dummies in the estimation of equation (9).[19]

In order to examine whether the use of X-11 adjusted data has been responsible for the rejections by others of the production smoothing model, we compare the tests of the model using seasonally unadjusted data and seasonal dummies, to the tests using X-11 seasonally adjusted data.

When we include seasonal dummies in the equation, we lose all power to test the model at seasonal frequencies, i.e., we cannot test whether the seasonal movements in the data are consistent with the model. In the latter part of the paper, therefore, we make the stronger identifying assumption that the weather variables capture all of the seasonal shifts in productivity. Under this assumption, we can exclude seasonal dummies and perform two further tests that directly use seasonal fluctuations in the data. We test the implication that once the other factors in the cost function are taken into account, the remaining seasonal movements in output should be uncorrelated with the seasonal movements in sales. This is a strong implication of the

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[19]The fact that we include seasonal dummies does not mean that we assume purely deterministic seasonality. Since the right hand side variables may exhibit stochastic seasonality, our model allows for both stochastic and deterministic seasonality in output growth. We should also note that because we are working in log first differences, using additive seasonal dummies

production smoothing model that has not been tested to date. In addition, we examine whether the model fits at purely seasonal frequencies. We describe these latter two tests in Section VI.

Section IV: The Data

This section describes the data set that we employ. There are a number of technical issues to be considered with respect to both the adjusted and unadjusted data on inventories and production; we discuss these in detail below. Readers who are not interested in these details can skip to Section V.

The equations are estimated using monthly data from April 1967 through December 1982.[20,21] Data on inventories and shipments at the two digit SIC level for 20 industries were obtained from the Department of Commerce. We estimate the equations only on the six industries identified by Belsley (1969) as being production to stock industries. The inventory data were end of month inventories of finished goods, adjusted by the Bureau of Economic Analysis (BEA) from the book value reported by firms into constant dollars.[22,23] We followed West (1983), and adjusted the BEA series from "cost" to "market," so

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[20]Most of our data run through December 1984, but we only have weather data through December 1982.

[21]A month seems like a reasonable planning horizon for a firm, but there is no obvious reason why it need be so. For a discussion of time aggregation issues in inventory models, see Christiano and Eichenbaum (1986).

[22]This adjustment attempts to take into account whether firms used LIFO or FIFO accounting. See Hinrichs and Eckman (1981) for a description of how the constant dollars inventory series are constructed. See Reagan and Sheehan (1985) for an excellent presentation of the stylized facts of these series at an aggregate (durables and non-durables) level.

[23]There is some disagreement over whether it is appropriate to use finished goods inventories only (West (1986)) or finished goods plus work in

that shipments and inventories were in comparable units. Shipments data are total monthly figures in constant dollars.

Two different measures of production are used. The first comes from the identity that production of finished goods equals sales plus the change in inventories of finished goods. Commerce Department data for sales and the change in inventories were used to compute a production measure (we call this measure "Y4"). The second measure of production used was the Federal Reserve Board's index of industrial production (IP), also available at the two digit SIC level.

In principle, the two production series measure the same variable and should therefore behave similarly over time. As documented in Miron and Zeldes (1986), however, the two series are in fact quite different. The correlations between growth rates of the two series range from .8 to .4 for the seasonally unadjusted data, and from .4 to less than .1 for the seasonally adjusted data. The serial correlation properties and seasonal patterns of the two series are also different. Since we have not resolved this discrepancy, we present results based on both output measures.

The nominal interest rate is the yield to maturity on Treasury Bills with one month to maturity as reported on the CRSP tapes. The marginal corporate tax rate series was calculated by Feldstein and Summers (1979). The input price series were wages, the price of crude materials for further processing, and energy prices, representing the three largest variable inputs in the production process. Wages and industrial production at the two digit SIC level, and aggregate measures of energy prices (the PPI for petroleum and coal products) and raw materials prices were available from the Citibank Economic Database.

The capital stock enters our equations as number of machine days used per month. Since we did not have access to industry capital stock data, we model the growth in the capital stock as a constant plus a function of the growth in the number of non-holiday weekdays in the month. Any remaining month to month variation in the growth in the capital stock is included in the error term.

The weather data includes estimates of total monthly precipitation and average monthly temperature. We construct a different temperature and precipitation measure for each industry, equal to weighted averages of the corresponding measures in the different states. The weights are equal to the historical share of the total shipments of the industry that originated in each state.[24] To capture non-linearities, we also include the weighted average of squared temperature, squared precipitation, and the cross-product of temperature and precipitation.

Seasonality

Whenever possible, we obtained both seasonally adjusted (SA) and seasonally unadjusted (NSA) data. The BEA reports real shipments and inventories data, but these constant dollar series are only available on a SA basis.[25] The Bureau of the Census reports NSA and SA current dollar shipments series and book value inventories series. As in Reagan and Sheehan (1985) and West (1986), we estimate the real NSA inventory series by multiplying the real SA series by the ratio of book value NSA to book value SA, thus adding back in an estimate of the seasonal. (Another way of thinking of this is that they

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[24]The weights change every five years but always correspond to averages of previous (never future) years.

[25]The reason for this has to do with the technique used to construct the constant dollar figures. The disaggregated nominal series are first

deflate the book value NSA series by the ratio of the book value to real SA series.) We estimate real NSA shipments by multiplying the real SA series by the ratio of nominal NSA shipments to nominal SA shipments. Each of these procedures assumes that there are no seasonal movements in the factors that convert from book value to current dollar value or in the deflators used to convert the series from current dollar to constant. An additional adjustment that we considered was to multiply the above series by the ratio of the SA to NSA PPI series for the finished goods, in order to adjust for the seasonal in the deflators. Thus, rather than assuming that there is no seasonal in the inventory deflator, this procedure would assume that the seasonal pattern matches that of the PPI for finished goods. We formally tested for seasonality in these prices and found none. Therefore, this last adjustment would make no difference in practice.[26]

The IP data are available both NSA and SA, and the energy price series, wage rates, raw materials prices and interest rates are all unadjusted.

Section V: Basic Results

In this section, we examine the basic results from estimating equation (9) and testing the implied overidentifying restrictions. In order to determine whether the use of X-11 adjusted data has been responsible for previous rejections of the production smoothing model, we run the same set of tests with (1) the standard X-11 seasonally adjusted data and (2) seasonally unadjusted data plus seasonal dummies.

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[26]We estimated our basic equation for three of the industries both with and without this adjustment, using data over a shorter period where data were available, and the results were virtually identical to each other.

A summary of the results is presented in Table 2.[27] There are four sets of results, since we carry out the estimation with both unadjusted and adjusted data, and we do this for both the Y4 and IP measures of output. In the first line of each set of results, we list the variables that entered equation (9) at a 95% significance level. In the second line of each set, we present the R^2 from the regression of the residual on all the instruments. The 95% critical value for this R^2 is .097; i.e., values higher than .097 mean that we can reject the overidentifying restrictions at the 95% level of confidence. In the last line of each set, we list the variables that entered this auxiliary test significantly.

We make the following observations about the results. First, neither the interest rate nor the growth rate in energy prices enters any of the equations significantly. In about one third of the cases, the growth in raw materials prices enters significantly, but usually with the wrong sign. Wage growth enters significantly only four times, twice with the wrong sign. Thus, the signs and statistical significance of the coefficient estimates are not supportive of the model.

The second observation we make is that the data reject the overidentifying restrictions on the model in virtually all cases using the Y4 data, and in about half using the IP data. For the Y4 data, the rejections are about as strong using seasonally adjusted as seasonally unadjusted data. For the IP data, the rejections are not quite as strong overall using the seasonally unadjusted data. On the whole, there is little evidence that the

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[27]Most of these estimations were also done using the sum of finished

use of unadjusted data with seasonal dummies provides better results than using seasonally adjusted data.[28]

Finally, note that in approximately half of the cases, at least one of the five weather variables enters the equation significantly. Even after including seasonal dummies, the weather has a significant influence on production in certain industries.

Thus far, we arrive at a negative assessment of the model for two reasons. First, the overidentifying restrictions are typically rejected. Second, the coefficient estimates are not sensible and rarely significant. Proponents of the model might make the following argument against these two reasons, respectively. First, the instrument list may include variables that are correlated with the error term even under the null hypothesis, thus invalidating the tests of the overidentifying restrictions. Second, the instruments may not do a very good job of explaining the right hand side variables. If this is the case, one should not expect the parameter estimates to be statistically significant, even under the null. We discuss each of these arguments in turn.

There are two circumstances in which the instrument list employed, consisting of lagged values of production, sales, input prices, and inventories, may be correlated with the error term. First, lagged output growth may not be a valid instrument, even if other lagged variables are, because productivity growth might be serially correlated. Since productivity growth is correlated with output growth, this implies that lagged output

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[28]There may be a problem in comparing the seasonally adjusted and unadjusted data in this way because the adjusted data have "fewer degrees of

growth will also be correlated with contemporaneous productivity growth (a component of the error term), making it an invalid instrument.

Second, if firms do not have complete current period information when they make their output decisions for period t, then variables dated time t may not be valid instruments. This could arise because firms do not know the demand for their own products for the period before choosing output (as in Kahn (1986) or Christiano (1986)). Alternatively, firms may know the total demand for their product, but not the aggregate component of demand. Since we are using data on firms aggregated to the industry level, this too might invalidate the use of time t instruments (see Goodfriend (1986)).

In order to take account of these possibilities, we have estimated equation (9) using two alternative instrument lists. The first excludes production from the instrument list and includes extra lags of sales. The second list excludes all variables dated time t and includes extra lags of the variables at earlier dates.

When we employ the first alternative instrument list we reject the overidentifying restrictions significantly less often than with the list used in our basic results.[29] When we employ the second we never reject the overidentifying restrictions. In both cases, however, we almost never find that the input price variables or the interest rate or level of inventories enter statistically significantly with the correct sign. Thus, although there is less statistical evidence against the model with these alternative instrument lists, there is still no evidence that it describes an important aspect of firm behavior.

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[29]In this case, the restrictions are rejected in a majority of cases for

This brings us to the second issue. It is possible that we are not finding that expected changes in input prices affect the timing of production because there are no expected changes in input prices. That is, the instruments that we employ, either in our basic results or alternative results, may be of such poor quality that they have no explanatory power for the right hand side variables in equation (9). If this is the case, the failure of these input prices to explain the pattern of production is not evidence against our model.

It is easy to check this possibility by examining directly the explanatory power of the instruments. For all three instrument lists, we find the following: there is statistically significant explanatory power in the instruments about half the time for wages; all the time for interest rates; and almost never for raw materials prices. Thus, with the exception of raw materials prices, the failure of input prices to explain production in any of our results is valid evidence against the model.

To summarize, the results presented provide evidence against the production smoothing model, even when it is expanded to incorporate a stochastic interest rate, measurable and unmeasurable cost shocks, and non-quadratic technology. Using seasonally unadjusted data and seasonal dummies does little better than using X-11 adjusted data.

Section VI: Seasonal-Specific Results

In this section, we examine the extent to which the seasonal fluctuations in production, shipments and inventories are consistent with the production smoothing model. The results presented above incorporate seasonal fluctuations into the analysis by using seasonally unadjusted data and including seasonal dummies and weather variables in the equations. This approach does prices determine the seasonal movements in output growth, nor does it answer the question of whether the seasonal movements in the data themselves satisfy the production smoothing model. In order to answer these questions, we cannot include seasonal dummies in the equation, and therefore must assume that any fluctuations (seasonal and nonseasonal) in the productivity measure not captured by the weather variables are orthogonal to the instruments used.

Before describing our formal tests, it is useful to consider a set of stylized facts about the seasonality in production, inventories, and sales. We saw in Table 1 that the seasonal variation in the data is large relative to the non-seasonal variation. Table 1 also presents the ratio of the seasonal variation in the growth of production to seasonal variation in the growth of sales.[30] As we have discussed above, if cost shocks are assumed to be "small," the production smoothing model restricts this ratio to be less than one. As it turns out, the two different measures of output give quite different results. For the Y4 data, the seasonal variance of production is consistently greater than the seasonal variance of sales, while for IP the inequality is usually reversed.[31]

If there are seasonal shifts in the cost function, then there is no reason to expect the above ratio to be less than one. Even in this case, however, there is further information to be learned from examining the seasonal movements. Whether or not seasonal shifts in productivity affect the seasonal pattern of production, there is no reason to expect that seasonal

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[30] In the last section of his paper, West (1986) describes a variance bounds test that includes deterministic seasonal variations in the data. He found that the variance bounds were rejected for each of the three industries that he examined.

pattern to match the seasonal pattern of sales. Figures 1-6 show the seasonal patterns in output and shipments for the six industries we examine and document behavior problematic for the production smoothing model.[32] *The seasonal movements in output and sales are in fact very similar*. The implication of these graphs is that inventories do not appear to be playing the role of smoothing seasonal fluctuations in sales.

In the tests we present in this section, we formalize this observation. First, we test whether the contemporaneous seasonal movement in sales growth helps predict residual output growth, once the movements in factor prices, the weather, and lagged inventories are taken into account. To do this, we use the same procedure as in Section V, except that seasonal dummies are excluded from the regression and the instrument list, and the seasonal component of contemporaneous sales growth is added to the instrument list. It is unusual when running this type of orthogonality test to include as an instrument a contemporaneous variable, but since this series is deterministic, it is part of the lagged information set. Since it is also assumed orthogonal to the unobservable productivity shifter, it is a valid instrument.[33]

The interpretation of this procedure is the following. By excluding seasonal dummies from the equation, we force the seasonal and non-seasonal movements in the right-hand side variables to affect output growth via the same coefficients. Given this restriction, we are then testing whether the part of output growth not explained by these variables is correlated with the seasonal component of sales growth. This allows us to compare the seasonals

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[32]The seasonal coefficient plotted for each month is the average percentage difference in that month from a logarithmic time trend.

[33]The series we actually use is, of course, the estimated rather than the

in sales and output, after taking into account the measured seasonality in factor costs, the weather, and the level of inventories.

This test of the production smoothing model using the seasonal fluctuations does involve one important maintained hypothesis, namely that the coefficients on the seasonal and non-seasonal components of input prices and the weather are the same. In our last set of tests, we relax this assumption and test whether the seasonal movements in the data, taken by themselves, are consistent with the model. This is accomplished as follows.

The first step is to construct the seasonal component of each of the relevant variables (output growth, input prices, weather variables, etc.) by regressing them on seasonal dummies and calculating the fitted values of these regressions. We then regress the seasonal component of output growth on the seasonal in input prices, weather, the level of inventories, and the contemporaneous seasonal component of sales, and we test the restriction implied by the model that this last coefficient should be zero.[34] This procedure is equivalent to using IV band spectrum regression where the seasonal frequency band is the narrowest one possible, i.e., it consists only of the principal seasonal frequency and harmonics.[35]

The results are summarized in Tables 3 and 4. Table 3 presents the same type of information as Table 2, but it also shows the t-statistic on the seasonal component of contemporaneous sales in the test of the overidentifying

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[34]Since we found there to be essentially no seasonality in energy prices, raw materials prices, or interest rates, we excluded these variables.

[35]Mankiw and Miron (1986) show that even though the error term in the equation is only predetermined (rather than strictly econometrically exogenous), band spectrum regression is still consistent as long as the band employed satisfies a certain symmetry condition. The band we employ satisfies this condition. It is trivial to extend their argument to IV band spectrum

restrictions. Table 4 is also set up similarly to Table 2, but it simply reports whether the seasonal in sales significantly affects the seasonal in output growth, after controlling for input prices, the weather, and the level of inventories.

In both tables, there is striking evidence against the production smoothing model. In Table 3, we reject the overidentifying restrictions in every instance. In almost all cases, the seasonal component of sales is significantly correlated with the movement in output, even after taking account of any seasonals in input prices, lagged inventories, and the weather. This is true for every industry using at least one of the output measures, and for 4 of the 6 industries using both output measures. In Table 4 (the seasonal-only results) the seasonal in sales growth is always statistically significant.

When we use the alternative instrument lists discussed above (leaving out time t variables or lagged output growth) we again reject the overidentifying restrictions and find that the seasonal in sales growth is significantly correlated with the residual output growth in most cases.

These results on the behavior of production and sales at seasonal frequencies are perhaps the most problematic yet presented for the production smoothing model. To a large extent, firms appear to be choosing their seasonal production patterns to match their seasonal sales patterns, rather than using inventories to smooth production over the year. Moreover, since the seasonal variation in production and sales accounts for more than 50% of the total variation in these variables, this problematic behavior is a quantitatively important feature of the data.[36]

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[36] A key assumption that we have made here is that the seasonal in the productivity shifter is uncorrelated with the seasonal in demand. Are there circumstances under which this assumption would not hold? An example that

Section VII: Conclusions

The results presented above show a strong rejection of the production smoothing model. This is despite the fact that we have extended the standard model considerably, by allowing for non-quadratic technology, a stochastic interest rate, convex costs of holding inventories, and measurable and non-measurable cost shocks, and by including seasonal fluctuations explicitly. Although previous work has examined many of these features, none has simultaneously allowed for all of them.

The rejections of the basic production smoothing model that we report are robust with respect to the treatment of seasonal fluctuations. To begin with, we reject the model about as strongly when we treat seasonality in the standard way, by using adjusted data, as when we treat it more explicitly by specifying the economic sources of the seasonal movements in production and inventories. Even more surprisingly, our results show that the seasonal movements in production, inventories and shipments are inconsistent with the basic model. Specifically, the seasonal component of output growth, even

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that individuals, all else equal, would rather take vacations in certain months. This would induce a corresponding seasonal in output. If each industry's output is an input into another industry, then we might expect to see a corresponding seasonal in shipments: leading optimally to the same seasonal patterns in output and shipments.

Theoretically, our approach accounts for this by including the wage as a determinant of the desired production. However, if the measured wage differs from the true shadow cost of utilizing labor, then the residual will include the seasonal in labor supply and therefore still be correlated with the seasonal in shipments. This explanation would suggest that we should see the same seasonal movements in output in all industries. If we look at Figures 1-6, we do see common seasonal patterns in output across industries, but we also see a fair amount of seasonal movements that differ across industries.

It is not clear what conclusion to draw from this discussion. Although it is possible that the hypothesis proposed above is the explanation for the seasonal results, it is somewhat unsatisfactory to posit an unobservable aggregate shock in order to reconcile the data with the model. In particular, one needs to think about whether the same type of arguments could be made about non-seasonal movement, i.e., do we believe that the failure of the production smoothing model at non-seasonal frequencies is due to economy-wide after adjusting for the seasonality in interest rates, wages, energy prices, raw materials prices, and the weather, is still highly correlated with the seasonal component of sales growth, contrary to the prediction of the model.

We conclude the paper by discussing what we believe to be the implications of our results for a number of hypotheses that have been offered for the failure of the production smoothing model. We first discuss those hypotheses on which our results provide direct evidence and then turn to more indirect implications.

Our results provide direct evidence that the limited role given to cost shocks in previous papers is not the major reason for the rejections of the model. In this paper we have included a more general set of cost shocks than in earlier work, and we still find that the data reject production smoothing. Moreover, we find relatively little evidence that cost shocks play any role in determining the optimal timing of production. It is possible, of course, that we have omitted the "key" cost shock, or that one of our identifying assumptions is invalid. We believe, however, that the set of costs we have included covers all of the major ones, and we think that the identifying assumptions we make are minimally restrictive. It seems to us unlikely, therefore, that the treatment of cost shocks is a major factor in explaining the poor performance of the model.

The second area in which our results provide direct evidence is on whether the inappropriate use of data seasonally adjusted by X-11 has been responsible for the failure of the model. As we discussed above, X-11 data are (approximately) a two-sided moving average of the underlying seasonally unadjusted data. This means that such data likely violate the crucial orthogonality conditions that are tested in the kinds of models considered above, even if the unadjusted data satisfy them. Although it seemed likely to us on a priori grounds that the use of X-11 adjusted data was a major problem, our results indicate otherwise. The particular method of treating seasonal fluctuations does not appear crucial to an evaluation of the model.

So much for direct implications. We now turn to more indirect implications, specifically, the implications of our tests using only the seasonal movements in the data.

To begin with, since seasonal fluctuations are anticipated, it seems unlikely that the failure of the model at seasonal frequencies could be due to any kind of irrationality or disequilibrium. If so, this rules out a large class of possible explanations of the failure of the model.

A second issue that is illuminated by our seasonal specific results is that of costs of changing production. We have omitted costs of changing production (or, more generally, costs of changing inputs) from our specification above; the addition of these costs might "help the data fit the model." We regard this tactic as unsatisfactory, however. The fact that there are extremely large seasonal changes in the rate of production makes it seem quite unlikely that there are large costs of adjustment, although it is true that costs may be lower when they are anticipated.

Blinder (1986a) suggests that the production smoothing model could be saved by including persistent demand shocks and small cost shocks. Even if the non-seasonal movements in sales are very persistent, however, the same is not true of the seasonal movements. Therefore, our seasonal results suggest that Blinder's explanation will not suffice to "save" the production smoothing model.

Finally, our seasonal specific results allow us to rule out a concern regarding the choice of appropriate instruments. In Kahn (1986), for example, current period demand when they choose the current period level of production. In our estimation, we assume that firms do know current demand, and therefore time t dated sales is a valid instrument. If this assumption is a more appropriate abstraction, then our general results are inconsistent. When we correct for this by using only variables dated t - 1 and earlier as instruments, we can no longer reject the model. However, it is still valid to include the seasonal component of contemporaneous sales growth, since the seasonal component of demand would be known even if the overall level were not. Since the results from this test show a strong rejection of the model, this suggests that the assumption that firms observe demand before choosing output is not, by itself, to blame.

What remains, then, as a possible explanation for the failure of the production smoothing model? There are two main possibilities: non-convexity of the cost function, and stockout costs. Giving up convexity of costs is unappealing because it requires also giving up much of neo-classical theory. This does not mean it is not the correct explanation; it simply suggests that we should turn to it only as a last resort. We end, therefore, by discussing the role of stockout costs.

An important maintained assumption above is that firms always hold non-negative inventories. This condition is satisfied by our data, but they may well be an artifact of aggregation. Kahn (1986) presents a model in which, because stockouts are costly, firms may well unsmooth production. There are both appealing and unappealing features of this model. On the one hand, it clearly and simply rationalizes several puzzling facts about production and inventories, including the "excess volatility" of production, the positive correlation between inventory levels and sales, and persistently high inventory-sales ratios. On the other hand, there is as yet relatively little direct evidence that stockout costs are high, or that firms cannot simply hold unfilled orders as a type of negative inventories. This line of research deserves further attention, in particular direct empirical testing.

Seasonality and Inventories: Table 1

Means; and total, seasonal, and non-seasonal "variance" of the first difference of logs:

	INDUSTRY					
	FOOD(20)	TOBACCO(21)	APPAREL(23)	CHEMICALS(28)	PETROLEUM(29)	RUBBER(30)
Shipments						
Mean:	0.17%	0.04%	0.07%	0.38%	0.21%	0.29%
Variance:						
-Non-seasonal	5.80E-04	6.62E-03	2.82E-03	1.09E-03	6.60E-04	1.24E-03
-Seasonal	1.47E-03	2.20E-03	1.52E-02	2.45E-03	2.60E-04	4.04E-03
-Total	2.05E-03	8.82E-03	1.80E-02	3.54E-03	9.20E-04	5.28E-03
-seasonal/total	72%	25%	84%	69%	28%	77%
Production (Y4 data)						
Mean:	0.16%	0.03%	0.08%	0.37%	0.19%	0.28%
Variance:						
-Non-seasonal	7.20E-04	2.57E-02	3.52E-03	9.50E-04	1.05E-03	1.89E-03
-Seasonal	1.58E-03	8.40E-03	1.20E-02	1.85E-03	2.60E-04	5.02E-03
-Total	2.30E-03	3.41E-02	1.55E-02	2.80E-03	1.31E-03	6.91E-03
-seasonal/total	69%	25%	77%	66%	20%	73%
Var. Production/Var. Sales:						
-Non-seasonal	1.24	3.88	1.25	0.87	1.59	1.52
-Seasonal	1.07	3.82	0.79	0.76	1.00	1.24
-Total	1.12	3.87	0.86	0.79	1.42	1.31
Production (IP)						
Mean:	0.28%	.00%	0.12%	0.48%	0.16%	0.55%
Variance:						
-Non-seasonal	1.90E-04	2.76E-03	1.64E-03	3.80E-04	5.50E-04	1.20E-03
-Seasonal	8.80E-04	1.56E-02	3.66E-03	4.40E-04	3.80E-04	2.20E-03
-Total	1.07E-03	1.84E-02	5.30E-03	8.20E-04	9.30E-04	3.40E-03
-seasonal/total	82%	85%	69%	54%	41%	65%
Var. Production/Var. Sales:						
-Non-seasonal	0.33	0.42	0.58	0.35	0.83	0.97
-Seasonal	0.60	7.11	0.24	0.18	1.46	0.55
-Total	0.52	2.09	0.29	0.23	1.01	0.64

nventories: Table 2

	INDUSTRY					
	FOOD(20)	TOBACCO(21)	APPAREL(23)	CHEMICALS(28)	PETROLEUM(29)	RUBBER(30)

R INC, DUMMIES INC) T=188 95% conf level for Rsq=[CHISQ(10)/T]=.097

	SD,-WRM	TEM,-TEM2	SD	SD,TEM,-PRE,-TEM2	-W,— DAY,-TEM2,-PRE2	SD
?,Rsq	.17	.23	.09	.15	.13	.16
	W-1,-W-2	TEM-1	-	-Y-1,X-1,-N-2,N-3,SD	WE-2	W,SD
	-	WRM,TEM,-TEM2	-N-1,WRM	WRM	-W,- DAY,-PRE2,TPR	W
?,Rsq	.10	.14	.11	.14	.14	.11
	-	-	-	-	-	-
	SD	-SD,W,-PRE2	SD,DAY-1	SD,WRM	SD,- PRE2	WRM
?,Rsq	.16	.16	.09	.04	.08	-.02
	-Y-1,-W-2	-Y-1,SD	-Y-1	-	-	-
	-	-PRE2	-PRE2	TEM,-TEM2	-DAY -1	WRM,TEM,-TEM2
?,Rsq	.15	.28	.09	.13	.09	-.06
	-Y-1,-WE-2	-Y-1,-Y-2,-TEM-1,-TPR-1	-Y-1	X-1,X-2	-	-N-1

rowth, SD:seasonal dummies, Y:output growth, X:sales growth, DAY:number of prod. days,
price growth, WRM:raw materials price growth, N:inventories, R:interest rate
pitation, PRE2:precip squared, TEM:temperature, TEM2:temp squared, TPR:temp*precip

efficient indicates that the sign was negative
"reject overid restr" is the R squared of the regression of the residuals on the instruments

nventories: Table 3

R INCLUDED, NO DUMMIES, FITTED VALUES FROM REGRESSION OF SALES ON SEAS DUMMIES IN INSTRUMENT LIST)
vel for Rsq=[CHISQ(11)/T]=.105

	INDUSTRY FOOD(20)	TOBACCO(21)	APPAREL(23)	CHEMICALS(28)	PETROLEUM(29)	RUBBER(30)
	-W,TEM,-TEM2	-W,-TEM2	W,TEM,-TEM2	-W,TEM,-TEM2	-DAY	TEM,-PRE,-TEM2
?,Rsq	.54	.17	.21	.30	.17	.26
	-X-2,-TEM2-1,-WRM-1,XSEAS	-	XSEAS	-TEM2-1,XSEAS	WE-2	XSEAS
AS	3.71	0.99	3.06	3.41	0.73	2.76
	-W,TEM,-TEM2,TPR	-W	W,TEM,-PRE,-TEM2	TEM, -TEM2	-W	TEM,-PRE,-TEM2
?,Rsq	.41	.24	.32	.19	.13	.28
	-Y-1,-Y-2,-W-2,PRE-1,-WRM-1,XSEAS	-Y-1,-TEM2-1,XSEAS	-DAY,-PRE-1,TPR-1,XSEAS	-Y-1 ,N-3	R-1,-R-2,XSEAS	XSEAS
AS	3.30	2.44	4.06	1.70	2.13	3.18

rowth, SD:seasonal dummies, Y:output growth, X:sales growth, DAY:number of prod. days,
price growth, WRM:raw materials price growth, N:inventories, R:interest rate
pitation, PRE2:precip squared, TEM:temperature, TEM2:temp squared, TPR:temp*precip
sonal component of sales growth

efficient indicates that the sign was negative
'reject overid restr" is the R squared of the regression of the residuals on the instruments

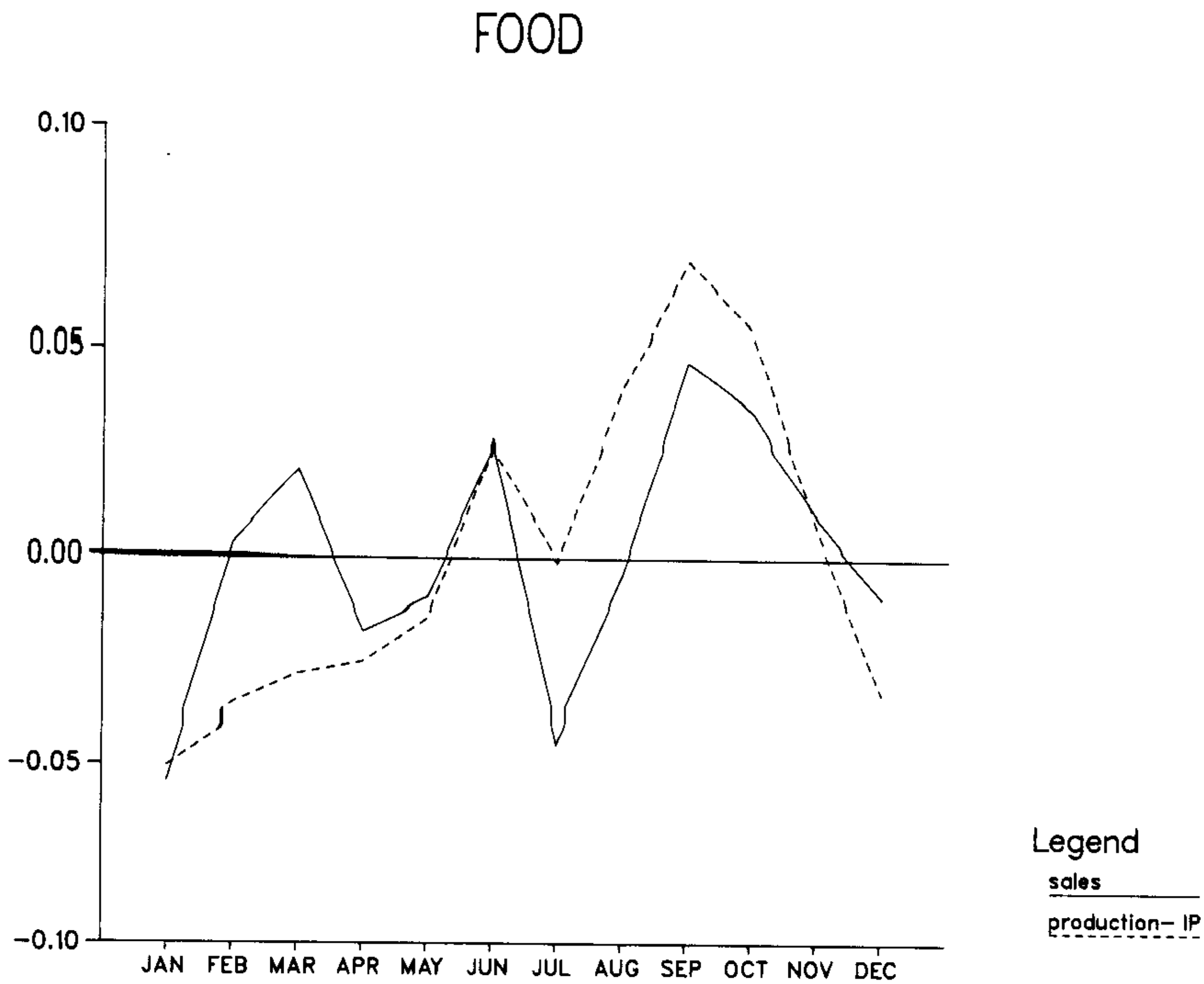
Seasonality and Inventories: Table 4

TEST	FOOD(20)	TOBAC(21)	INDUSTRY APPAR(23)	CHEMICALS(28)	PETROLEUM(29)	RUBBER(30)
MODEL 52 (WEATHER INCLUDED, DUMMIES EXCLUDED)						
(1-4:Y4)						
(NSA)						
1. What signif?	-TEM2,X,-N	-TEM,-PRE,TEM2, -CROSS,-N,W,X	-TEM,PRE,-TEM2, -PRE,CROSS,N,W,X	TEM,-PRE,PRE2, -CROSS,-N,-W,X	TEM,-PRE,-TEM2, PRE2,-CROSS,-N,-W,X	-TEM,PRE,TEM2, PRE2,-CROSS,X
2. t-stat on XSEAS	32.97	63.18	27.12	102.7	80.07	388.6
(5-8:IP)						
(NSA)						
5. What signif?	-TEM,PRE,TEM2, -PRE2,CROSS ,-N, W,X	-TEM,-PRE,TEM2 -N,W,X	-TEM,PRE,-TEM2, -PRE,CROSS,W,X	TEM,-PRE2,-CROSS, -N,W,X	TEM,-PRE,TEM2,PRE2, -CROSS,-N,-W,X	TEM,PRE,TEM2, PRE2,CROSS,-N,-W,X
6. t-stat on XSEAS	53.97	33.13	17.34	33.09	11.65	165.1

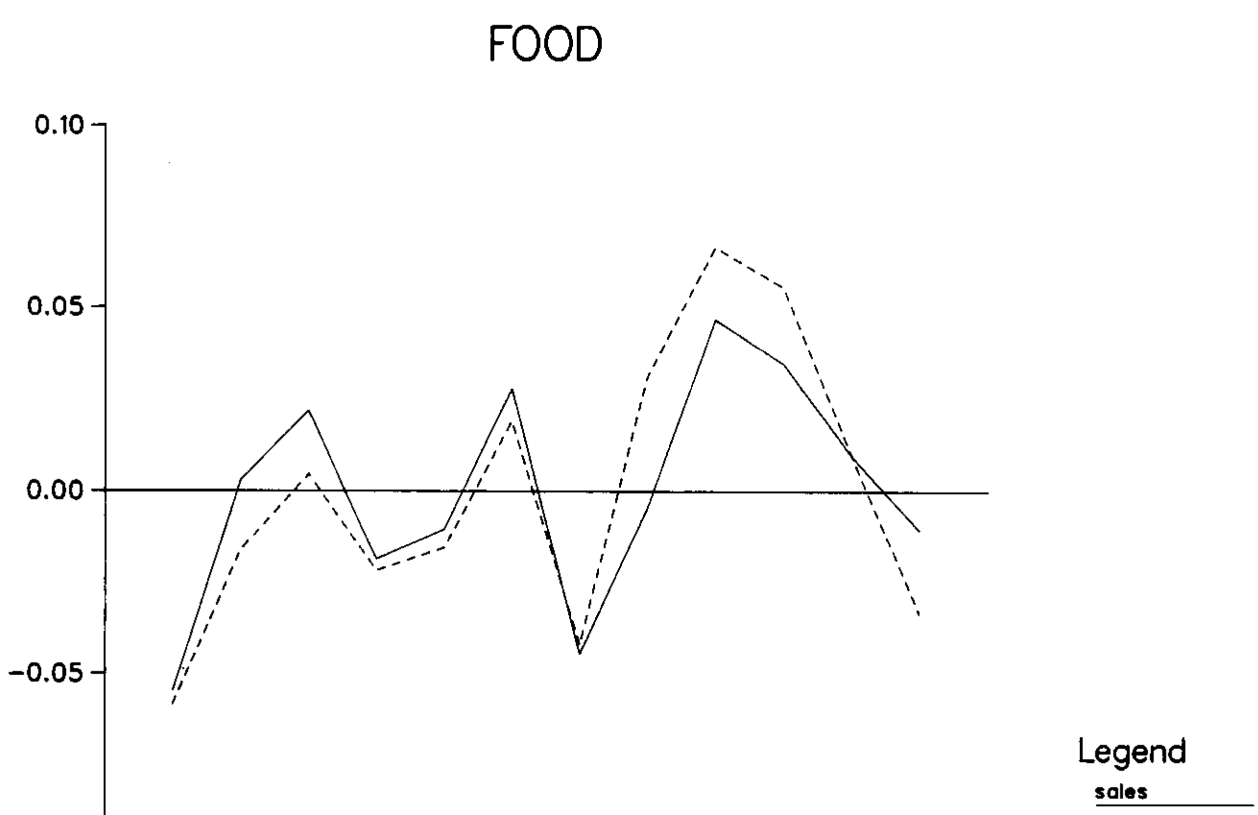
SYMBOLS: W:wage growth, SD:seasonal dummies, Y:output growth, X:sales growth, DAY:number of prod. days,
WE:energy price growth, WRM:raw materials price growth, N:inventories, R:interest rate
PRE:precipitation, PRE2:precip squared, TEM:temperature, TEM2:temp squared, TPR:temp*precip
XSEAS:seasonal component of sales growth

A (-) before a coefficient indicates that the sign was negative
The number after "reject overid restr" is the R squared of the regression of the residuals on the instruments

FIGURE 1

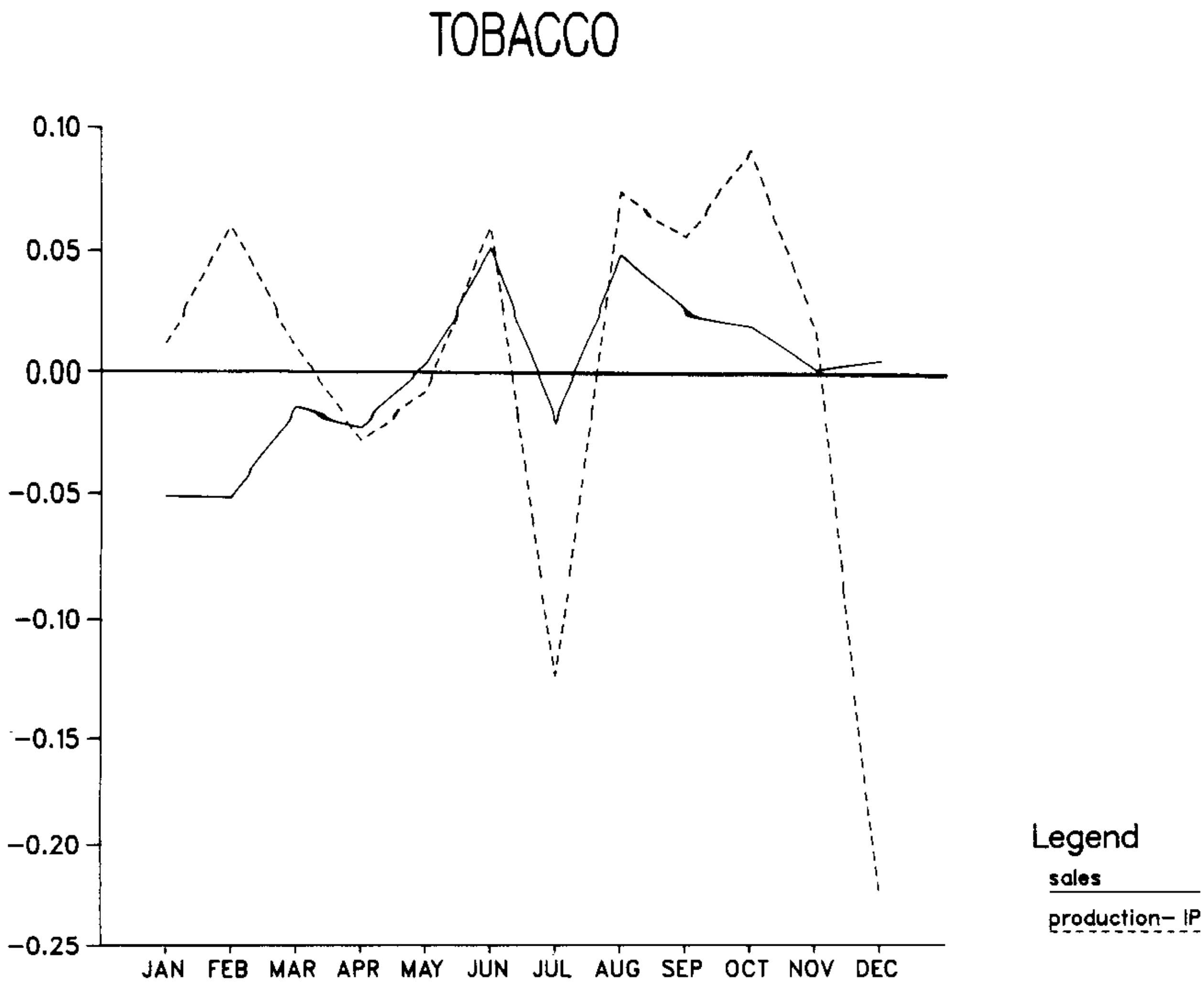


FOOD
0.10
0.05
0.00
-0.05
-0.10
JAN
FEB
MAR
APR
MAY
JUN
JUL
AUG
SEP
OCT
NOV
DEC
Legend
sales
production- IP



FOOD
0.10
0.05
0.00
-0.05
Legend
sales

FIGURE 2


TOBACCO
0.10
0.05
0.00
-0.05
-0.10
-0.15
-0.20
-0.25
JAN FEB MAR APR MAY JUN JUL AUG SEP OCT NOV DEC
Legend
sales
production- IP

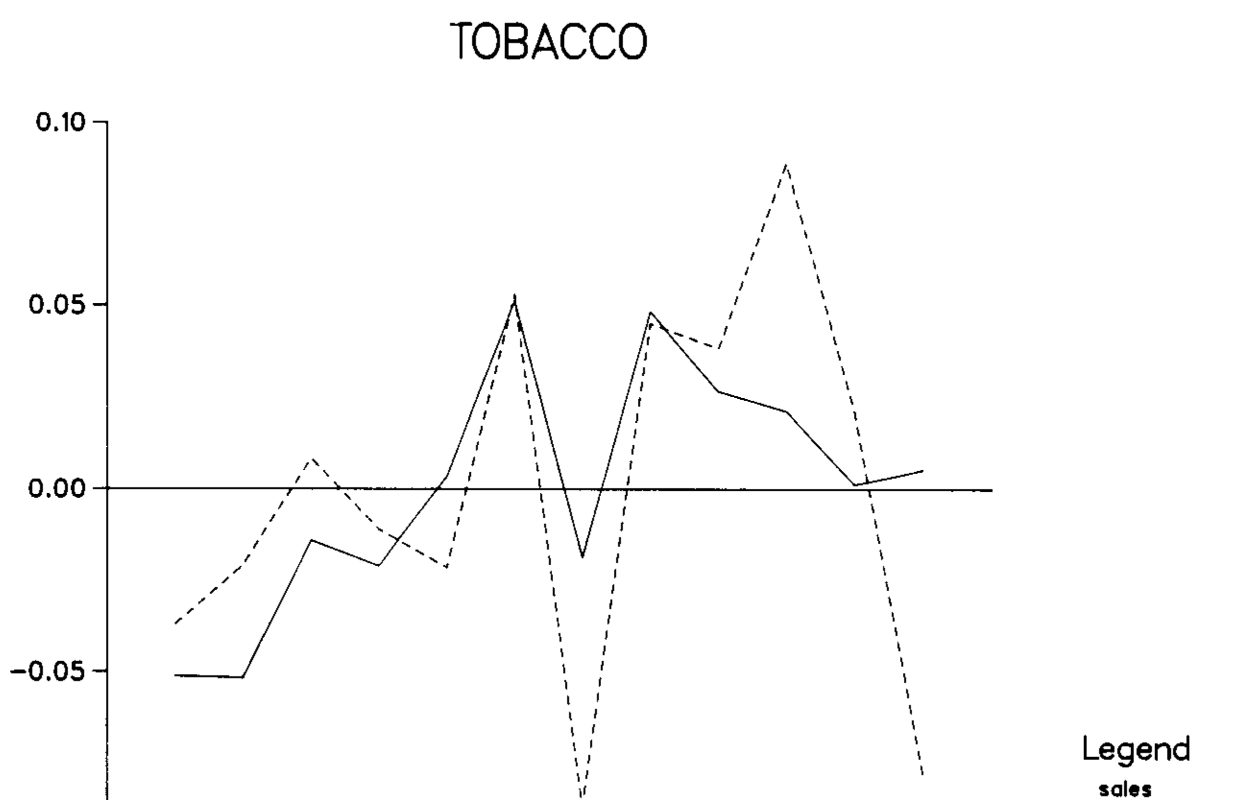
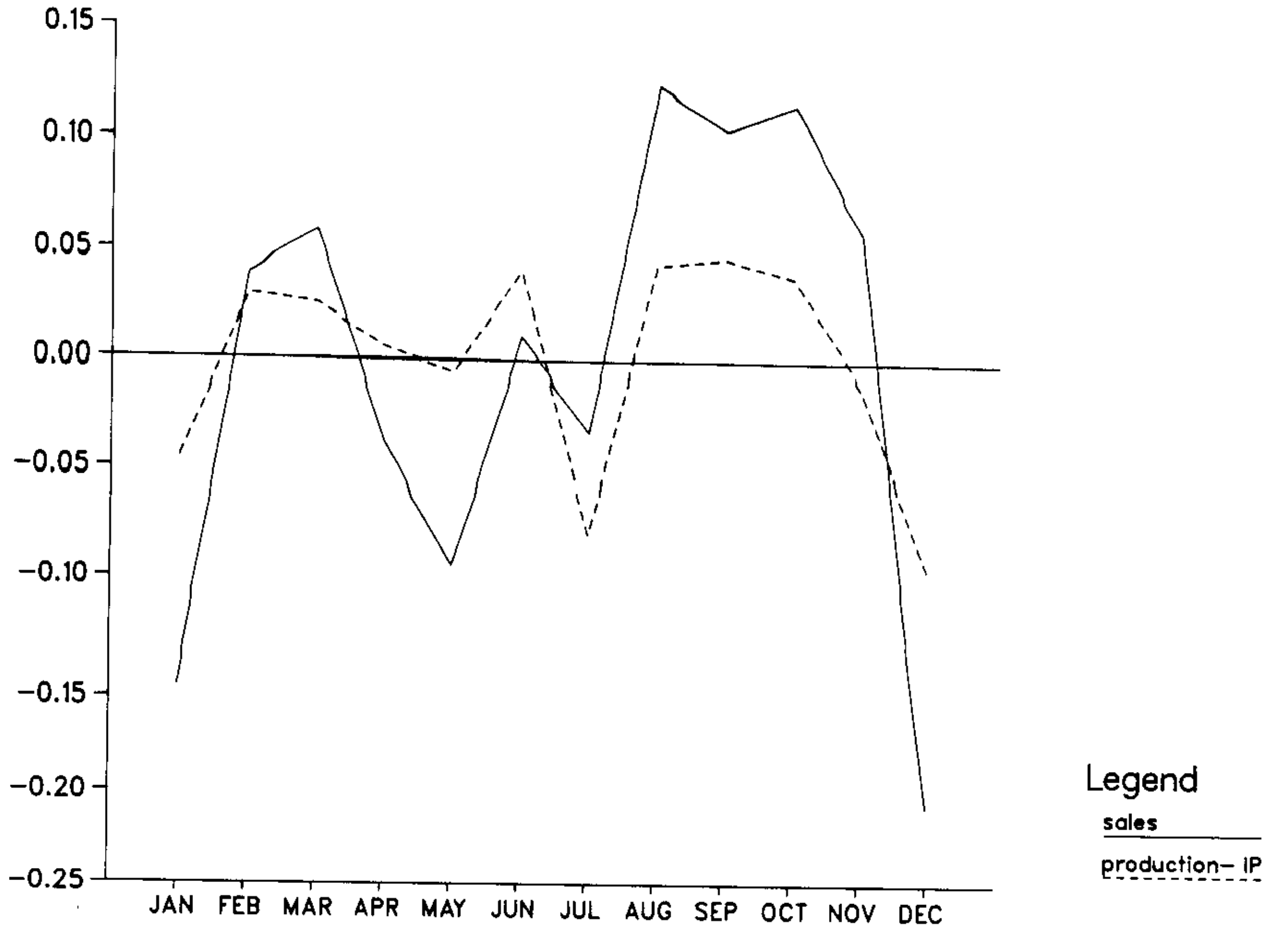

TOBACCO
0.10
0.05
0.00
-0.05
Legend
sales

FIGURE 3

APPAREL



APPAREL

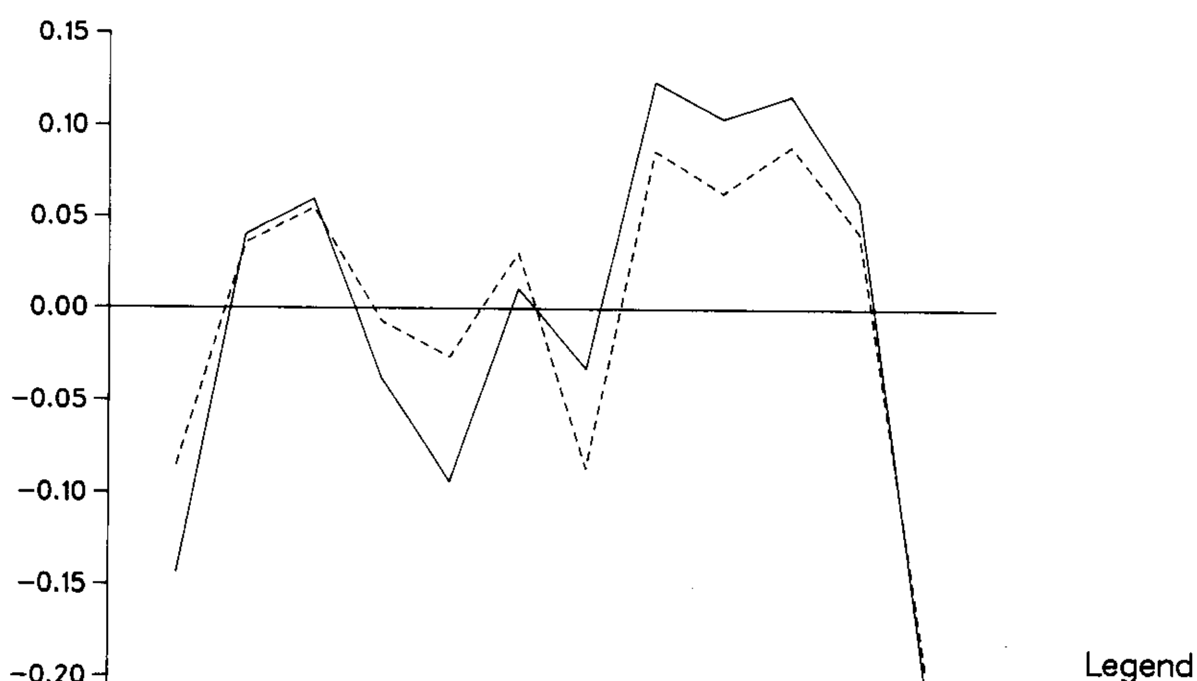
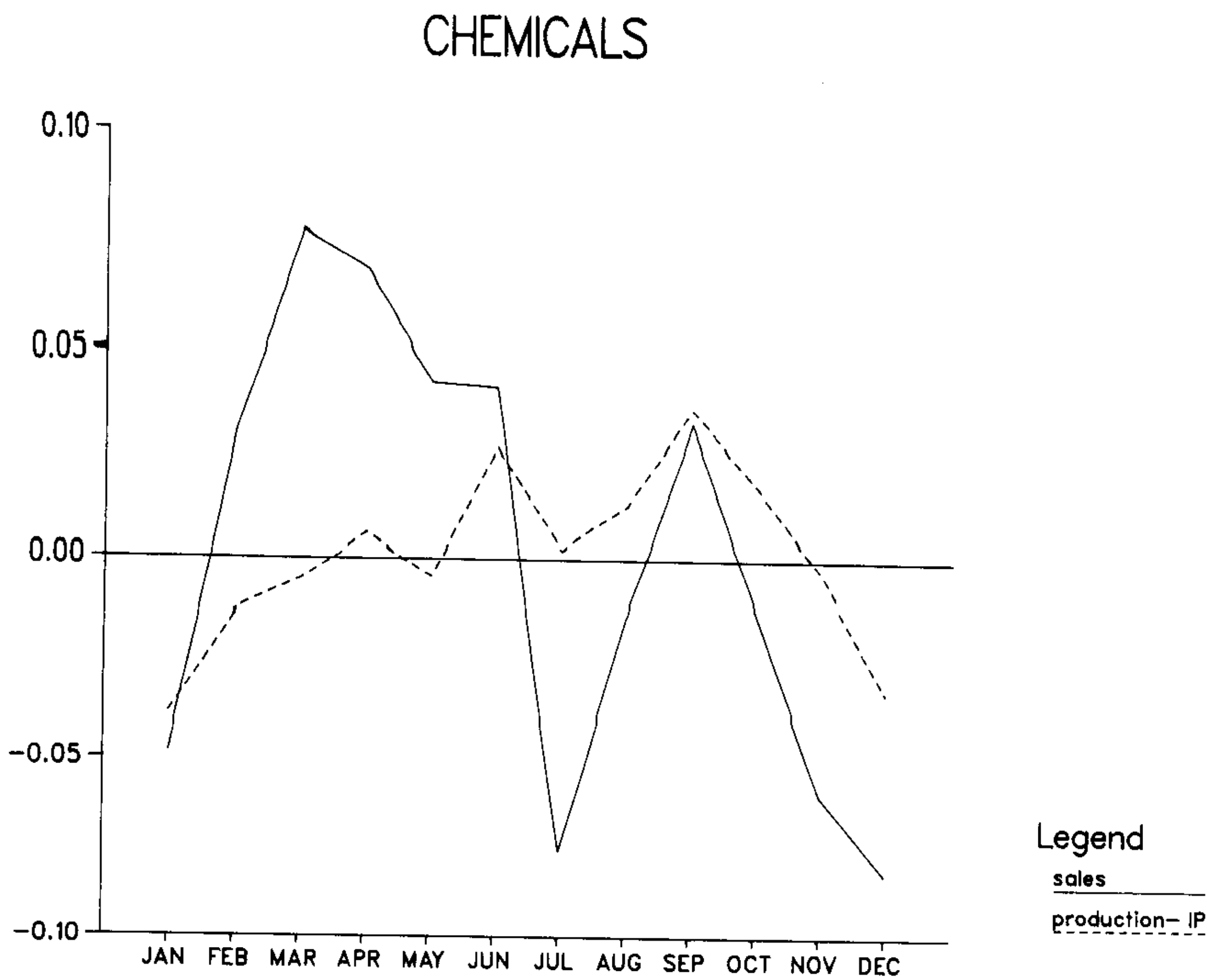
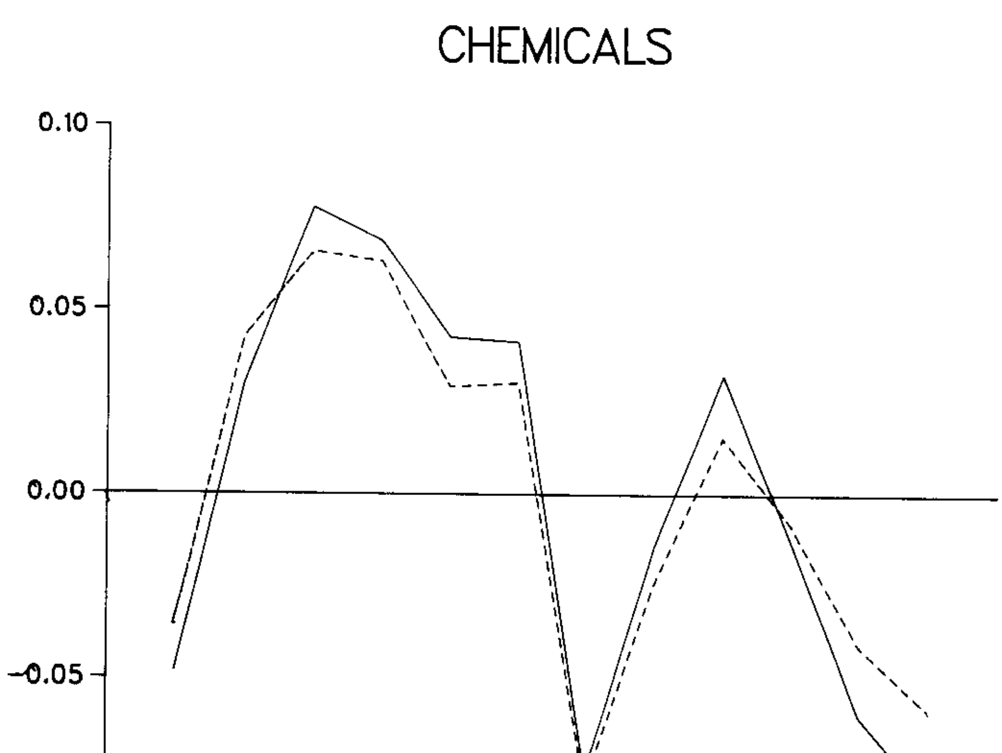


FIGURE 4

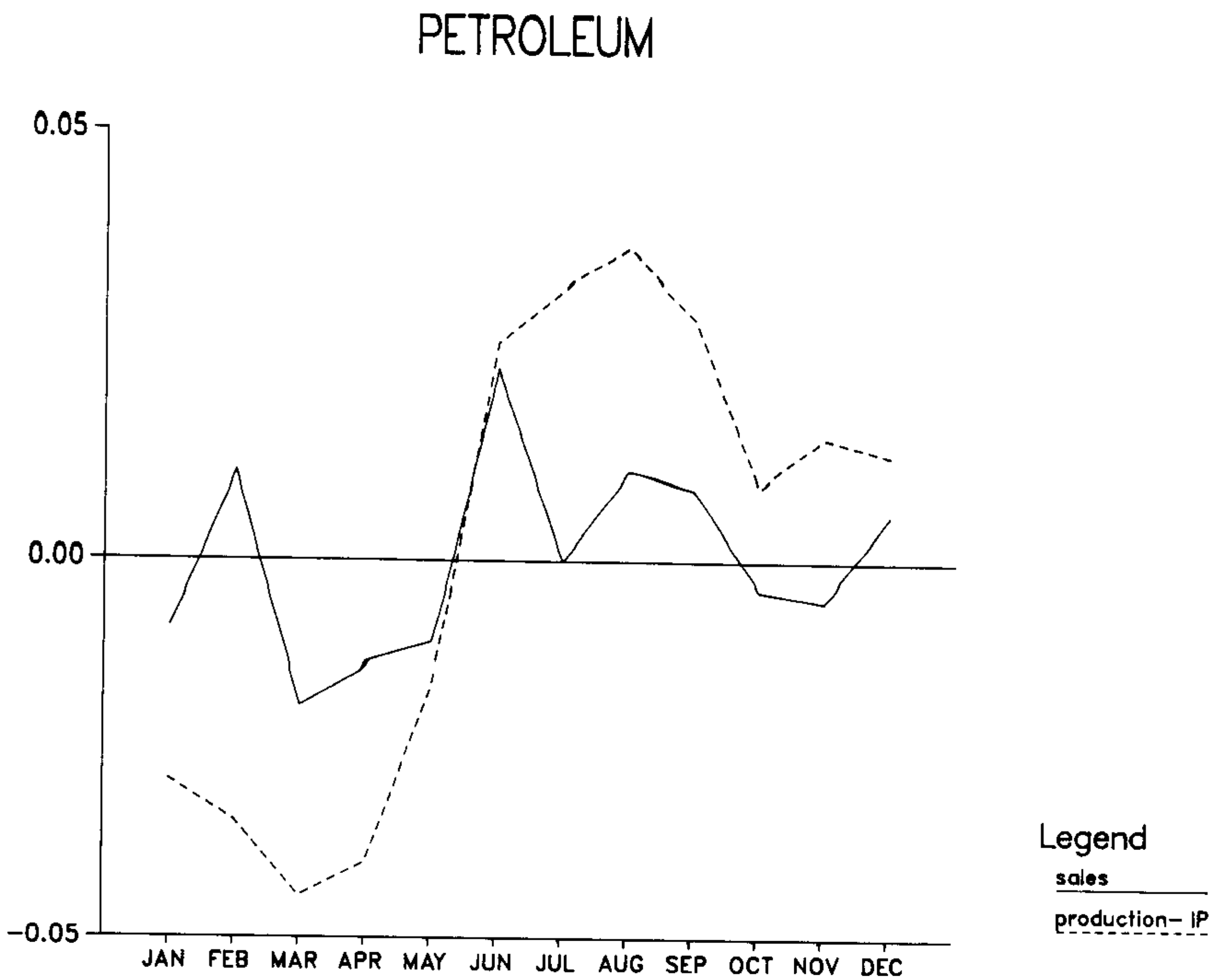


CHEMICALS
0.10
0.05
0.00
-0.05
-0.10
JAN
FEB
MAR
APR
MAY
JUN
JUL
AUG
SEP
OCT
NOV
DEC
Legend
sales
production- IP



CHEMICALS
0.10
0.05
0.00
-0.05

FIGURE 5


PETROLEUM
0.05
0.00
-0.05
JAN FEB MAR APR MAY JUN JUL AUG SEP OCT NOV DEC
Legend
sales
production- IP

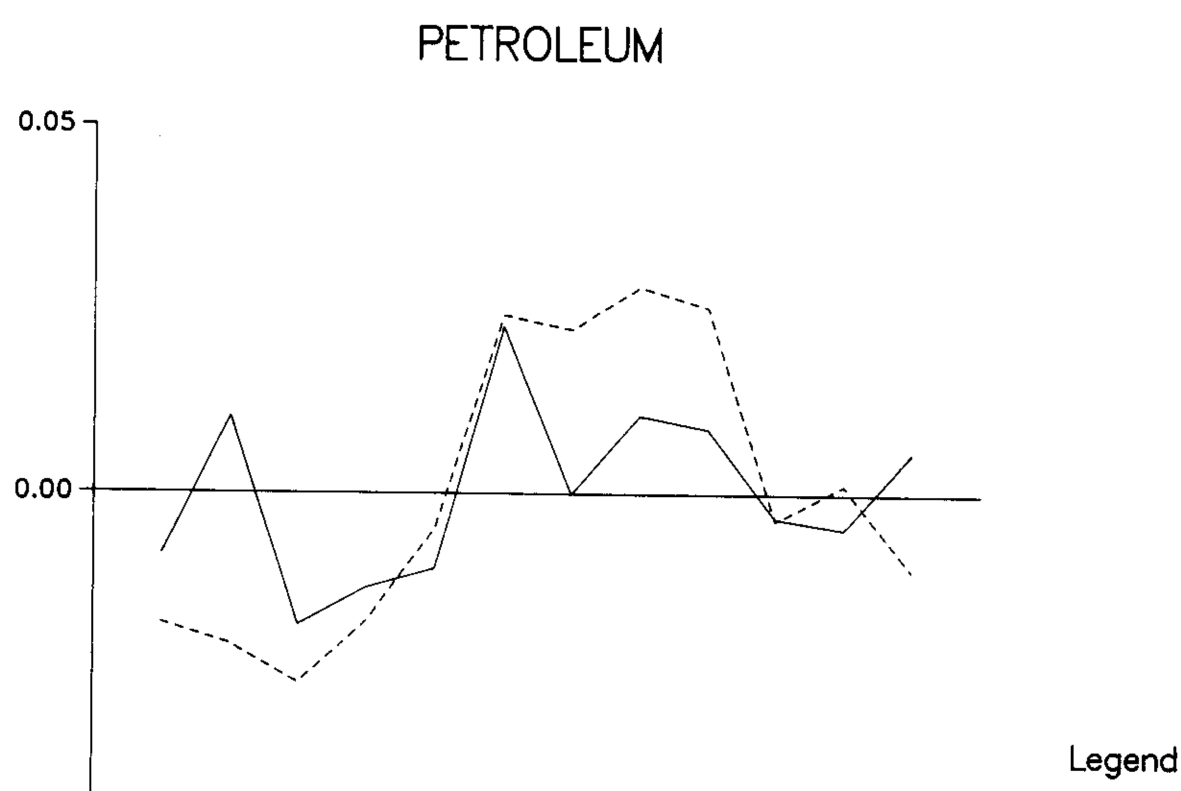
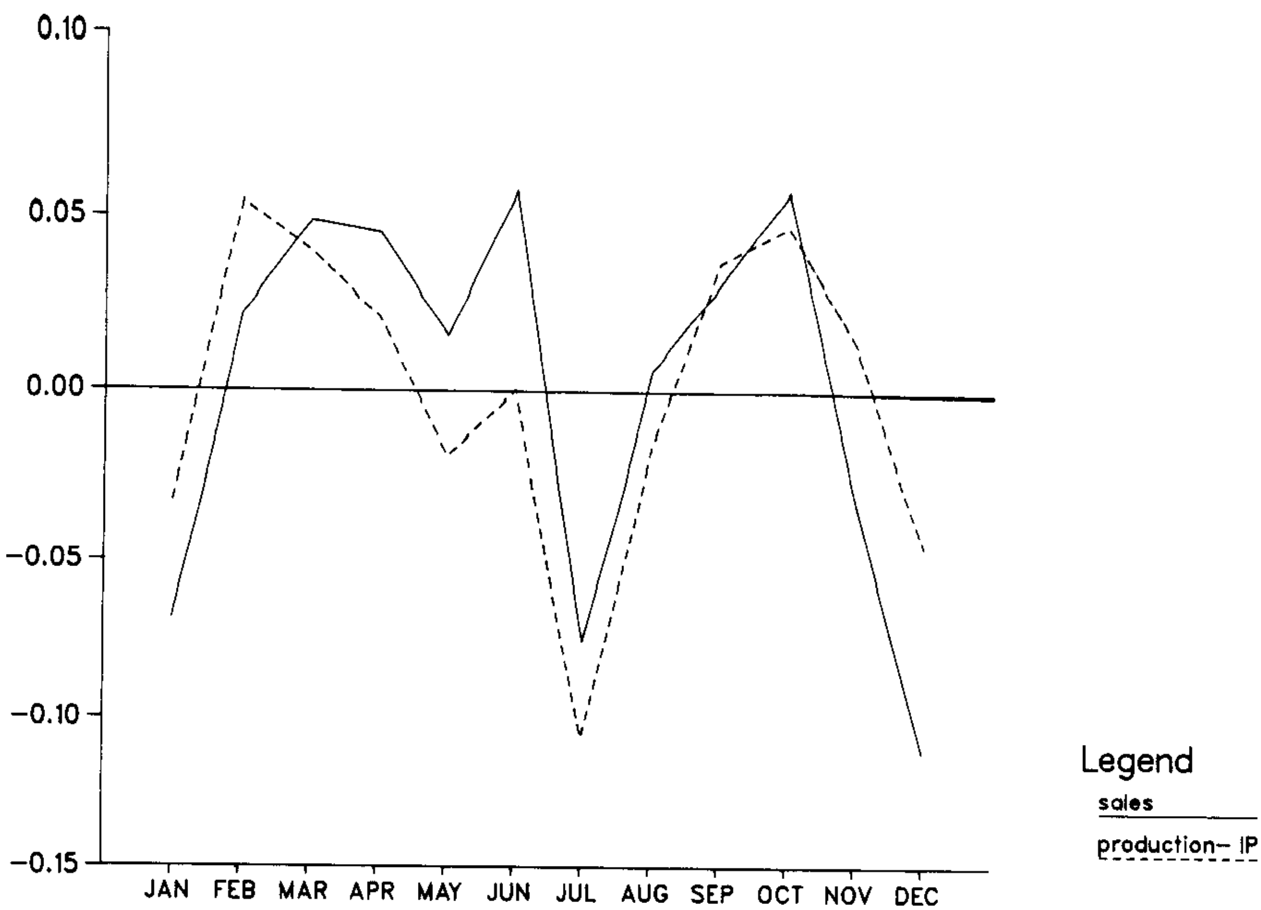
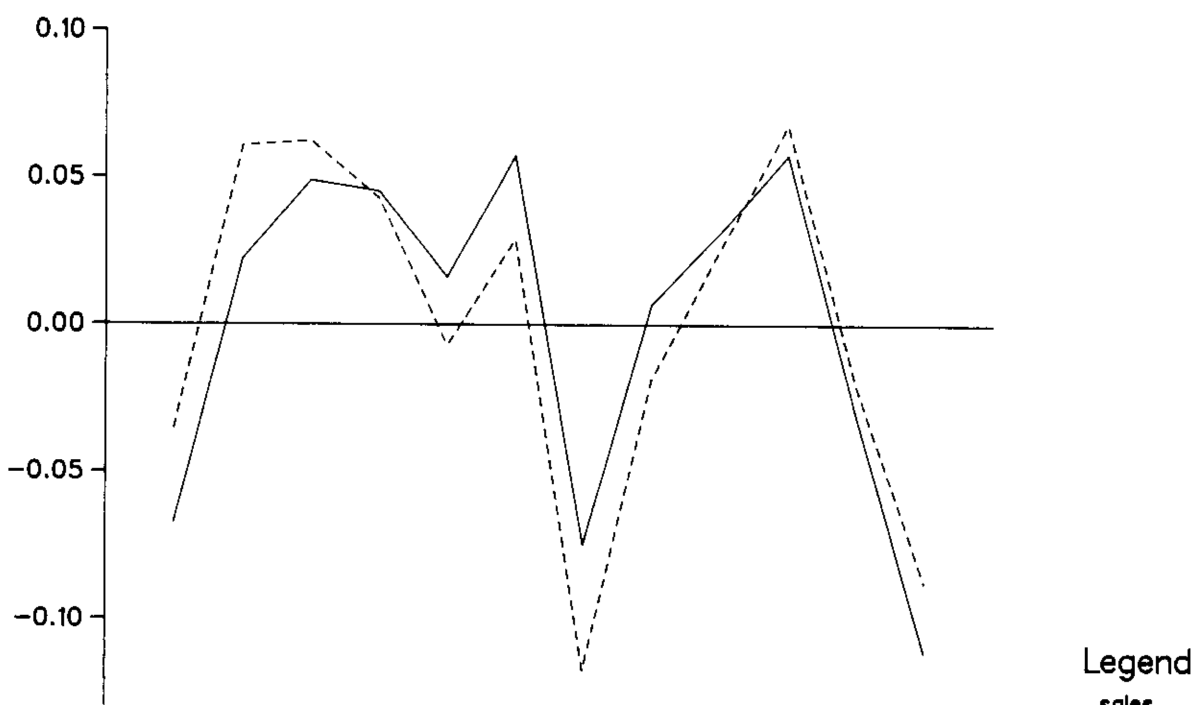

PETROLEUM
0.05
0.00
Legend

FIGURE 6

RUBBER



RUBBER



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