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Jeffrey A. Miron
Stephen P. Zeldes

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DEPARTMENT OF ECONOMICS
University of Michigan
Ann Arbor, Michigan 48109

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by

Jeffrey A. Miron* and Stephen P. Zeldes**

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*Economics Department
University of Michigan

**Finance Department
The Wharton School
University of Pennsylvania

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Abstract

In this paper we examine two different measures of monthly production that have been used by economists. The first measure, which we refer to as IP, is the index of industrial production constructed by the Board of Governors of the Federal Reserve. This measure is used extensively in empirical work on the business cycle, as well as by policymakers and others to assess the current state of the economy. The second measure, which we refer to as Y4, is constructed from the accounting identity that output equals sales plus the change in inventories. Sales and inventory data are reported by the Department of Commerce. This measure of output is frequently used to estimate models of inventory accumulation. Theoretically, these two series measure the same underlying economic variable--the production of goods by firms during the month.

We show here that the time series properties of these two series are radically different. We examine means, variances, and serial correlation coefficients of the log growth rates, and show that these statistics differ substantially between the two series. In addition, the cross-correlations between the two seasonally adjusted series range from .7 to .0 and are in most cases less than .4. We then demonstrate the significance of these differences in two ways. First, we estimate a model of white noise measurement error for the two series. The estimates indicate that in 15 out of 20 2-digit industries measurement error accounts for over 40% of the variation in the monthly growth rates of seasonally adjusted industrial production data. Second, we show that the variance bounds results of Blinder's (1986) study of inventory behavior are partially reversed when the IP rather than the Y4 output measure is used.

Jeffrey A. Miron
Department of Economics
University of Michigan
Ann Arbor, MI 48109
(313) 764-2363

Stephen P. Zeldes
Finance Department
The Wharton School
University of Pennsylvania
Philadelphia, PA 19104-6367
(215) 898-3477

I. Introduction

In this paper we examine two different measures of monthly production that have been used by economists. The first measure, which we refer to as IP, is the index of industrial production constructed by the Board of Governors of the Federal Reserve. This measure is used extensively in empirical work on the business cycle, as well as by policymakers and others to assess the current state of the economy. The second measure, which we refer to as Y4, is constructed from the accounting identity that output equals sales plus the change in inventories. Sales and inventory data are reported by the Department of Commerce. This measure of output is frequently used to estimate models of inventory accumulation. Theoretically, these two series measure the same underlying economic variable--the production of goods by firms during the month.

We show here that the time series properties of these two series are radically different. We examine means, variances, and serial correlation coefficients of the log growth rates, and show that these statistics differ substantially between the two series. In addition, the cross-correlations between the two seasonally adjusted series range from .7 to .0 and are in most cases less than .4.[1] We then demonstrate the significance of these differences in two ways. First, we estimate a model of white noise measurement error for the two series. The estimates indicate that in 15 out of 20 2-digit industries measurement error accounts for over 40% of the variation in the monthly growth rates of seasonally adjusted industrial production data. Second, we show that the variance bounds results of

[1]The correlations between the growth rates of the raw seasonally unadjusted series are always higher, ranging from .4 to .9.

Blinder's (1986) study of inventory behavior are partially reversed when the IP rather than the Y4 output measure is used.

These results are important for all those who use the IP or Y4 data. This includes particularly researchers on inventories, since some studies use the IP measure while others use the Y4 measure, without generally offering an explanation as to why one measure is chosen over the other.[2] More generally, many studies of the business cycle employ IP as a measure of economic activity. Our results supplement the work of Lichtenberg and Griliches (1986) who show that substantial measurement error exists in industry level price indexes.

The remainder of the paper is organized as follows. Section II describes how the two data series are constructed. Section III presents summary statistics that demonstrate the differences between the two series, and then examines the economic significance of the discrepancies. In section IV, we briefly discuss our attempts to reconcile these discrepancies and identify the types and sources of measurement error in each of the series. Section V concludes the paper.

II. Data Construction

In this section we describe how the data released by the relevant government agencies are constructed, and how we use these data to construct Y4.

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[2]Blinder (1986) and West (1986) use the Y4 measure, while Maccini and Rossana (1984) and Reagan and Sheehan (1985) use the IP measure. Miron and Zeldes (1986) report two sets of results: one using IP and the other using Y4. West points out in his footnote 13 that he estimated his equations for a few of the industries using the IP measure as well. He found that the parameters were uniformly non-sensical and therefore did not report them.

A. Construction of IP

The Federal Reserve Board's (FRB) index of industrial production is available monthly, both seasonally adjusted (SA) and seasonally unadjusted (NSA), at the 2-digit level, from 1959 to the present. The series is published in the Survey of Current Business and the Federal Reserve Bulletin. The IP index is constructed from three types of data: physical product measures, kilowatt-hours of electrical power input, and man-hours of labor input. Each of these is collected at either the establishment (plant) level or at the more specific product level. For the physical product measures, the FRB uses information from the Department of Energy, the Bureau of the Census and other public and private sources. Most of this is data on units of output goods, although occasionally (e.g., steel) it is constructed as the sum of sales and inventory changes. For the kilowatt-hour data, the FRB surveys utility companies and asks them to report their sales of kilowatt hours of electric power to firms in manufacturing.[3] For the man-hours series, the Bureau of Labor Statistics provides data from its payroll reports.[4] The FRB constructs production factor coefficients (PFC) to convert input data to estimates of monthly output. These PFCs are adjusted to incorporate trends and cyclical movements in productivity.[5] Approximately 67% of the overall IP index of manufacturing is based on input data. Finally, the indexes are

[3]The FRB also asks "self-generators" of electricity in the manufacturing industry to report power used in manufacturing.

[4]Only one week of data (the week containing the 12th day of the month) is used to estimate the monthly labor input. (Federal Reserve Board (1986).)

[5]The PFCs are extrapolated from an annual time series of the ratio of (Census data) output to input. These are then adjusted "based on the historical behavior of the series in earlier cycles and on an assessment of the position of the series in the current cycle." (Federal Reserve Board, 1986, p. 49.)

aggregated to industry level (and higher level) indexes using value-added weights.

B. Construction of Y4

The Y4 measure of production is defined as:

$$y_t^{Y4} = x_t + n_t - n_{t-1}$$

where y_t^{Y4} is real production during period t, x_t is the real value of shipments during period t, and n_t is the real value of the stock of finished goods inventories at the end of period t.[6] Constant dollar shipments and inventories are provided by the Bureau of Economic Analysis of the Department of Commerce (BEA) and are available monthly from 1959 to the present at the 2-digit level. We adjust the inventory series from cost to market using the correction described in West (1983).[7]

To arrive at the constant dollar inventory series, the BEA begins with data on the book value of inventories collected by the Bureau of the Census at the Commerce Department and adjusts these for differences between book and current dollar values and also for differences between current and constant dollar values. This procedure incorporates information about whether firms

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[6]We also consider an alternative version of Y4 in which n_t is equal to the quantity of finished goods inventories plus the quantity of work in progress inventories. Although the use of finished goods inventories is more standard, Blinder (1986) argues that the alternative definition is a more desirable measure of production, stating that "this is the definition of output used by the BEA in constructing the price indexes used to deflate inventory stocks, and hence is the only definition of output consistent with the data." Since the results were extremely similar using the two different definitions, we confine the discussion here to the more conventional definition. We present the results for the alternative definition in the Appendix and discuss them briefly in Section IV.A.

[7]For the alternative definition of Y4, we also use the correction of WIP inventories given in Blinder and Holtz-Eakin (1983). Both of these corrections simply involve multiplying an inventory series by an industry-specific constant.

use LIFO or non-LIFO accounting methods and involves estimating the accounting age structure of the existing stock of goods. The conversion procedures are described in detail in Hinrichs and Eckman (1981) and in Foss, et al. (1980).[8]

The book value is collected by the Census through three surveys: the monthly M3 (Manufacturers' Shipments, Inventories, and Orders), the Annual Survey of Manufactures, and the quinquennial Census data. The M3 is a voluntary survey of large companies. There are a total of only 4500 reporting units, made up of 3400 companies and 1100 divisions of 450 companies. Reporting units often produce more than one type of good, and sometimes these goods fall into different industry classifications. In this case, all of the inventories and shipments of the reporting unit are lumped into the primary industry classification. Units report total book value inventories, and then a breakdown into three stages of fabrication: materials and supplies, goods

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[8]The book value data measure the value of the goods currently in inventory, at acquisition cost. For example, when prices are rising over time, an item in inventory that is three years "old" in accounting terms will have a lower book value than an identical item that is one year "old," because it is on the books as having been acquired in different years at different costs. The accounting age of goods in inventory very much depends on the method of inventory accounting used.

When a firm uses LIFO accounting, positive changes in book value inventory levels accurately measure current dollar increases. These changes are deflated into constant dollars, and then cumulated to get a constant dollar stock. Negative changes in book value numbers imply that goods from previous LIFO layers were sold, and an estimate must be made of the acquisition date and cost.

When a firm uses non-LIFO accounting, the procedure is more complicated. Even if the number of goods in inventory does not change in a month, the book value of inventories may still change, because "old" lower cost inventories were replaced on the books with "new" higher cost inventories (again assuming prices are rising). The BEA must estimate the entire age structure of inventories (based on turnover ratios), and then the book value of the goods of each age must be divided by an estimate of the acquisition cost of the goods of that age.

in process, and finished goods.[9] On each monthly survey, units are given the opportunity to revise the previous two months' information.

The BEA reports only SA data, and therefore the above procedure gives seasonally adjusted Y4. We create NSA shipments and inventories data using the procedures in Reagan and Sheehan (1985), West (1986), and Miron and Zeldes (1986). The technique is to multiply the real seasonally adjusted series produced by the BEA by a seasonal factor, equal to the ratio of the seasonally unadjusted to the seasonally adjusted nominal book value data. This procedure is appropriate as long as there is relatively little seasonality in prices or in the factors used to convert from book to nominal.[10] We have tested the hypothesis of no seasonality in the producer prices of finished goods and found that the seasonal coefficients were small in size and statistically insignificant.

III. The Properties of the Two Measures of Production

The description of the construction of the two series makes it clear that they are not necessarily identical. In this section we show that in fact the differences are significant. We first present summary statistics for the two series; these quantify the extent to which the series diverge. We then look at two indicators of the economic significance of the differences between the series.

The analysis is carried out for all twenty 2-digit manufacturing industries, as well as for three aggregates of these industries (durables,

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[9]The reliability of the stage of fabrication data is lower than for the totals: some firms group work in process inventories in with either materials or finished goods, and others double count because one stage in a reporting unit may overlap another stage in another reporting unit for the same firm.

[10]The book/nominal distinction is only relevant for inventories (not for shipments).

non-durables, and total). We consider first the seasonally adjusted data, since these are the ones most familiar to a majority of readers. We also present results for seasonally unadjusted data, however, and we examine the seasonal movements themselves. With the exception of the variance bounds tests, the results presented below all focus on the logarithmic growth rates of the relevant series. We employ growth rates because the resulting series are stationary whether the secular growth is generated by a unit root or by a deterministic time trend. In the Appendix, we present results of Dickey Fuller tests of the hypothesis of no unit root in the autoregressive representation of these series. In most cases we do not reject the null hypothesis of a unit root at the 95% level of significance.

A. Descriptive Statistics

Table 1a presents the means, standard deviations, and first order autocorrelation coefficients of the log growth rates of the seasonally adjusted IP and Y4 series. The sample period is 1967 through 1984.[11]

The results in the table indicate that the time series properties of IP and Y4 are substantially different. Consider first the cross correlations between the growth rates of the two different measures of production. These correlations range from a low of .005 for Printing to a high of .66 for Transportation Equipment. Eighteen of the twenty-three correlations reported

[11]We use only post-1967 data because there were changes in the definitions of the SIC codes in 1967 that make the pre-1967 data not completely compatible with post-1967 data.

are less than .4.[12] The correlations are higher for the aggregates, which is consistent with a positive correlation of the true series across industries.[13] Examination of the first order autocorrelations reveals the surprising result that in thirteen out of twenty-three cases, the autocorrelation is positive for IP but negative for Y4. For example, for non-durables as a whole, the first order serial correlation of growth rates equals .29 for IP and -.25 for Y4. The difference in the autocorrelation coefficients is statistically significant in 17 of 23 cases. (See Tables 2a and 2b.) Turning to the standard deviations, the results indicate that in all but three cases the standard deviation is significantly higher for the Y4 measure than for the IP measure, and in about half of the industries the point estimates indicate it is more than twice as large.[14] Finally, in several cases the mean growth rate is twice as high for one measure as for the other, and for two industries the growth rate is positive for one series but negative for the other. The differences in means, however, are in most cases not statistically significant.

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[12]Harrison and Stewart (1986) report similar results for the two corresponding Canadian data series. They calculate the correlation between the detrended seasonally adjusted levels (rather than growth rates) and report correlation coefficients as low as .56, with the majority of industries between .7 and .8.

Sims (1974), using U.S. data, reports a result that may be related to the one reported here. He finds that labor input is estimated as a one sided distributed lag of IP but a two sided distributed lag of the BEA's measure of shipments. Sims interprets this as evidence that shipments, as a proxy for output, may be measured with greater error than IP. Given that shipments necessarily differ from output by the change in inventories, it is not clear why Sims would expect it to be as good a measure of output as IP or Y4.

[13]Table A4 in the Appendix presents results analogous to those in Table 1a for quarterly averages of monthly data. The cross correlations of the quarterly growth rates are higher than those of the monthly data, but still less than .7 in 18 out of 23 cases.

[14]The statistical tests of the hypothesis that the ratio of the standard deviations equals one is presented in Tables 3a, 3b, 3c.

In Table 1b we present summary statistics for the seasonally unadjusted data. The correlations between the two series are in every case higher than with adjusted data, reflecting the comovements due to seasonality, but the correlations are nevertheless well below one in most cases. For eight of the twenty-three series, the sign of the first order autocorrelation coefficient is positive for one series and negative for the other series. The difference in the autocorrelation coefficient is statistically significant in 12 of 23 cases. The standard deviations of the two series are in all but two cases statistically different.

Figures 1-23 plot the seasonal movements in the log growth rates of the two measures of production.[15] In most of the industries, the two seasonal patterns are similar both with respect to the timing of the peaks and troughs and with respect to the amplitude of the various peaks and troughs. In several industries, however, the timing of the seasonal patterns is similar but the magnitude of certain peaks or troughs appears substantially different (e.g., Electrical Machinery and Fabricated Metals). Hypothesis tests indicate that the seasonal coefficients are statistically different in all 23 cases.

The evidence presented above demonstrates that there are dramatic differences between the time series properties of the IP and and Y4 measures of production. The standard deviations and autocorrelations of the two series differ systematically, and the cross correlations between the two series indicate that there is remarkably little variation that is common to both series.

The remainder of this paper is devoted to addressing two questions that are raised by these results. First, are the differences between the two

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[15]The overall mean growth rate has been subtracted from each seasonal dummy coefficient so that the plotted coefficients have mean zero.

series important for economic analyses that use measures of production? Second, can we identify the types and sources of measurement error in the two series?

B. Estimating the Importance of Measurement Error

The fact that IP and Y4 differ means that at least one of them is measured with error. One way to gauge the importance of the differences between the two measures is to ask how big this error is in comparison to the variation in the true, underlying series. Any such calculation requires identifying assumptions about the properties of the measurement errors. The measurement error model we consider is the simplest one possible and is thus a useful benchmark for judging the accuracy of the two series.

Assume that each series is equal to the true series plus measurement error:

$$y_t^{IP} = y_t^* + e_t^{IP}$$

$$y_t^{Y4} = y_t^* + e_t^{Y4}$$

where y_t^* is the log of the true series, y_t^{IP} and y_t^{Y4} are the logs of the two measured series, and e_t^{IP} and e_t^{Y4} are mutually uncorrelated measurement errors that are assumed to be uncorrelated with y^*.[16] The log growth rates of the two measured series are:

$$\Delta y_t^{IP} = \Delta y_t^* + \Delta e_t^{IP} ,$$
$$\Delta y_t^{Y4} = \Delta y_t^* + \Delta e_t^{Y4} .$$

If the serial correlation in the measurement error is less than that of true output, there will be a tendency for the first order autocorrelation of

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[16] In Section IV.B, we consider an alternative model in which measurement error is correlated with the true series.

growth rates to be biased toward a negative number. The bias will be stronger the greater the variance of the measurement error. Thus, the series that has a higher standard deviation will also tend to have more negative autocorrelations. We find that in almost all industries, the standard deviations are higher and the first order autocorrelations lower for Y4 than for IP.[17]

Since the change in the measurement error is, by assumption, uncorrelated with the change in the true series, we can ask what fraction κ of the variation in each measured series is due to measurement error. We estimate this fraction simply by regressing the change in Y4 on the change in IP. If there were no measurement error in IP, the estimated coefficient on IP would be 1. If there is measurement error, the coefficient will be biased downward, and the bias will be greater the greater is the variance of the measurement error in IP relative to the variance in the true series. One minus the estimated coefficient in this regression is a consistent estimate of κ^{IP}.[18] We can obtain estimates of the analogous quantity for Y4 by regressing the change in IP on the change in Y4. Both estimates are consistent because the

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[17]We also estimate the Spearman rank correlation between the difference in autocorrelations and the ratio of standard errors of IP and Y4 across industries. This correlation should be negative under the model above: industries where measurement error in IP is high relative to that in Y4 should have relatively low autocorrelation coefficients. The rank correlations are negative for both the NSA and SA data (-.13, -.14), but not significantly different from zero in either case.

[18]Call $\hat{\beta}_{Y4,IP}$ the estimated coefficient when Δy^{Y4} is regressed on Δy^{IP}. Then $\text{plim}(1 - \hat{\beta}_{Y4,IP}) = 1 - \text{cov}(\Delta y^{IP}, \Delta y^{Y4})/\text{var}(\Delta y^{IP})$
$= 1 - \text{var}(\Delta y^*)/[\text{var}(\Delta y^*) + \text{var}(\Delta y^{IP})] = \text{var}(\Delta e^{IP})/[\text{var}(y^*) + \text{var}(\Delta e^{IP})]$
$= \text{var}(\Delta e^{IP})/\text{var}(\Delta y^{IP}) = \kappa^{IP}$.

sample covariance of Δy^{IP} and Δy^{Y4} is a consistent estimate of $V(\Delta y^{*})$.[19] Using this simple regression technique has the advantage of enabling us to calculate in a straightforward way the standard errors of these variance ratios. We employ the Hansen and Hodrick (1980) procedure, as modified by Newey and West (1987), to calculate standard errors that are consistent given the serial correlation in the residuals.

The results are presented in Tables 3a, 3b, and 3c. Looking at the seasonally adjusted data, these estimates indicate that in all but one industry at least 60% of the variation in the growth rate of Y4 is due to measurement error, and in 14 out of 20 industries it is over 80%. Looking at IP, we find that in 15 out of 20 industries measurement error accounts for over 40% of the variation in the monthly growth rate. The estimated standard errors of the κs indicate that in most cases these ratios are estimated precisely. When we turn to the seasonally unadjusted data in Table 3b, we find a different set of results. Relative to the seasonally adjusted data, the measurement error shares are estimated to be smaller for the Y4 and IP, and often negative for IP. The κs would be expected to be smaller if seasonality in the measurement error is small relative to the seasonality in the true series. However, the negative estimates suggest a misspecification; this may be due to seasonality in the measurement error that is correlated with the true series. Table 3c shows the results for the seasonal dummy adjusted data. These are similar to the results in Table 3a.

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[19]Prescott (1986) makes this observation and estimates the variance of true hours of employment based on household and firm measures of hours. Lichtenberg and Griliches (1986) estimate the same variance ratios as we do for two measures of output <u>prices</u>. They examine long run inflation rates, and base their measurement error estimates on sample moments computed across industries for a single time period, rather than across time for a single industry as is done here.

When two measures with independent errors exist, the optimal indicator of the true series is a linear combination of these two measures. In Tables 3a, 3b, and 3c, we report estimates of the optimal weight for the IP series (λ^{IP}). This weight is the ratio of the variance of the measurement error in Y4 to the sum of the two measurement error variances. (See de Leeuw and McKelvey (1983).) We can again use a simple regression technique to calculate an estimate of λ^{IP} and its standard error. The coefficient in the regression of Δy^{Y4} on $\Delta y^{Y4} - \Delta y^{IP}$ is a consistent estimate of λ^{IP}. The seasonally adjusted results indicate that λ^{IP} is almost always significantly greater than .5, suggesting that IP might be a better measure of production.[20]

The estimates presented in these tables, based on a simple model of measurement error, indicate that both series are measured with substantial error. This is important information not just for researchers doing work on inventory accumulation, but for anyone using two-digit level industrial production data.

C. The Variance of Production and the Variance of Sales

We conclude this section by showing that the results of one widely cited study of firms' inventory behavior are sensitive to the choice of output measure. Blinder (1986) emphasizes that, in the absence of cost shocks, the production smoothing model implies that the variance of production should be

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[20]The seasonally unadjusted results indicate that the optimal weight on IP is greater than one, again suggesting the possibility of misspecification. The seasonal dummy adjusted results are similar to the X-11 adjusted results.

less than the variance of sales (shipments).[21] Using the Y4 measure of output, Blinder shows that the variance of production is greater than the variance of shipments for all but one of the industries examined, and he interprets this as strong evidence against the production smoothing model.

In Table 4, we present the ratio of the variance of output to the variance of shipments based on each of the two output measures. The sample period, inventory definition, and detrending techniques were all chosen to correspond as closely as possible to Blinder (1986). Thus, unlike the data in the previous tables, these data are levels (not growth rates), detrended with an exponential trend, and cover the period 1959:2 to 1981:7[22] We convert the IP measure from an index into a constant dollar figure by multiplying it by the ratio of average Y4 to average IP (in other words, we set the average of the two series equal to each other).[23]

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[21]If cost shocks are present, then this inequality need not hold (Eichenbaum (1984), Blinder (1986)). Kahn (1986) argues that if production for the period must be chosen before sales are known and if stockouts are possible then this inequality can be violated even in the absence of cost shocks.

[22]Blinder's estimation procedure is the following. For both shipments and Y4, the log level is regressed on a constant, time, a dummy variable that is one beginning in October 1973, and a dummy that is one beginning in 1967. The coefficients are estimated by GLS, assuming a second order autoregressive process for the error term. The antilogs of the fitted values of this regression are then subtracted from the actual data, in levels, to define the detrended data. Blinder (1986) states that he includes a dummy that is one starting in 1966 in order to account for a data revision that goes back only to 1966. Our information from both BEA and Census is that the data revision begins in January 1967, so the dummy that we include begins then. (We have also carried out the calculations using a dummy that starts in January 1966, with negligible effects on the results.) Note that since the level of inventories, the level of shipments, and the Y4 level of production are all detrended separately, the identity relating them does not hold exactly in the detrended data, although Blinder states that it holds approximately.

[23]Because the ratio of average Y4 to average IP is different for different averaging periods, the choice of base period for conversion of IP sometimes affects the resulting variance bounds ratio for a few industries. Results for different base periods consistently show, however, that the (continued)

The results for the Y4 measure match Blinder's results almost exactly.[24] For all but one industry, the variance of output is greater than the variance of shipments. The results for the IP measure, however, are quite different. The variance ratio is often less than the one based on Y4, and for ten industries the variance inequality is actually reversed.[25] These reversals occur in five of the six industries identified by Belsley (1969) as being production to stock, which are the industries for which the production smoothing model is the most plausible theoretically. Had Blinder originally chosen to use the IP measure of output instead of the Y4 measure, he would have reached substantially different conclusions about the empirical validity of the production smoothing model.[26]

IV. Attempts at Reconciliation

In this section we briefly discuss which of the differences in the construction of the two output series, if any, might be responsible for the results reported above. We attempt to distinguish between two types of measurement error: one that increases and one that decreases the variance of the measured series. Unfortunately, we are not able to reconcile the differences nor are we able to conclude that one series is necessarily a better measure than the other. We have discussed the differences with

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variance ratio using IP data is less than one in a significant number of cases.

[24]The minor differences between the Y4 results in our Table 4 and Blinder's Table I are probably due to data revisions that were released subsequent to Blinder's work but incorporated in our data.

[25]This reversal of the variance bounds inequality was first pointed out by West (1986, footnote 13).

[26]While this may be interpreted as mild support for the production smoothing model, Miron and Zeldes (1986) present additional tests and find that a generalized production smoothing model is rejected for both the Y4 data <u>and</u> the IP data (although the rejections are not as strong based on IP data).

researchers at the BEA and the FRB, and, while both are aware of the problem and of numerous differences in the construction of the data, neither is able to offer a definitive explanation.[27]

A. Production of Intermediate Goods.

One possible source of discrepancy between the two series is that they may be based on different concepts of output. There is no obvious single choice for the appropriate measure of output in the presence of intermediate goods. The measure of Y4 that we have used so far is based on the change in finished goods inventories only. This excludes production that adds to the stock of inventories of work in progress. Blinder has suggested that this might be the source of the discrepancy between Y4 and IP, and suggests instead using an alternative definition of Y4 equal to shipments plus the change in the sum of work in progress and finished goods inventories (see West (1986) footnote 13, and Blinder (1986)).[28]

As a check against Blinder's suggestion, we have calculated the statistics in Tables 1a and 1b using his alternative definition of Y4. The results, presented in the Appendix, are very similar to those in Tables 1a and 1b. This does not appear to be the explanation for the discrepancies.

B. Different Types of Measurement Error

In Section III, we assumed a model of measurement error in which the error was uncorrelated with the true level of output. If this model is valid,

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[27]We had conversations with Frank de Leeuw (BEA) and Richard Raddock (FRB).

[28]Blinder's definition of Y4 has a different problem: it excludes production that turns work in progress inventories into finished goods. It may be that there is yet a third way of constructing Y4 that more closely corresponds to IP, but we have not been able to determine an appropriate way of constructing such a measure.

it suggests that the variance of the measurement error in Y4 is greater than that of IP.

An important part of the measurement error in IP may be due to the fact that a large number of the individual IP series are constructed based on input data. Table 5 gives the fraction of output in each industry that is based on actual physical product data, electricity use, and labor use, respectively. While the use of input data is likely to increase the amount of measurement error in the IP series, this measurement error may not be uncorrelated with the true series. Consider the case in which measured productivity is positively correlated with true output. This could arise because of labor hoarding by firms or because of true productivity shocks.[29] As a simple (although extreme) example of this, we examine the following model for the log of output:

$$y^{IP} + u^{IP} = y^* + e^{IP}$$

$$y^{Y4} = y^* + e^{Y4}$$

where y^{IP} is the log of the measure of production based on labor input, and u^{IP} measures productivity and is assumed to be positively correlated with y^* and uncorrelated with y^{IP}.[30]

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[29]As indicated previously, the FRB attempts to correct for this by using cyclically adjusted PFCs. Here we allow for the possibility that this adjustment does not fully capture productivity changes.

[30]The model in low growth rates obviously becomes:

$$\Delta y^{IP} + \Delta u^{IP} = \Delta y^* + \Delta e^{IP}$$

$$\Delta y^{Y4} = \Delta y^* + \Delta e^{Y4}$$

We can use this model to contrast the properties of the two types of measurement error: e^{IP} and u^{IP}. All else equal, higher variances of e^{IP} or u^{IP} will lead to a lower correlation of the (growth rates of the) measured series and the true series. However, while a higher variance of e^{IP} will cause a higher variance in the measured series, a higher variance of u^{IP} will cause a lower variance in the measured series.[31] Thus, in contrast to the previous model, if measurement error that artificially smooths the data is an important part of IP, IP could have a lower variance than Y4 and yet be a worse measure of output (i.e., have a lower correlation with the true output series).

We observe that the variance of the growth rate of IP is less than that of Y4. We would like to know whether this is due to a relatively low variance of e^{IP} or a high variance of u^{IP}. The former would imply that IP is a better series, in that it has a high correlation with the true series, while the latter would imply that IP has a lower correlation with the true series.

Unfortunately, with only two indicators, we cannot separately identify the magnitude of three sources of measurement error, and therefore cannot directly distinguish between these two hypotheses. We can, however, use the information in Table 5 to shed some light on this issue. First, if an important source of both e^{IP} and u^{IP} is the use of input data, then those industries that are based most on physical product data (and thus least on input data) should exhibit the highest IP:Y4 correlations. Second, if the error induced by the use of input data is primarily of the smoothing variety (u^{IP}), then those industries that are based most on input data should exhibit the most smoothing behavior, and thus should have the lower standard deviation

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[31]We see this by observing that $V(\Delta y^{IP}) = V(\Delta y^{*}) - V(\Delta u^{IP}) + V(\Delta e^{IP})$.

(relative to that of Y4). However, if the use of input data simply causes more white noise measurement error (e^{IP}), the high input data industries should have relatively high standard deviations.

To test these hypotheses, we examine Spearman rank correlation coefficients. The results are mixed. First, there is a positive correlation between the use of physical product data and the IP:Y4 correlations, but this correlation is only .15 for NSA data and .16 for the SA data, neither of which is statistically significant. This suggests that the use of input data is not an important source of the discrepancy between IP and Y4.

Second, however, we do find a strong negative correlation across industries between the use of input data and the ratio of the standard deviation of IP to that of Y4. The Spearman correlations are -.78 and -.65 for NSA and SA data respectively, each significant at the 1% level. The correlations between the use of labor input data and the ratio of standard deviations are -.33 and -.55 for NSA and SA data, with only the second of these statistically significant. This provides some evidence in favor of the argument that the use of inputs for IP serves to artificially smooth the data, and therefore that the relatively low standard deviation of IP should not necessarily be taken to mean that it is a better measure of the true output measure.

V. Concluding Remarks

In this paper, we have documented the radically different time series properties of two different measures of manufacturing output. Standard deviations and serial correlations for the log growth rates of the two series are very different. Correlation coefficients between the two measures are surprisingly low, considering the two series are supposed to be measuring the same economic variable. A large fraction of the variation in the observed growth rate of both measures of output is due to measurement error. Finally, while the variance of the Y4 measure of production is almost always greater than the variance of sales (Blinder 1986), the inequality is reversed in half of the industries when the IP data is used.

Unfortunately, we have not discovered the exact source of these discrepancies, and cannot therefore recommend one measure over the other for the use in studies of production and/or inventory accumulation. Our recommendation is therefore that tests be run either separately with each measure of output separately, or with an optimal linear combination of the two series.

Table 1a: Summary Statistics, Seasonally Adjusted Data							
	Mean		*Standard Deviation*		*Autocorrelation*		*Correlation*
	IP	Y4	IP	Y4	IP	Y4	
Food	.00250	.00142	.00945	.02107	-.270	-.339	.157
Tobacco	.00042	-.00043	.04582	.08062	-.528	-.502	.212
Textiles	.00135	.00167	.02134	.03227	.289	-.385	.267
Apparel	.00102	.00096	.02405	.04814	-.257	-.271	.049
Lumber	.00149	.00250	.02639	.04453	.040	-.280	.328
Furniture	.00297	.00320	.02043	.04533	.052	-.436	.176
Paper	.00275	.00228	.01865	.02193	-.015	-.304	.371
Printing	.00301	.00190	.01228	.02881	-.141	-.516	.005
Chemicals	.00413	.00303	.01483	.02309	.101	-.212	.192
Petroleum	.00086	.00175	.02061	.02298	-.123	-.376	.072
Rubber	.00539	.00233	.03060	.03841	.101	-.236	.365
Leather	-.00279	-.00301	.02925	.06901	-.211	-.458	.038
Stone,Clay,Glass	.00217	.00098	.01981	.03116	-.007	-.246	.388
Primary Metal	-.00066	.00049	.04136	.04393	.186	.034	.547
Fab Metal	.00126	.00121	.01423	.03419	.408	-.264	.341
Machinery	.00350	.00295	.01476	.02915	.302	-.270	.358
Elec Machinery	.00493	.00456	.01642	.02614	.160	-.172	.374
Trans Equip	.00161	.00167	.03135	.05277	.289	-.041	.655
Instruments	.00477	.00410	.01071	.03855	.095	-.422	.226
Other	.00135	.00132	.02046	.04874	-.228	-.398	.072
Non-Durables	.00279	.00177	.00936	.01393	.287	-.253	.437
Durables	.00238	.00219	.01363	.02232	.471	-.021	.627
Total	.00256	.00201	.01075	.01604	.437	-.062	.611

Notes:

1. The sample period is 1967:5-1984:12.
2. The statistics in the table are computed for logarithmic growth rates.
3. The Y4 results are based on the finished goods only definition of output.

Table 1b: Summary Statistics, Seasonally Unadjusted Data							
	Mean		*Standard Deviation*		*Autocorrelation*		*Correlation*
	IP	Y4	IP	Y4	IP	Y4	
Food	.00247	.00126	.03117	.04725	-.167	-.122	.721
Tobacco	-.00085	-.00045	.14393	.12677	-.442	-.508	.508
Textiles	.00084	.00130	.08205	.11191	-.322	-.401	.864
Apparel	.00088	-.00027	.07420	.12160	-.318	-.236	.676
Lumber	.00090	.00177	.05388	.08120	-.008	-.172	.730
Furniture	.00297	.00290	.05893	.11185	-.384	-.383	.783
Paper	.00216	.00173	.06250	.05726	-.302	-.367	.884
Printing	.00295	.00181	.03831	.05214	.437	-.169	.461
Chemicals	.00253	.00400	.05582	.02662	.057	-.124	.521
Petroleum	.00112	.00166	.03217	.03603	.133	-.281	.415
Rubber	.00505	.00154	.06301	.08083	-.095	-.188	.814
Leather	-.00309	-.00328	.08208	.10843	-.387	-.388	.645
Stone,Clay,Glass	.00191	.00034	.04311	.06599	.107	-.006	.807
Primary Metal	-.00136	-.00132	.06441	.07500	.146	.009	.826
Fab Metal	.00124	.00072	.02638	.08063	-.069	-.328	.727
Machinery	.00330	.00304	.02931	.10091	.003	-.362	.634
Elec Machinery	.00492	.00445	.03209	.08541	.030	-.298	.703
Trans Equip	.00137	.00105	.07018	.12178	.030	-.035	.881
Instruments	.00488	.00417	.02009	.08221	-.084	-.352	.569
Other	.00117	.00082	.04864	.10551	-.072	-.177	.675
Non-Durables	.00260	.00145	.03532	.04640	-.082	-.217	.905
Durables	.00218	.00180	.03226	.08056	.006	-.183	.895
Total	.00236	.00165	.03179	.06204	-.052	-.205	.911

Notes:

1. The sample period is 1967:5-1984:12.
2. The statistics in the table are computed for logarithmic growth rates.
3. The Y4 results are based on the finished goods only definition of output.

Table 2a: Hypothesis Tests, Seasonally Adjusted Data						
	$\hat{\mu}^{IP} - \hat{\mu}^{Y4}$	se	t	$\hat{\rho}_{IP} - \hat{\rho}_{Y4}$	se	t
Food	.0011	.0006	-1.77	.074	.094	.79
Tobacco	.0008	.0017	-.48	-.012	.064	-.19
Textiles	-.0003	.0014	.23	.700	.142	4.93
Apparel	.0001	.0016	-.04	.045	.109	.41
Lumber	-.0010	.0014	.72	.321	.143	2.24
Furniture	-.0002	.0010	.24	.489	.098	4.97
Paper	.0005	.0007	-.64	.292	.190	1.54
Printing	.0011	.0008	-1.39	.383	.106	3.62
Chemicals	.0011	.0007	-1.57	.305	.147	2.08
Petroleum	-.0009	.0013	.69	.255	.105	2.43
Rubber	.0031	.0013	-2.35	.321	.103	3.10
Leather	.0002	.0017	-.13	.251	.104	2.41
Stone,Clay,Glass	.0012	.0007	-1.78	.241	.107	2.26
Primary Metal	-.0002	.0012	.15	.154	.117	1.32
Fab Metal	.0001	.0011	-.05	.675	.132	5.12
Machinery	.0005	.0007	-.76	.576	.120	4.80
Elec Machinery	.0004	.0008	-.46	.337	.097	3.46
Trans Equip	-.0001	.0012	.06	.331	.094	3.51
Instruments	.0007	.0009	-.75	.501	.108	4.64
Other	.0000	.0013	-.03	.170	.117	1.45
Non-Durables	.0010	.0004	-2.47	.553	.170	3.26
Durables	.0002	.0004	-.44	.492	.109	4.52
Total	.0006	.0003	-1.67	.500	.125	4.00

Notes:

1. The sample period is 1967:5-1984:12.
2. The statistics in the table are computed for logarithmic growth rates.
3. The Y4 results are based on the finished goods only definition of output.
4. $\hat{\mu}^{IP} - \hat{\mu}^{Y4}$ is the difference in the mean growth rate of IP and Y4; $\hat{\rho}_{IP} - \hat{\rho}_{Y4}$ is the difference in autocorrelations.

Table 2b: Hypothesis Tests, Seasonally Unadjusted Data							
	$\hat{\mu}^{IP} - \hat{\mu}^{Y4}$	se	t	$\hat{\rho}_{IP} - \hat{\rho}_{Y4}$	se	t	χ^2
Food	.0012	.0008	-1.536	.290	.061	4.72	114.2
Tobacco	-.0004	.0029	.135	.065	.053	1.23	202.7
Textile	-.0005	.0017	.276	.078	.050	1.54	133.7
Apparel	.0011	.0024	-.476	.073	.054	-1.35	142.2
Lumber	-.0009	.0015	.573	.165	.075	2.21	91.5
Furniture	.0001	.0015	-.047	-.002	.050	-.03	445.1
Paper	.0004	.0008	-.523	.067	.053	1.27	168.1
Printing	.0011	.0012	-.987	.609	.064	9.47	922.7
Chemicals	.0015	.0012	-1.255	.177	.084	2.11	842.0
Petroleum	-.0005	.0013	.404	.415	.109	3.81	40.0
Rubber	.0035	.0015	-2.400	.085	.066	1.28	127.1
Leather	.0002	.0018	-.105	.001	.058	.01	74.6
Stone,Clay,Glass	.0016	.0009	-1.790	.114	.058	1.96	273.0
Primary Metal	-.0000	.0012	.032	.139	.077	1.80	38.8
Fab Metal	.0005	.0015	-.360	.264	.066	3.99	190.1
Machinery	.0003	.0018	-.147	.365	.055	6.59	1175.8
Elec Machinery	.0005	.0014	-.339	.328	.067	4.92	874.4
Trans Equip	.0003	.0016	-.198	.065	.047	1.39	581.0
Instruments	.0007	.0015	-.481	.266	.071	3.76	517.8
Other	.0004	.0018	-.197	.106	.058	1.81	206.9
Non-Durables	.0011	.0005	-2.130	.136	.055	2.46	326.0
Durables	.0004	.0011	-.359	.189	.047	4.05	981.5
Total	.0007	.0007	-.985	.154	.053	2.90	798.7

Notes:

1. The sample period is 1967:5-1984:12.
2. The statistics in the table are computed for logarithmic growth rates.
3. The Y4 results are based on the finished goods only definition of output.
4. $\hat{\mu}^{IP} - \hat{\mu}^{Y4}$ is the difference in the mean growth rate of IP and Y4; $\hat{\rho}_{IP} - \hat{\rho}_{Y4}$ is the difference in autocorrelations; and χ^2 is the test statistic for the null of no seasonality in the difference in the growth rates. The 99% critical value of the $\chi^2(11)$ is 24.73.

Table 3a: Estimates of Measurement Error, Seasonally Adjusted Data							
	Weight for IP			*Measurement Error Share, IP*		*Measurement Error Share, Y4*	
	$\hat{\lambda}_{IP}$	se	t	$\hat{\kappa}_{IP}$	se	$\hat{\kappa}_{Y4}$	se
Food	.877	.031	12.21	.649	.150	.929	.030
Tobacco	.813	.066	4.77	.627	.156	.880	.052
Textiles	.759	.041	2.70	.597	.103	.824	.060
Apparel	.812	.050	6.29	.902	.200	.976	.048
Lumber	.837	.051	6.63	.447	.137	.806	.066
Furniture	.881	.034	11.09	.610	.139	.921	.030
Paper	.627	.079	1.61	.564	.101	.684	.125
Printing	.847	.022	15.52	.988	.179	.998	.033
Chemicals	.752	.040	6.27	.701	.089	.877	.044
Petroleum	.692	.063	3.03	.896	.090	.951	.043
Rubber	.674	.101	1.72	.542	.091	.709	.080
Leather	.858	.030	11.83	.910	.186	.984	.034
Stone,Clay,Glass	.827	.059	5.59	.390	.098	.753	.045
Primary Metal	.566	.130	.51	.419	.125	.485	.096
Fab Metal	.965	.036	12.85	.180	.154	.858	.030
Machinery	.916	.025	16.34	.292	.098	.819	.040
Elec Machinery	.827	.032	10.20	.405	.105	.765	.064
Trans Equip	1.060	.048	11.79	-.102	.087	.611	.078
Instruments	.985	.017	29.26	.186	.205	.937	.019
Other	.869	.039	9.50	.829	.175	.970	.029
Non-Durables	.818	.061	5.23	.350	.074	.707	.077
Durables	1.016	.046	11.27	-.026	.075	.617	.051
Total	.937	.068	6.38	.089	.089	.591	.058

Notes:

1. The sample period is 1967:5-1984:12.
2. The statistics in the table are computed for logarithmic growth rates.
3. The Y4 results are based on the finished goods only definition of output.
4. λ^{IP} is the weight on IP in an optimal forecast of the true series:

$$\lambda^{IP} = Var(\Delta e^{Y4})/(Var(\Delta e^{Y4}) + Var(\Delta e^{IP}))$$

The t-statistic reported under this set of columns is for the test of the hypothesis that λ is .5. This is equivalent to a test of the hypothesis that IP has the same variance as Y4.

5. κ^i, i=IP,Y4, is the fraction of the variation in series i due to measurement error:

$$\kappa^i = Var(\Delta e^i)/(Var(\Delta y^i)$$

Table 3b: Estimates of Measurement Error, Seasonally Unadjusted Data							
	Weight for IP			*Measurement Error Share, IP*		*Measurement Error Share, Y4*	
	$\hat{\lambda}_{IP}$	se	t	$\hat{\kappa}_{IP}$	se	$\hat{\kappa}_{Y4}$	se
Food	1.084	.066	8.84	-.094	.083	.524	.039
Tobacco	.373	.109	1.17	.552	.051	.423	.121
Textile	1.353	.088	9.69	-.178	.048	.367	.032
Apparel	1.073	.040	14.21	-.107	.070	.588	.059
Lumber	1.093	.056	10.63	-.100	.065	.516	.037
Furniture	1.297	.051	15.59	-.485	.113	.588	.022
Paper	.134	.141	2.60	.190	.027	.035	.039
Printing	.767	.048	5.58	.372	.067	.661	.030
Chemicals	1.029	.041	12.81	-.092	.134	.751	.020
Petroleum	.596	.054	1.77	.536	.053	.630	.060
Rubber	1.804	.139	4.17	-.045	.082	.365	.044
Leather	.858	.091	3.91	.148	.094	.512	.037
Stone,Clay,Glass	1.27	.063	12.33	-.235	.062	.473	.025
Primary Metal	.911	1.220	3.36	.038	.052	.291	.045
Fab Metal	1.207	.015	46.83	-1.22	.198	.762	.016
Machinery	1.139	.017	37.47	-1.18	.114	.816	.014
Elec Machinery	1.201	.040	17.32	-.871	.110	.736	.027
Trans Equip	1.556	.056	18.97	-.529	.073	.492	.032
Instruments	1.102	.012	48.83	-1.329	.214	.861	.011
Other	1.167	.031	21.47	-.464	.121	.689	.018
Non-Durables	1.541	.111	9.65	-.188	.052	.311	.034
Durables	1.447	.046	20.66	-1.24	.090	.641	.022
Total	1.619	.061	18.28	-.777	.071	.533	.024

Notes:

1. The sample period is 1967:5-1984:12.
2. The statistics in the table are computed for logarithmic growth rates.
3. The Y4 results are based on the finished goods only definition of output.
4. λ^{IP} is the weight on IP in an optimal forecast of the true series:

$$\lambda^{IP} = Var(\Delta e^{Y4})/(Var(\Delta e^{Y4}) + Var(\Delta e^{IP}))$$

The t-statistic reported under this set of columns is for the test of the hypothesis that λ is .5. This is equivalent to a test of the hypothesis that IP has the same variance as Y4.

5. κ^i, i=IP,Y4, is the fraction of the variation in series i due to measurement error:

$$\kappa^i = Var(\Delta e^i)/(Var(\Delta y^i)$$

Table 3c: Estimates of Measurement Error, Seasonal Dummy Adjusted Data							
	Weight for IP			*Measurement Error Share, IP*		*Measurement Error Share, Y4*	
	$\hat{\lambda}_{IP}$	se	t	$\hat{\kappa}_{IP}$	se	$\hat{\kappa}_{Y4}$	se
Food	.831	.038	8.67	.798	.169	.951	.039
Tobacco	.870	.045	8.23	.474	.133	.857	.041
Textiles	.732	.071	3.27	.740	.088	.886	.044
Apparel	.620	.038	3.13	.977	.083	.986	.051
Lumber	.833	.038	8.73	.474	.161	.818	.075
Furniture	.845	.036	9.59	.783	.172	.952	.038
Paper	.632	.065	2.01	.508	.087	.640	.101
Printing	.822	.029	11.05	.761	.130	.936	.036
Chemicals	.794	.036	8.11	.679	.131	.891	.050
Petroleum	.704	.055	3.71	.678	.085	.834	.048
Rubber	.748	.086	2.88	.466	.090	.722	.058
Leather	.852	.034	10.20	.978	.213	.996	.038
Stone,Clay,Glass	.768	.060	4.51	.437	.070	.720	.044
Primary Metal	.575	.089	.85	.393	.096	.467	.082
Fab Metal	.959	.029	15.87	.229	.137	.875	.027
Machinery	.908	.036	11.36	.346	.138	.840	.036
Elec Machinery	.786	.041	7.01	.622	.148	.858	.059
Trans Equip	1.092	.068	8.76	-.085	.064	.480	.059
Instruments	.949	.020	22.63	.469	.187	.942	.022
Other	.831	.040	8.31	.955	.193	.991	.040
Non-Durables	.800	.069	4.32	.331	.086	.665	.066
Durables	.986	.052	9.39	.024	.086	.624	.047
Total	.906	.056	7.24	.128	.080	.587	.063

Notes:

1. The sample period is 1967:5-1984:12.

2. The statistics in the table are computed for logarithmic growth rates that have been seasonally adjusted by regression on seasonal dummies.

3. The Y4 results are based on the finished goods only definition of output.

4. λ^{IP} is the weight on IP in an optimal forecast of the true series:

$$\lambda^{IP} = Var(\Delta e^{Y4})/(Var(\Delta e^{Y4}) + Var(\Delta e^{IP}))$$

The t-statistic reported under this set of columns is for the test of the hypothesis that λ is .5. This is equivalent to a test of the hypothesis that IP has the same variance as Y4.

5. κ^i, i=IP,Y4, is the fraction of the variation in series i due to measurement error:

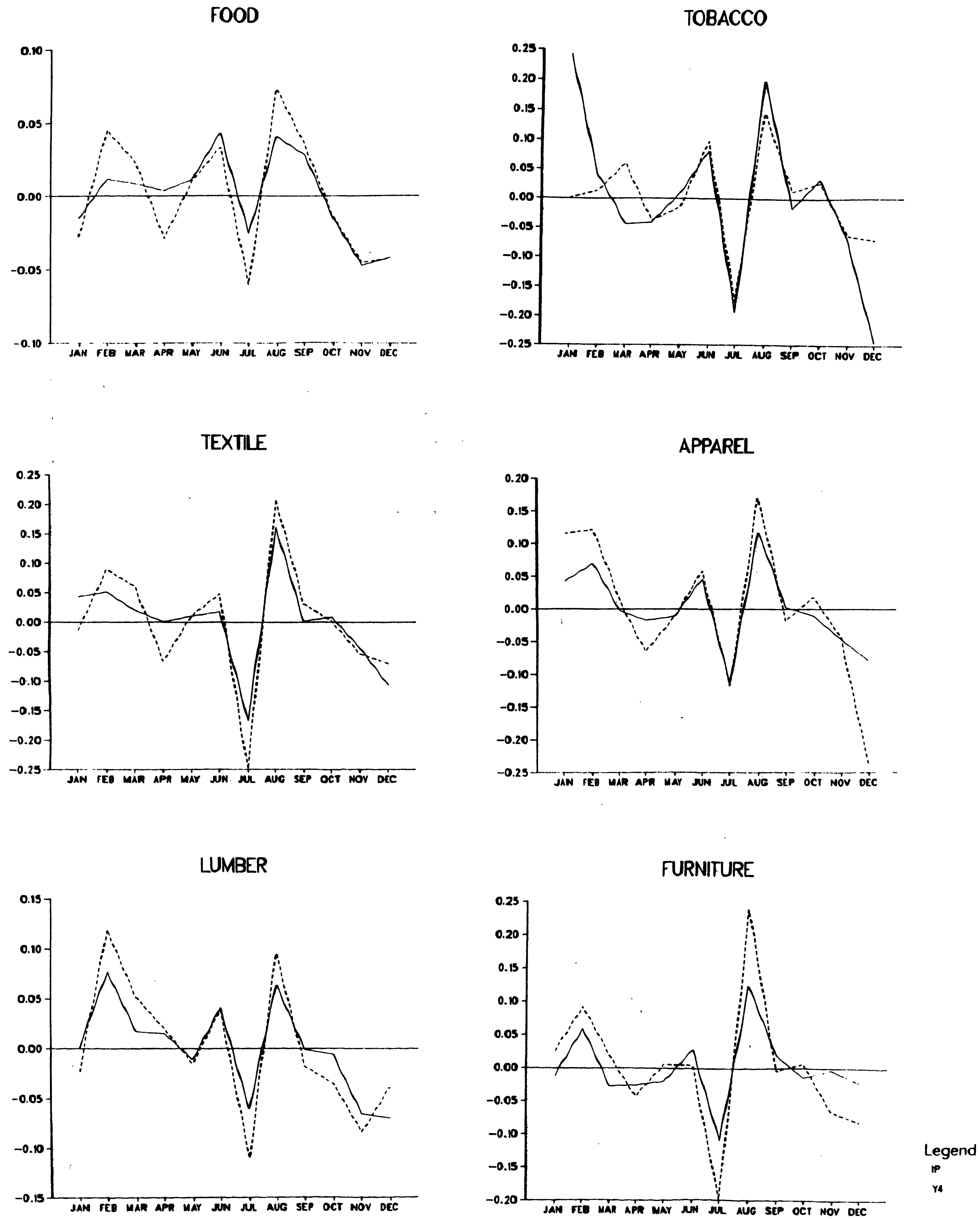
$$\kappa^i = Var(\Delta e^i)/(Var(\Delta y^i)$$

Table 4: Variance of Production over Variance of Sales, Seasonally Adjusted Data		
	IP	Y4
Food	.62	1.20
Tobacco	.54	2.43
Textiles	1.17	1.06
Apparel	.91	1.38
Lumber	.94	1.12
Furniture	.96	1.24
Paper	1.42	1.02
Printing	1.15	1.18
Chemicals	.82	1.01
Petroleum	.59	1.06
Rubber	1.12	1.13
Leather	1.09	1.36
Stone,Clay,Glass	1.08	1.12
Primary Metal	.98	.96
Fab Metal	.59	1.13
Machinery	1.28	1.35
Elec Machinery	1.13	1.26
Trans Equip	-	-
Instruments	.75	1.81
Other	.81	1.42
Non-Durables	-	-
Durables	-	-
Total	-	-

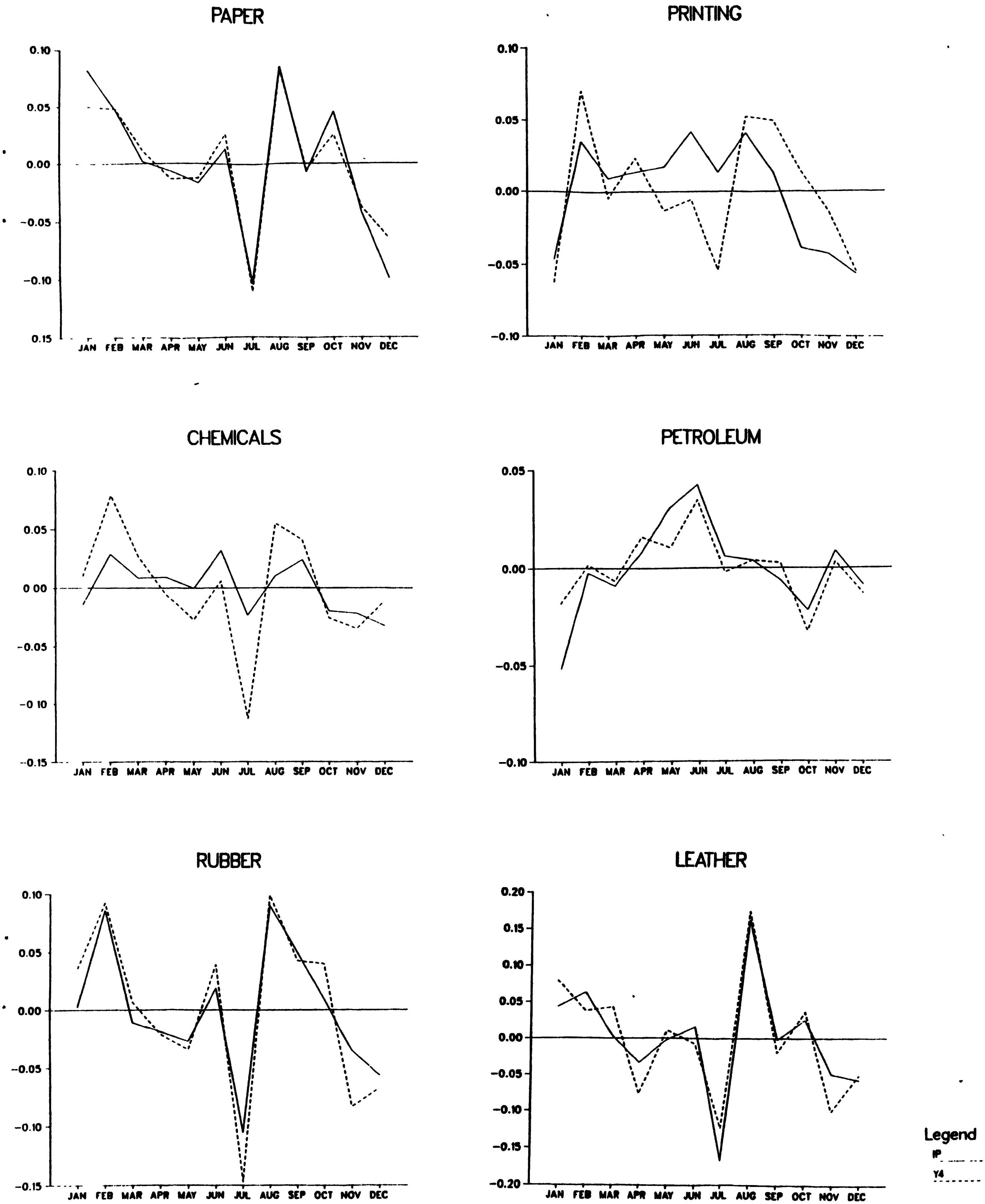
Notes:

1. The sample period is 1959:2 -1981:7.
2. The statistics in the tables are computed for deviations from exponential trend; see text for details.
3. The Y4 results are based on the finished goods plus work-in-progress definition of output.
4. The entries for Transportation Equipment and Non-Durables, Durables, and Totals are missing because of a data revision that went back only until 1967.

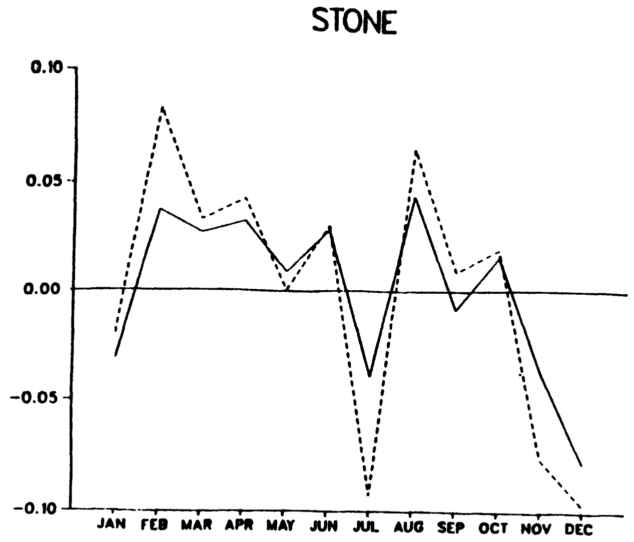
Figures 1-6: Seasonal patterns in growth rates of IP and Y4

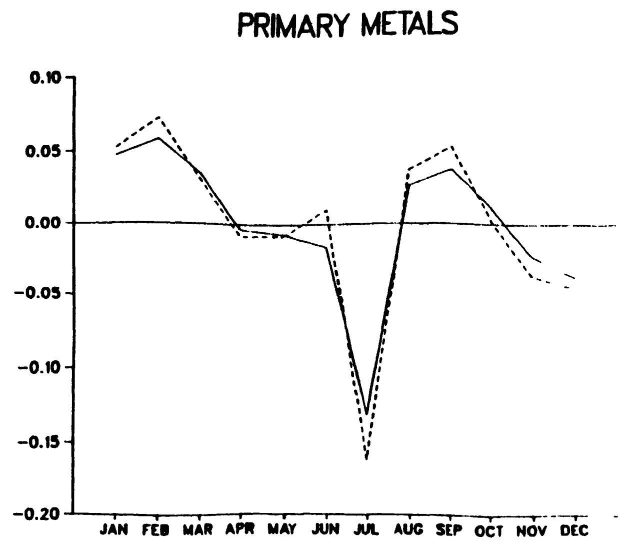


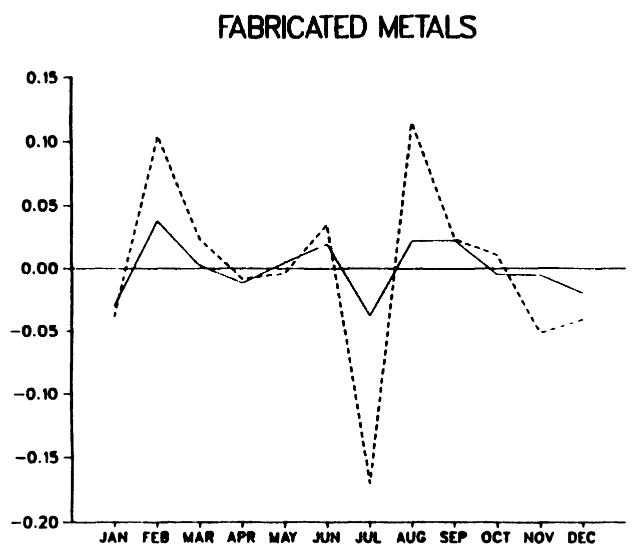
Figures 7-12: Seasonal patterns in growth rates of IP and Y4

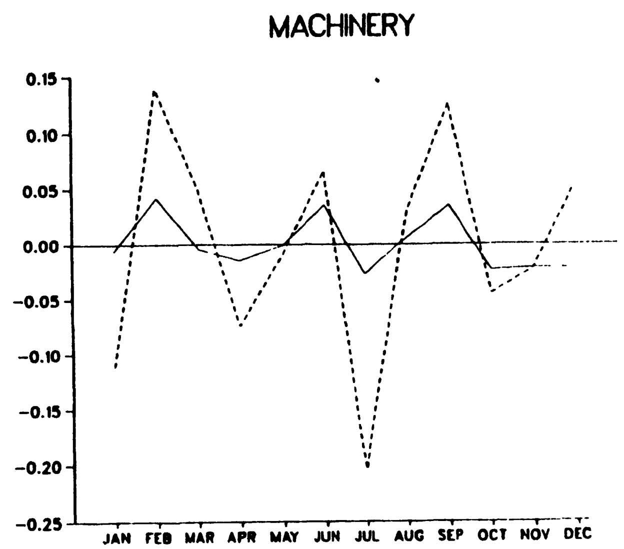


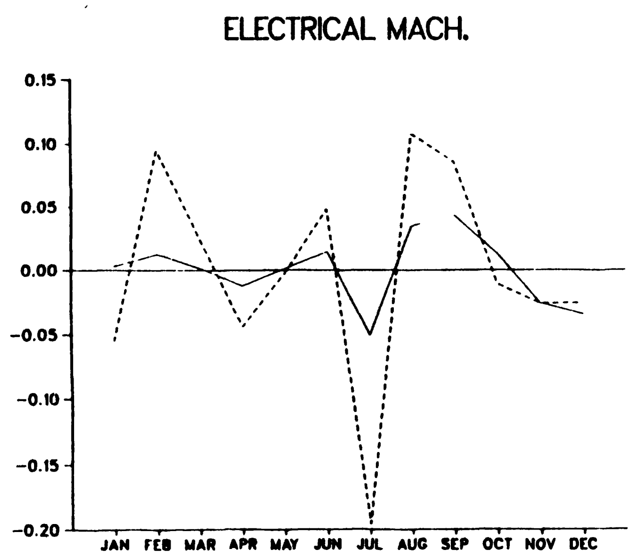
Figures 13-18: Seasonal patterns in growth rates of IP and Y4

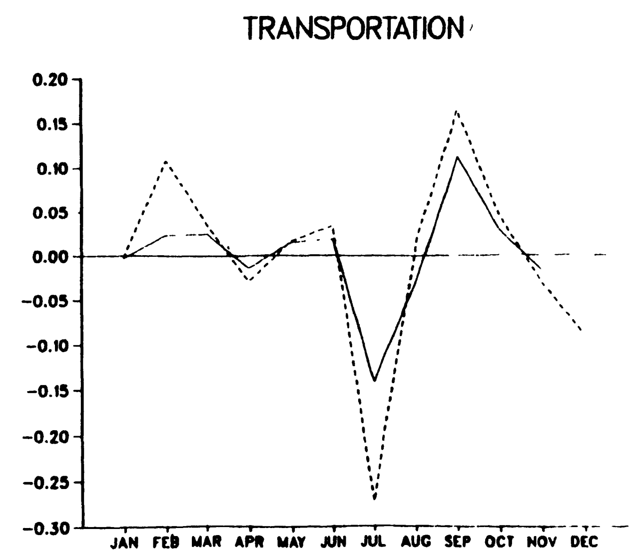






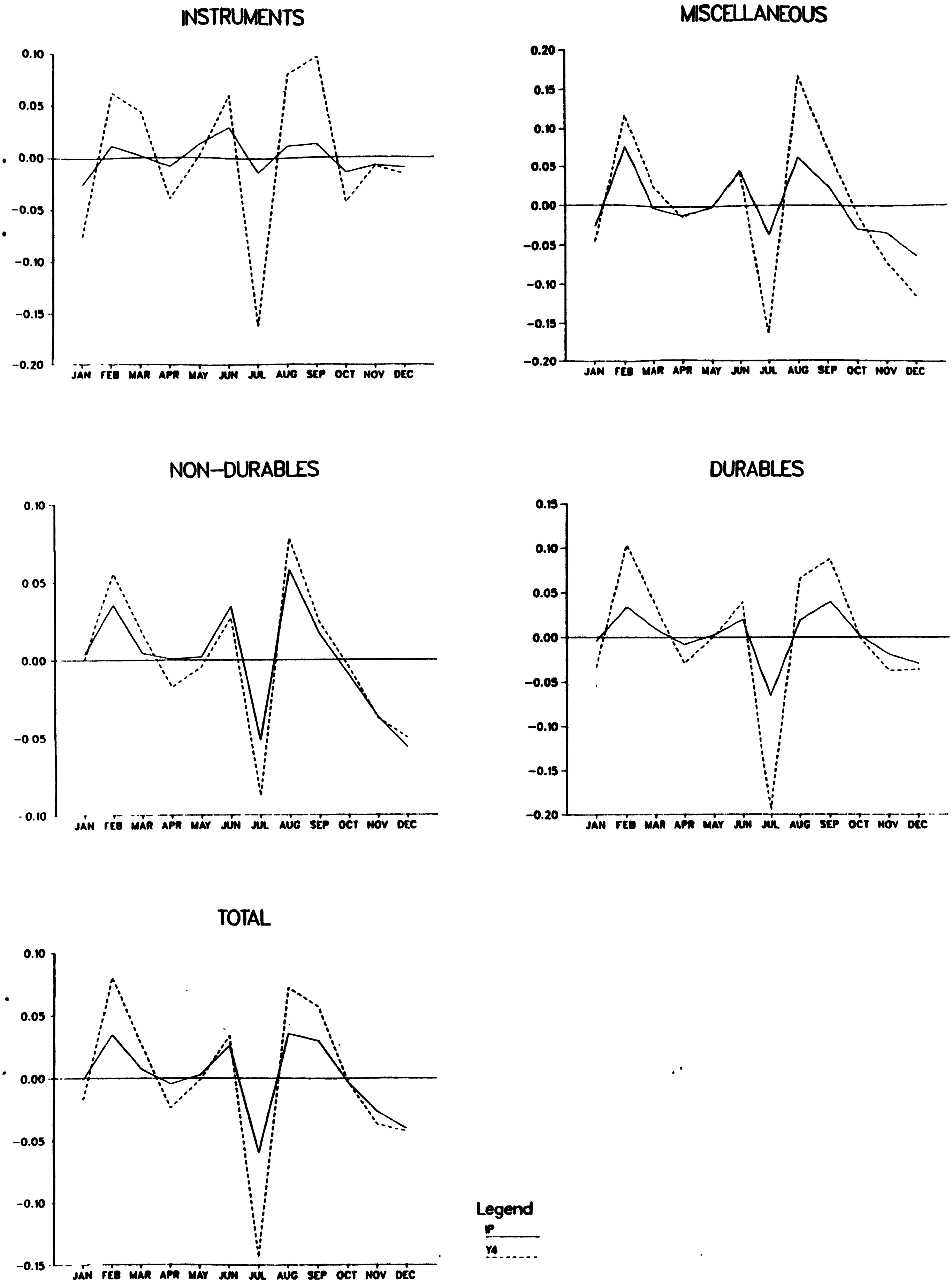






Legend
IP
Y4

Figures 19-23: Seasonal patterns in growth rates of IP and Y4



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Appendix

Table A1a: Summary Statistics, Seasonally Adjusted Data							
	Mean		*Standard Deviation*		*Autocorrelation*		*Correlation*
	IP	Y4	IP	Y4	IP	Y4	
Food	.00250	.00141	.00945	.02143	-.270	-.341	.180
Tobacco	.00042	.00017	.04582	.09830	-.528	-.469	.185
Textiles	.00135	.00158	.02134	.03485	.289	-.393	.254
Apparel	.00102	.00096	.02405	.05680	-.247	-.343	.089
Lumber	.00149	.00230	.02639	.05082	.040	-.320	.320
Furniture	.00297	.00309	.02043	.06131	.052	-.506	.159
Paper	.00275	.00226	.01865	.02353	-.015	-.341	.377
Printing	.00301	.00210	.01228	.03337	-.141	-.520	-.024
Chemicals	.00413	.00299	.01483	.02562	.101	-.239	.170
Petroleum	.00086	.00166	.02061	.03063	-.123	-.370	.080
Rubber	.00539	.00234	.02060	.04278	.101	-.273	.366
Leather	-.00279	-.00317	.02925	.07453	-.211	-.444	.085
Stone,Clay,Glass	.00217	.00093	.01981	.03399	-.007	-.343	.334
Primary Metal	-.00066	-.00070	.04136	.04174	.186	.095	.644
Fab Metal	.00126	.00107	.01423	.05144	.408	-.443	.253
Machinery	.00350	.00276	.01476	.03876	.302	-.353	.335
Elec Machinery	.00493	.00453	.01642	.03950	.160	-.395	.285
Trans Equip	.00161	.00157	.03135	.05870	.289	-.100	.589
Instruments	.00477	.00414	.01071	.06602	.095	-.473	.249
Other	.00135	.00132	.02046	.05728	-.228	-.386	.099
Non-Durables	.00279	.00177	.00936	.01440	.287	-.252	.446
Durables	.00238	.00207	.01363	.02489	.471	-.093	.585
Total	.00256	.00194	.01741	.01075	.437	-.098	.605

Notes:

1. The sample period is 1967:5-1984:12.
2. The statistics in the table are computed for logarithmic growth rates.
3. The Y4 results are based on the finished goods plus work-in-progress definition of output.

Table A1b: Summary Statistics, Seasonally Unadjusted Data							
	Mean		*Standard Deviation*		*Autocorrelation*		*Correlation*
	IP	Y4	IP	Y4	IP	Y4	
Food	.00247	.00125	.03117	.04727	.167	-.096	.728
Tobacco	-.00085	-.00081	.14393	.15307	-.442	-.342	.599
Textiles	.00084	.00114	.08205	.11023	-.322	-.408	.874
Apparel	.00088	-.00042	.07420	.12347	-.318	-.276	.639
Lumber	.00090	.00163	.05388	.08635	-.008	-.182	.732
Furniture	.00297	.00271	.05893	.11582	-.384	-.395	.712
Paper	.00216	.00164	.06250	.05932	-.302	-.386	.893
Printing	.00295	.00196	.03831	.05152	.437	-.282	.371
Chemicals	.00400	.00246	.02662	.05659	.057	-.122	.517
Petroleum	.00112	.00150	.03217	.03671	.133	-.337	.367
Rubber	.00505	.00149	.06301	.08466	-.095	-.245	.792
Leather	-.00309	-.00346	.08208	.11087	-.387	-.428	.623
Stone,Clay,Glass	.00191	.00032	.04311	.06528	.107	-.121	.746
Primary Metal	-.00136	-.11065	.06441	.07194	.146	.020	.854
Fab Metal	.00124	.00044	.02638	.09791	-.069	-.379	.630
Machinery	.00330	.00272	.02931	.09629	.003	-.315	.651
Elec Machinery	.00429	.00423	.03209	.09253	.030	-.276	.696
Trans Equip	.00137	.00079	.07018	.11803	.030	-.007	.825
Instruments	.00488	.00395	.02009	.10052	-.084	-.383	.446
Other	.00117	.00084	.04864	.10372	-.072	-.194	.620
Non-Durables	.00260	.00140	.03532	.04550	-.082	-.190	.911
Durables	.00218	.00155	.03226	.07851	.006	-.143	.892
Total	.00236	.00149	.03179	.06072	-.052	-.167	.918

Notes:

1. The sample period is 1967:5-1984:12.
2. The statistics in the table are computed for logarithmic growth rates.
3. The Y4 results are based on the finished goods plus work-in-progress definition of output.

Table A2: Dickey-Fuller Tests on Production Series								
	Finished Goods Only				*Finished Goods plus WIP*			
	Seasonally Adjusted		Seasonally Unadjusted		Seasonally Adjusted		Seasonally Unadjusted	
	IP	Y4	IP	Y4	IP	Y4	IP	Y4
Food	-2.32	-2.54	-2.36	-2.42	-2.32	-2.44	-2.36	-2.37
Tobacco	-2.38	-1.71	-1.62	-1.56	-2.38	-1.83	-1.62	-1.28
Textiles	-3.06	-2.19	-3.05	-2.10	-3.06	-2.31	-3.05	-2.17
Apparel	-2.91	-2.84	-2.64	-2.86	-2.91	-3.00	-2.64	-2.96
Lumber	-2.87	-2.67	-3.01	-2.69	-2.87	-2.66	-3.01	-2.59
Furniture	-3.63	-2.76	-3.70	-2.58	-3.63	-2.88	-3.70	-2.61
Paper	-3.50	-3.54	-3.49	-3.78	-3.50	-3.57	-3.49	-3.78
Printing	-1.71	-2.64	-1.81	-2.36	-1.71	-2.58	-1.81	-2.31
Chemicals	-2.39	-2.97	-2.43	-2.91	-2.39	-2.98	-2.42	-2.83
Petroleum	-1.16	-1.93	-1.06	-1.84	-1.16	-1.97	-1.06	-1.84
Rubber	-2.86	-2.81	-2.76	-2.59	-2.86	-2.85	-2.76	-2.61
Leather	-3.44	-1.51	-3.50	-1.56	-3.44	-1.41	-3.50	-1.43
Stone,Clay,Glass	-3.25	-2.37	-3.32	-2.36	-3.25	-2.45	-3.32	-2.36
Primary Metal	-2.84	-3.02	-2.75	-2.87	-2.84	-2.96	-2.75	-2.99
Fab Metal	-3.34	-2.48	-3.19	-2.65	-3.34	-2.91	-3.19	-2.80
Machinery	-3.57	-3.14	-4.37	-3.29	-3.57	-3.53	-4.37	-3.61
Elec Machinery	-3.37	-2.55	-3.57	-2.71	-3.37	-2.95	-3.57	-2.81
Trans Equip	-2.97	-3.07	-3.04	-3.06	-2.97	-3.32	-3.04	-3.23
Other	-2.79	-3.53	-2.82	-3.28	-2.79	-3.68	-2.82	-3.26
Instruments	-2.56	-2.12	-2.63	-2.00	-2.56	-2.10	-2.63	-1.98
Non-Durables	-3.26	-2.43	-3.50	-2.45	-3.26	-2.42	-3.50	-2.46
Durables	-3.71	-3.91	-4.12	-4.05	-3.71	-4.47	-4.12	-4.34
Total	-3.57	-3.58	-4.06	-3.72	-3.57	-3.87	-4.06	-3.89

Notes:

1. The sample period is 1967:5-1984:12.
2. The statistics in the table are computed for logarithmic growth rates.
3. The entries in the table are the t-statistics for the hypothesis of no unit root. A value of -3.68 is required to reject the null at the 95% level.
4. The Y4 results in columns 2 and 4 are based on the finished goods only definition of output. The Y4 results in columns 6 and 8 are based on the finished goods plus work-in-progess definition of output.

Table A3: Variance of Production over Variance of Sales, Seasonally Adjusted Data		
	IP	Y4
Food	.57	1.17
Tobacco	.46	1.37
Textiles	1.09	1.00
Apparel	1.27	1.43
Lumber	.98	1.08
Furniture	1.02	1.10
Paper	1.28	1.03
Printing	3.31	1.17
Chemicals	.85	1.06
Petroleum	.63	1.02
Rubber	.91	1.12
Leather	.44	1.28
Stone,Clay,Glass	1.13	1.13
Primary Metal	1.09	1.00
Fab Metal	1.08	1.24
Machinery	1.18	1.22
Elec Machinery	1.85	1.41
Trans Equip	.58	1.15
Instruments	.93	1.59
Other	.79	1.40
Non-Durables	1.34	1.08
Durables	.95	1.29
Total	1.11	1.21

Notes:

1. The sample period is 1967:5-1984:12.
2. The statistics in the tables are computed for deviations from exponential trend; see text for details.
3. The Y4 results are based on the finished goods plus work-in-progress definition of output.

Table A4: Summary Statistics, Seasonally Adjusted Data Quarterly averages of monthly data							
	Mean		*Standard Deviation*		*Autocorrelation*		*Correlation*
	IP	Y4	IP	Y4	IP	Y4	
Food	.00791	.00438	.01033	.03079	-.047	-.111	.437
Tobacco	.00183	-.00279	.03066	.05808	-.382	-.248	.464
Textile	.00483	.00475	.04234	.03748	.422	.034	.414
Apparel	.00327	.00345	.03169	.06856	.363	-.238	.287
Lumber	.00463	.00687	.04474	.06570	.235	-.001	.697
Furniture	.00918	.00929	.03396	.05235	.466	.057	.640
Paper	.00843	.00655	.03133	.02728	.351	.209	.653
Printing	.00935	.00553	.01732	.02717	.524	-.045	.348
Chemicals	.01238	.00975	.02570	.03392	.516	.162	.662
Petroleum	.00258	.00515	.02805	.04185	-.101	-.095	.414
Rubber	.01606	.00802	.04481	.06037	.345	-.049	.678
Leather	-.00899	-.00820	.03647	.08262	.172	-.250	.421
Stone,Clay,Glass	.00608	.00253	.03055	.04156	.424	.130	.680
Primary Metal	-.00183	-.00140	.07320	.07873	.198	.023	.792
Fab Metal	.00359	.00278	.03023	.04842	.626	-.009	.548
Machinery	.01098	.01034	.03132	.03976	.705	.470	.729
Elec Machinery	.01511	.01255	.02981	.03797	.574	.358	.737
Trans Equip	.00506	.00267	.05408	.06274	.024	.004	-.022
Instruments	.01455	.01151	.01928	.04988	.562	-.122	.455
Other	.00417	.00453	.02636	.07550	.428	-.143	.341
Non-Durables	.00861	.00548	.01897	.02059	.493	.216	.604
Durables	.00730	.00633	.02988	.03505	.499	.271	.885
Total	.00786	.00596	.02404	.02475	.538	.347	.864

Notes:

1. The sample period is 1967:5-1984:12.
2. The statistics in the table are computed for logarithmic growth rates.
3. The Y4 results are based on the finished goods only definition of output.

TABLE 5

COMPOSITION OF INDUSTRIAL PRODUCTION INDEXES BY DATA SOURCE

INDUSTRY	SIC	DUR/ NONDUR	PHYSICAL UNITS %	KILOWATT HOURS %	PRODUCTION WORKER HOURS %	OTHER %	Y4-IP CORREL (SA DATA)	Y4-IP CORREL (NSA DATA)	RANK BY SA CORR	RANK BY NSA CORR	RANK BY PHYSICAL UNITS %
FOOD	20	N	40.9%	39.0%	20.0%	0.0%	0.157	0.721	15	10	9
TOBACCO	21	N	90.3%	9.7%	0.0%	0.0%	0.212	0.508	12	18	4
TEXTILES	22	N	67.1%	30.7%	2.2%	0.0%	0.267	0.864	10	3	5
APPAREL	23	N	0.0%	16.5%	83.5%	0.0%	0.049	0.676	18	12	16
LUMBER	24	D	53.9%	3.5%	31.3%	11.3%	0.328	0.730	9	8	7
FURNITURE	25	D	0.0%	95.3%	4.7%	0.0%	0.176	0.783	14	7	18
PAPER	26	N	99.0%	0.0%	1.0%	0.0%	0.371	0.884	5	1	1
PRINTING	27	N	29.7%	70.3%	0.0%	0.0%	0.005	0.461	20	19	11
CHEMICALS	28	N	33.4%	37.6%	22.7%	6.2%	0.192	0.521	13	17	10
PETROLEUM	29	N	92.4%	7.6%	0.0%	0.0%	0.072	0.415	17	20	2
RUBBER	30	N	23.4%	69.5%	0.0%	7.1%	0.365	0.814	6	5	13
LEATHER	31	N	54.7%	15.1%	30.2%	0.0%	0.038	0.645	19	14	6
STONE,CLAY,GLASS	32	D	25.5%	62.8%	11.7%	0.0%	0.388	0.807	3	6	12
PRIMARY METALS	33	D	90.8%	2.1%	7.1%	0.0%	0.547	0.826	2	4	3
FAB. METALS	34	D	0.0%	51.0%	49.0%	0.0%	0.341	0.727	8	9	17
MACHINERY	35	D	0.5%	67.3%	24.0%	8.2%	0.358	0.634	7	15	15
ELEC. MACH.	36	D	13.4%	27.1%	55.4%	4.1%	0.374	0.703	4	11	14
TRANS. EQUIP.	37	D	41.8%	0.5%	57.7%	0.0%	0.655	0.881	1	2	8
INSTRUMENTS	38	D	0.0%	17.3%	71.1%	11.7%	0.226	0.569	11	16	19
MISC.	39	D	0.0%	100.0%	0.0%	0.0%	0.072	0.675	16	13	20
NON-DURABLES		N	44.6%	36.3%	17.1%	2.0%	0.437	0.905			
DURABLES		D	24.2%	34.8%	37.5%	3.4%	0.627	0.895			
TOTAL			32.8%	35.5%	28.9%	2.8%	0.611	0.911			

NOTES:

1. Fraction of industrial production index of each industry that is based on physical units data, kilowatt-hour data, and production worker-hour data, respectively.
2. "Other" category includes Federal Reserve estimates, and combined kilowatt-hour and production worker-hour data.
3. Source: Federal Reserve Board, INDUSTRIAL PRODUCTION 1986.

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