NBER WORKING PAPERS SERIES

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Working Paper No. 3635

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
February 1991

We thank Robert Barsky, Olivier Blanchard, Charlie Brown, Tom Cooley, David Cutler, Eric Ghysels, Ned Gramlich, Phil Howrey, James Kahn, Miles Kimball, Andrew Oswald, Charles Plosser, Danny Quah, Larry Summers, Steve Zeldes and seminar participants at the NBER Economic Fluctuations Winter Program Meeting, the NBER Summer Institute, the Summer Econometric Society Meetings, the MIT Macro Lunch Group, the Board of Governors, Maryland, UCSD, MIT, Virginia, Western Ontario, Dartmouth and the University of Washington for comments, Ed Glasser for research assistance, and Todd Clark and Larry Katz for help with data. This paper is part of NBER's research program in Economic Fluctuations. Any opinions expressed are those of the authors and not those of the National Bureau of Economic Research.

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ABSTRACT

We show there is a strong, positive correlation across countries and industries between the standard deviation of the seasonal component and the standard deviation of the non-seasonal component of aggregate variables such as output, labor input, interest rates, and prices. After documenting this stylized fact, we discuss possible explanations and develop a model that generates our empirical finding. The main feature of the model is that firms endogenously choose their degree of technological flexibility as a function of the amounts of seasonal and non-seasonal variation in demand. Although this model is intended to be illustrative, we find evidence supporting one of its key empirical implications.

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1. Introduction

In this paper we show that countries and industries with large seasonal cycles also have large business cycles. We then discuss the elements required in a model to generate our finding and explain why the finding suggests that the economic mechanism propagating seasonal fluctuations is closely linked to that propagating business cycle fluctuations. We also propose a particular model that incorporates this property and that is consistent with our empirical result. The model is preliminary but it illustrates our main point: the robust finding that the amounts of seasonal and business cycle variation are positively correlated across sectors is likely to require an explanation in which the two kinds of fluctuations are intimately related.

In the first part of the paper we show there is a strong, positive correlation across both countries and industries between the standard deviation of the seasonal component and the standard deviation of the non-seasonal component of aggregate variables such as output, labor input, interest rates, and prices. That is, large seasonal cycles are cross-sectionally correlated with large business cycles. This result is robust to the treatment of outliers and to controlling for country or industry characteristics; it is insensitive to the treatment of stationary stochastic seasonality; and it is strongly independent of sample period.

After documenting this stylized fact, we discuss possible explanations. In general three factors can generate the cross-sectional correlations. First, there may be cross-sectional correlations between the amounts of seasonal and non-seasonal variation in the exogenous forcing variables. Second, there may be nonlinearities in the structural model that relates the seasonal and non-seasonal variation in the economy. Third, the economic propagation mechanism transmitting seasonal fluctuations from exogenous to endogenous variables may be systematically related to that transmitting business cycle fluctuations.

We also discuss the significance of our empirical finding for comparisons between seasonal and non-seasonal fluctuations. Earlier work (Barsky and Miron (1989), Beaulieu and Miron (1990a,b)) demonstrates that the seasonal and business cycle fluctuations in modern economies display a number of striking similarities. In particular, both kinds of fluctuations exhibit many of the crucial stylized facts about business cycles. This general similarity between the two kinds of fluctuations suggests that the same economic propagation mechanism produces the two kinds of fluctuations, but the similarity is not by itself conclusive. We show using the framework described below that the evidence provided in this paper constitutes much stronger evidence that the propagation mechanism for seasonal fluctuations is intimately related to that for business cycle fluctuations.

In the final substantive section of the paper, we develop a simple model that generates our empirical finding. We assume firms endogenously choose their degree of technological flexibility in response to the variance of seasonal and non-seasonal demand shocks. Firms facing bigger seasonal or non-seasonal shocks choose more flexible technologies and thus are better able to respond to both kinds of shocks. Although this model is intended to be illustrative, we find evidence supporting one of its key empirical implications.

We conclude by discussing the implications of our model for issues in the study of aggregate fluctuations. The first and perhaps most important is that in our model the propagation mechanism links the seasonal and non-seasonal behavior of the economy, suggesting that one cannot understand the business cycle without also understanding the seasonal cycle. Because of the interconnections, anticipated and unanticipated shocks cannot always be sharply distinguished, and both have real effects on the economy. Second, in our world technology is not something that is exogenously determined, as it is in real business cycle models; instead, the degree of technological flexibility is chosen endogenously by firms in response to the degree of demand variability. Finally, our model is consistent with the view that the stabilization of output has a first-order effect on welfare by raising the average level of output in addition to reducing its variance.

2. Methods and Data

The main empirical question we address is whether there is a correlation across "sectors" between the amount of seasonal variation and the amount of business cycle variation in macroeconomic time series. We formalize this question as follows.

Assume we have time-series observations on a variable X for each of I sectors, where sector denotes either a country or an industry within a country. Let X_t^i denote the observation in sector i at time t. For instance, X_t^i may denote output in the ith U.S. manufacturing industry at date t. Following Barsky and Miron (1989), we assume

$$x_t^i = \sum_{k=1}^{12} \xi_k^i d_t^k + \epsilon_t^i \ , \tag{1}$$

where x_t^i is the first difference of the log of X_t^i, d_t^k is a dummy for month k, and ϵ_t^i is covariance stationary. We define the seasonal and non-seasonal components of x_t^i as

$$x_t^{i,s} \equiv \sum_{k=1}^{12} \xi_k^i d_t^k \ , \tag{2}$$

$$x_t^{i,n} \equiv x_t^i - \sum_{k=1}^{12} \xi_k^i d_t^k \ . \tag{3}$$

The two components are orthogonal according to this decomposition.

We note that the decomposition is not universally accepted in the literature because it assumes there is no seasonal integration and defines any stationary stochastic seasonality as non-seasonal.[1] Beaulieu and Miron (1991) show there is little evidence of seasonal integration in aggregate U.S. data series similar to those examined here.[2] We show in Section 3 that our treatment of stationary stochastic seasonality has no significant effect on our results. For the remainder of the paper, therefore, we use the terms "non-seasonal" and "business cycle" interchangeably.

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[1] As far as we know, there is no precise definition of stationary, stochastic seasonality. Roughly speaking, it can be defined as peaks in the spectrum of $x_t^{i,n}$ at seasonal frequencies.

[2] Hylleberg, Engle, Granger and Yoo (1990) explain how to test for seasonal integration.

We measure the amounts of seasonal and non-seasonal variation by the standard deviations of the seasonal and non-seasonal components of the variables:

$$\sigma_i^s(x) \equiv (\mathrm{var}(x_t^{i,s}))^{\frac{1}{2}} \ ,$$

$$\sigma_i^n(x) \equiv (\mathrm{var}(x_t^{i,n}))^{\frac{1}{2}} \ .$$

We then examine whether the amounts of seasonal and non-seasonal variation are correlated across sectors, i.e., whether β_2 is non-zero in the equation

$$\sigma_i^n = \beta_1 + \beta_2 \sigma_i^s + \nu_i \ , \tag{4}$$

where $i = 1, \ldots, I$ denotes either countries or industries. There is nothing in our assumptions about the processes generating the data that implies a correlation in either direction.

Our strategy for estimating β_2 is as follows. We first estimate the seasonal dummy coefficients, ξ_k, in equation (1) with OLS for each variable in each sector. We then compute measures of the seasonal and non-seasonal standard deviations by substituting the estimates of the ξ_k into equations (2)–(3) and taking standard deviations over time.[3] Finally, we estimate the cross-sectional regression,

$$\hat{\sigma}_i^n = \beta_1 + \beta_2 \hat{\sigma}_i^s + \zeta_i \ , \tag{5}$$

by least squares.[4]

There is a potential for bias in estimates of β_2 because $\hat{\sigma}_i^s$ and $\hat{\sigma}_i^n$ are estimated and therefore measured with error. This measurement error, and thus the bias in estimates of β_2, disappears

[3] The formulas for the standard deviations include a degrees of freedom correction to account for the fact that $x_t^{i,s}$ and $x_t^{i,n}$ are estimated:

$$\hat{\sigma}_i^s(x) = (\tfrac{T-1}{T-12}\mathrm{var}(\hat{x}_t^{i,s}))^{\frac{1}{2}}, \quad \hat{\sigma}_i^n(x) = (\tfrac{T-1}{T-12}\mathrm{var}(\hat{x}_t^{i,n}))^{\frac{1}{2}}.$$

[4] In the cross-sectional regressions for countries, the number of time series observations on a given variable often differs across countries. This difference produces heteroskedasticity in the cross-sectional errors. To correct for this heteroskedasticity, we weight $\hat{\sigma}_i^n$ and $\hat{\sigma}_i^s$ by $(T_i - 1)^{\frac{1}{4}}$ where T_i is the number of time series observations for a specific series in country i. The same procedure is applied to the price regression for manufacturing industries. For the remaining series, we estimate (5) by OLS.

as the number of time series observations on the x_t^i approaches infinity.[5] There may be a bias in finite samples, however. In an appendix available on request, we present results of Monte Carlo experiments designed to estimate the magnitude of the small sample bias. The results show that the amount of such bias is insignificant in most cases.[6]

We use two different data sets. The first consists of time-series observations on six aggregate variables from twenty-five OECD countries (see Beaulieu and Miron (1990b) for details). The variables are real retail sales, industrial production, the money stock, the consumer price index, nominal interest rates and *ex post* real interest rates.[7] Most series are available monthly, seasonally unadjusted, for the period 1960:1 – 1987:12, although some are available only for a subsample. There is no variable for which we have data for all twenty-five countries.

The second data set consists of time-series observations on ten different variables in each of twenty 2-digit U.S. manufacturing industries (see Beaulieu and Miron (1990a) for details). The variables are two measures of production (shipments plus the change in inventories (Y4) and industrial production), shipments, inventories, four measures of labor input (production worker employment, total employment, average production worker hours, and total production worker hours), nominal wages, and prices. Each series is available monthly, seasonally unadjusted for all twenty industries for the period 1967:4–1987:12, except for the price series, which is available only for a subset of

[5] The OLS standard error of $\hat{\beta}_2$, however, does not converge to the true, asymptotic standard error as the number of sectors grows large. Even if ν_i is homoskedastic, the measurement error in $\hat{\sigma}_i^n$ surely varies across sectors (i) when the number of time series observations is held constant. Thus, the observed residuals in the cross-sectional regression, which include both ν_i and measurement error, are heteroskedastic. To account for this heteroskedasticity, we use White's (1980) method to estimate the covariance matrix. This method is consistent as the number of countries or industries grows large.

[6] When the "true" cross-sectional correlation is zero in our experiments, we do obtain a positive bias. Under several different data generating processes, however, the bias is only about one tenth the magnitude of the coefficient we estimate in the real data. Further, when we run experiments where the true correlation is about the same magnitude as those estimated in real data, we obtain a small negative bias, suggesting that the results reported below may underestimate the strength of the positive cross-sectional correlation. The simulations do suggest that if the cross sectional variation in the standard deviations of the seasonal component is small compared to that in the non-seasonal component, the bias can be substantial. Given the results in Beaulieu and Miron (1990a,b) on the seasonal patterns in aggregate data, this implies that one should place less weight on the results below for variables such as prices, wages and interest rates than on those for other variables.

[7] All variables are measured as log growth rates except where noted in Section 3.2 and except for real rates, which are measured as levels of the nominal rate minus the log growth rate of prices over the time horizon of the nominal rate.

industries and in one case—Transportation—only for a restricted sample period.

3. Cross–Sectional Correlation Results

In this section of the paper we first establish that the amounts of seasonal and business cycle variation are strongly, positively correlated across both countries and industries. We then demonstrate the robustness of the result along a number of dimensions.

3.1 Main Results

We examine the cross-country evidence first. Figures 1–6 plot the non-seasonal standard deviation versus the seasonal standard deviation for real retail sales, industrial production, the nominal money stock, the price level, the nominal interest rate, and the real interest rate.[8] The figures also show the OLS regression of the non-seasonal standard deviation on the seasonal standard deviation and a constant. Table 1 reports weighted least squares regressions. The table gives the coefficient and t-statistic from the regression of the non-seasonal standard deviation on the seasonal standard deviations across countries, for each of the six variables. The results in the table confirm the impression given in the figures that there is a strong, positive correlation across countries between the amount of business cycle variation and the amount of seasonal variation. The sign of the correlation is statistically significant at better than the 3 percent level for all six variables.

Figures 7–16 plot the standard deviation of the non-seasonal component against the standard deviation of the seasonal component for the ten variables on which we have data across 2-digit U.S. manufacturing industries. Table 2 reports OLS estimates of the regressions illustrated in the figures.[9] For both measures of output, shipments, and inventories, the amounts of seasonal and business cycle variation are strongly, positively correlated across industries. The same result

[8] The results for industrial production use Total Industrial Production. We have also computed the regressions reported in this subsection with Manufacturing Industrial Production, with results that are virtually identical to those presented in the text.

[9] For prices, the table reports a weighted least squares regression because the Transportation price series is available only beginning in 1969:1.

holds for total hours, average hours, total employment, and production worker employment. The cross-sectional correlation is quite strong for wages but only modest for prices.

3.2 Robustness

We now report our checks for robustness. As a first step, we re-estimate the regressions reported in Tables 1 and 2 omitting the observations substantially off the regression line (see Tables A1-A2).[10] The signs and magnitudes of the correlations are generally not sensitive to the exclusion of the obvious outliers. The only exceptions are Retail Sales in the cross-country regressions and the two employment measures in the cross-industry regressions. In these three cases the coefficients are still positive but insignificant at the 5 percent level. Overall, exclusion of outliers increases rather than decreases the statistical significance of the results.

As a second robustness check, we re-estimate the regressions in Tables 1 and 2 with various country or industry characteristics included as controls (see Tables A3-A4). For countries we consider four variables: total GNP, per capita GNP, the share of output in agriculture, and the share of output in manufacturing.[11] For industries we use the percent of the industry that is unionized, the ratio of non-production workers to total employment, the four-firm concentration ratio, a dummy variable for whether an industry produces to stock (Belsley (1969)), and a dummy variable for whether the industry is classified as producing durables or nondurables. The results show that for both countries and industries, the cross-sectional relation between seasonal and non-seasonal variation is robust to the inclusion of cross-sectional characteristics. Although controlling for the various country and industry effects considered sometimes slightly reduces the magnitude

[10] For countries, we re-estimate the following regressions: retail sales, omitting Spain and Yugoslavia; industrial production, omitting Sweden; money, omitting Iceland and Turkey; and prices, omitting Greece, Turkey, and Yugoslavia. For industries, we re-estimate all regressions excluding Tobacco, as well as the following: production worker hours, production worker employment, and total employment, omitting Tobacco and Petroleum; and prices, omitting either Transportation only or Transportation and Lumber.

[11] The sources of the variables are the World Bank's *World Development Report, 1987* and *World Tables, 1987*. We have also used the Summers and Heston (1988) estimates of real GDP to measure output; this has no effect on the results.

of the correlations, the correlations are still positive and significant in almost all cases.[12]

Our third robustness check addresses the issue of stationary, stochastic seasonality. Although we are aware of no micro-theoretic model in which stochastic seasonality and deterministic seasonality are intimately related (with both completely unrelated to the non-seasonal stochastic component), traditional decompositions such as

$$y = trend + deterministic\ seasonals + stochastic\ seasonals + other\ stochastic\ components$$

suggest that the cross–sectional correlations documented above may be generated by mislabeling stochastic seasonality as stochastic non-seasonal variation.

To check the possibility that stationary stochastic seasonality explains our results, we compare the standard deviation of the seasonal dummy component of the seasonally-unadjusted series to the standard deviation of the seasonally-adjusted series, where the seasonal adjustment technique is one that removes both stationary stochastic seasonality and deterministic dummies. Since there is no universally agreed upon definition of stochastic seasonality, there is no universally agreed upon seasonal adjustment technique. We use the official Census X-11 adjusted data when these are available. In addition, for all series we adjust the data ourselves using the version of X-11 provided in the EZ-X11 program documented in Doan (1989).[13] The results are presented in Tables A6 and A7. In most cases, the correlations between seasonal and non-seasonal standard deviations are trivially different from those reported in Tables 1 and 2, regardless of whether we use official X-11 adjusted data or EZ-X11 adjusted data.[14] The explanation is simply that in most series

[12] For countries, we have also experimented with a much larger set of control variables, with results similar to those presented in the text. See Table A5.

[13] Both the official X-11 and the EZ-X11 procedures can be approximated as two-sided moving average filters of the original data; see Cleveland and Tiao (1976), Wallis (1974), and Doan (1989). The full-scale implementations of both programs, however, are non-linear in two respects. First, observations that are more than a certain distance from the true series are attenuated. Second, end-points are treated differently from the bulk of the series.

[14] The exceptions are the cross-country regressions for Retail Sales and M1 and the cross-industry regression for Production Worker Hours. For Retail Sales and M1, the relation is still positive but statistically insignificant. For Production Worker Hours, the relation is insignificantly positive in the EZ-X11 data and insignificantly negative in the Census X-11 data.

stationary, stochastic seasonality accounts for a small fraction of the variation not explained by seasonal dummies.

As a fourth check, we also re-estimate the basic cross-sectional correlations using data on detrended log levels rather than on log growth rates (see Tables A6-A7). The data are detrended by removing a quadratic trend. Overall the results are less striking than those using growth rates but are broadly consistent with the results discussed above. For countries the correlation is positive for all six variables and statistically significant at the 5 percent level in four out of six cases.[15] For industries six of the ten variables show a positive correlation, but the correlation is significant at the 5 percent level for only two variables (Y4 and Average Hours). The correlation is not significant at the 5 percent level in any of the four cases where the point estimate is negative. Each of the negative estimates appears to depend heavily on the observations for Food and Tobacco. When these two industries are excluded the correlation is positive but insignificant at the 5 percent level. Excluding Food and Tobacco, however, makes the correlation for Inventories negative.

As a final check on our results we apply our procedure separately to the time-series data from the first and second halves of the sample periods. For countries we split the sample after 1973:12, estimate the seasonal and non-seasonal standard deviations for each subsample, and then re-estimate the regressions in Table 1. For the manufacturing series we split the sample after 1977:9 and re-estimate the regressions in Table 2. In both cases we obtain results strikingly similar to those presented above for the entire sample (see Tables A6-A7).

4. Explanations for the Cross-Sectional Correlations

Taken together, the cross-country and cross-industry correlations documented above constitute a robust stylized fact: countries and industries with large seasonal cycles also have large business cycles. In this section we discuss possible explanations for this finding. We first indicate in a

[15] This includes the result presented earlier on the real rate, which was conducted in levels.

general framework the factors that can account for the cross-sectional correlations. We then use this framework to discuss the implications of our results for the relation between seasonal cycles and business cycles.

4.1 A General Framework

Suppose the reduced-form equation for an endogenous variable, y, relates that variable to two exogenous variables x_1 and x_2,

$$y = f(x_1, x_2) \ ,$$

where we suppress time and sector subscripts for convenience. Each of x_1, x_2 is the sum of a stationary non-seasonal component and a deterministic seasonal component,

$$x_1 = x_1^n + x_1^s \ ,$$

$$x_2 = x_2^n + x_2^s \ .$$

This specification is consistent with a large range of models. For example, x_2 may represent lagged x_1. Alternatively, x_1 may be the seasonal component of a series while x_2 is the non-seasonal component of the same series (i.e., $x_1^n = x_2^s = 0$).

Define $\bar{x}_i$ as the unconditional mean of x_i^n plus the mean of x_i^s. Let $\tilde{x}_i^n$ and $\tilde{x}_i^s$ be the deviations from the respective means. The second–order Taylor expansion of $f(\cdot,\cdot)$ around $(\bar{x}_1, \bar{x}_2)$ is

$$y \approx f(\bar{x}_1, \bar{x}_2) + \sum_{i=1}^{2} f_i(\bar{x}_1, \bar{x}_2)(\tilde{x}_i^n + \tilde{x}_i^s) + \frac{1}{2} \sum_{i=1}^{2} \sum_{j=1}^{2} f_{ij}(\bar{x}_1, \bar{x}_2)(\tilde{x}_i^n + \tilde{x}_i^s)(\tilde{x}_j^n + \tilde{x}_j^s) \ ,$$

where subscripts on $f(\cdot,\cdot)$ denote differentiation.[16] Since x_1^s and x_2^s are deterministic we can define a seasonal and a non-seasonal component of y,

[16] We assume that x_1^n and x_2^n are stationary and ergodic. If the assumption is violated, then one can take $\bar{x}_1$ and $\bar{x}_2$ to be the initial values of x_1 and x_2 respectively. In this case, a Taylor approximation will likely be poor for t much larger than its initial value. Furthermore, this approximation is likely to be poor if $\tilde{x}_i^s$ or $\tilde{x}_i^n$ is large. Including further terms to provide a better approximation does not affect the subsequent analysis.

$$y^s = f(\bar{x}_1, \bar{x}_2) + \sum_{i=1}^{2} f_i(\bar{x}_1, \bar{x}_2)\tilde{x}_i^s + \frac{1}{2}\sum_{i=1}^{2}\sum_{j=1}^{2} f_{ij}(\bar{x}_1, \bar{x}_2)\left(\tilde{x}_i^s\tilde{x}_j^s + E[\tilde{x}_i^n\tilde{x}_j^n|t]\right) , \qquad (6)$$

$$y^n = y - y^s ,$$

where $E[\tilde{x}_i^n\tilde{x}_j^n|t]$ denotes the expectation of the product conditional on the season. Assuming that a decomposition such as (6) holds in each of I countries or industries, we want to know the conditions under which the standard deviations of y^n and y^s are correlated across sectors.

Cross-sectional correlation between the seasonal and non-seasonal standard deviations of the endogenous variable y can arise in three ways. First, there may be cross-sectional correlation between the seasonal and non-seasonal standard deviations of the exogenous variables. In our framework this possibility is captured by having $\sigma(x_i^s)$ correlated with $\sigma(x_i^n)$. Second, nonlinearities in the relationship between the endogenous and exogenous variables can generate our cross-sectional results. In taking the standard deviations of y^s and y^n in equation (6), the non-linearities in $f(\cdot,\cdot)$ produce a correlation between $\sigma(y^s)$ and $\sigma(y^n)$ because of the term $E[\tilde{x}_i^n\tilde{x}_j^n|t]$. Third, the parameters transmitting seasonal fluctuations from exogenous to endogenous variables may be systematically related to those transmitting non-seasonal fluctuations. For example, the parameters $f_i(\bar{x}_1, \bar{x}_2)$ may multiply both the seasonal and non-seasonal components of the x_i. The three possibilities are of course not mutually exclusive.

We do not pursue further the possibility that the seasonal and non-seasonal standard deviations of the exogenous variables are correlated cross-sectionally. The attractiveness of this explanation depends on the context. Sometimes the exogenous shocks are unobservable, so explaining the observed correlation in this way is neither testable nor enlightening. We show below that this explanation is particularly unappealing in some examples. The second possibility — nonlinearities — is potentially part of the explanation for our empirical results, but nonlinearities can produce a correlation in either direction so it is important to isolate the particular nonlinearities that are relevant.

In the next section we provide a model that explains our empirical findings by incorporating a link between the parameters relating seasonal and non-seasonal fluctuations.[17] Before presenting our model, however, we use the framework described above to discuss the implications of our empirical findings for understanding the relation between seasonal cycles and business cycles.

4.2 The Seasonal Cycle and the Business Cycle

It is common in economic modeling to abstract from seasonal variation, presumably because such variation is "irrelevant" for the study of what is interesting, the non-seasonal variation.[18] The irrelevance of seasonal variation may occur because seasonal fluctuations result from different exogenous sources than non-seasonal fluctuations. For instance, seasonality may result from holidays while business cycles result from monetary surprises. More importantly, seasonal variation might be irrelevant to the study of business cycle variation because the mechanism by which impulses are propagated treats seasonal shocks differently than non-seasonal shocks. One reason for this second condition to hold may be that seasonals are anticipated.

These assumptions about the nature of seasonal cycles relative to business cycles imply two restrictions on the analytic framework described above. The first amounts to saying that seasonal cycles are due, say, to x_1 while business cycles are due to x_2 (*i.e.*, $x_1^n = x_2^s = 0, \forall t$). The second assumption implies that the parameters transmitting seasonal fluctuations from exogenous to endogenous variables have no connection with those transmitting business cycle fluctuations (*e.g.*, $f_1(\bar{x}_1, \bar{x}_2)$ is unrelated to $f_2(\bar{x}_1, \bar{x}_2)$ in the case where $x_1^n = x_2^s = 0$).

If both these conditions hold, the discussion above shows that the model does not imply a cross-sectional correlation between the seasonal and non-seasonal standard deviations of y, assuming the

[17] The particular model we examine also incorporates a non-linearity, but this is not crucial for the results.

[18] One exception is Ghysels (1988), who models stationary stochastic seasonality in a dynamic context. In his model seasonal fluctuations in demand add power to the spectrum of production at non-seasonal frequencies.

other possible sources of this correlation are absent.[19] This means that when models assume *a priori* that there are significantly different sources and propagation mechanisms for seasonal cycles and business cycles, it is more difficult for those models to accommodate the empirical facts presented in this paper. We now demonstrate these points through two examples. The examples are deliberately overly simple, but we find them useful in order to fix ideas.

Consider first the textbook aggregate supply/aggregate demand model due to Lucas (1973):

$$m_t - p_t = y_t \tag{7}$$

$$y_t = \theta(p_t - \mathrm{E}_{t-1}p_t) + s_t \ , \tag{8}$$

where s_t is a seasonal dummy shifter in the technology (the natural rate), m_t is the nominal money stock, p_t is the price level, y_t is real output, and θ is a parameter. All variables are measured in logs. Equation (7) is a standard aggregate demand curve, and equation (8) is a standard Lucas supply function, with the natural rate replaced by the seasonals, s_t.

The solution for output is

$$y_t = \frac{\theta}{1+\theta}(m_t - \mathrm{E}_{t-1}m_t) + s_t \ .$$

This example embodies in a simple way both of the two notions described above. First, the sources of seasonal and business cycle fluctuations are different. Seasonal variation is due to technology shifts, while business cycle variation is due to monetary surprises. Second, the mechanism transmitting shocks from exogenous to endogenous variables is different as well. No parameter multiplies both the technology shocks and the money shocks. The model cannot explain the cross-sectional correlation in output across countries unless those countries in which the variance of the anticipated technology seasonal is large are also the ones in which the monetary authority puts a large variance into the money stock surprises. There is no obvious reason for this condition to hold.

[19] We also assume that the higher moments of x_2^n are independent of the season.

A second useful example is the standard permanent income model of consumption. Assume that a representative consumer faces the problem:

$$\max_{\{C_t\}} \mathrm{E}_t \sum_{t=0}^{\infty} \beta^t U(C_t)$$

$$\text{s.t. } A_{t+1} = R(A_t + y_t - C_t)$$

$$A_0 = \bar{A}_0$$

$$R\beta = 1 \ ,$$

where C_t is consumption, y_t is income, A_t is beginning-of-period wealth, r is the constant, gross real interest rate, and β is the consumer's rate of time preference.

Suppose the utility function is quadratic with a seasonal shifter in the intercept of the marginal utility function,

$$U(C_t) = \alpha_t C_t - \gamma C_t^2,$$

where α_t is a seasonal dummy process. Then the solution for the change in consumption is

$$C_t - C_{t-1} = \frac{1}{2\gamma}(\alpha_t - \alpha_{t-1}) + \frac{R-1}{R} \sum_{s=t}^{\infty} R^{-(s-t)} \left(\mathrm{E}_t y_s - \mathrm{E}_{t-1} y_s \right) \ .$$

The variance of the non-seasonal change in consumption depends only on R and the properties of y_t. The variance of the seasonal change in consumption depends only on γ and the properties of α_t.

This example shows why the sharp distinction between anticipated and unanticipated shocks makes our empirical findings hard to explain. Changes in consumption are driven by revisions in forecasts of permanent income, and such revisions are themselves unforecastable under rational expectations. If income is the only possible source of seasonality in this model, consumption is not seasonal. In order to explain the observed seasonality of consumption, it is necessary to postulate a seasonal in preferences. Then, in order for the model to accommodate our cross-sectional results there must be a cross-sectional correlation between the variance of the seasonal shift in preferences and the variance of the shock to income. Again, there is no obvious reason for this condition to hold.

The discussion is this subsection does not prove that the exogenous variables producing business cycles are the same as those producing seasonal cycles, nor does it prove that seasonal and non-seasonal shocks, whatever their source, propagate through the economy in the same manner. The discussion does show that models of aggregate fluctuations in which the sources and impact of seasonal fluctuations are fundamentally different from those of business cycle fluctuations have difficulty encompassing our empirical findings.

5. Capacity Choice and Output Fluctuations

In this section we present a model that generates some of the cross-sectional correlations documented above. This model is not the only way to explain the correlations; we focus on it partly to illustrate that a model consistent with our findings can produce interesting results.[20] Nevertheless, we believe the main innovation in our model is an important one that is worth pursuing in its own right. We present some suggestive evidence along these lines.

Our basic idea is illustrated graphically in Figure 17. The figure illustrates a firm's marginal cost curve along with the demand curves faced by that firm in various states of the world. The diagram portrays two seasons with the state of demand uncertain around its mean level in each season. The MC curve begins to rise steeply at some point, which we refer to loosely as "capacity." The firm obtains flexibility by purchasing "excess" capacity, so the firm can expand output over a larger range without a substantial increase in marginal cost. In the top panel, the firm faces a demand curve that does not shift much seasonally. It therefore chooses a level of capacity that is close to the average level of output. In the bottom panel, the firm faces a much greater seasonal

[20] Ghysels (1988), Todd (1989), Braun and Evans (1990), Chatterjee and Ravikumar (1990), and Hansen and Sargent (1990) also present models that are potentially consistent with the facts documented above. With the exception of Chatterjee and Ravikumar (1990), however, none of these papers discusses the cross-sectional correlations discussed here, and even Chatterjee and Ravikumar do not show that their model necessarily implies our stylized facts.

variance in demand, so optimal capacity choice is greater, implying that non-seasonal shocks in the low demand season have a bigger effect on output than they would in the world described in the top panel. There is of course nothing special about seasonal variation in demand; an increase in the amount of non-seasonal variation also leads to an increase in optimal capacity.

5.1 The Basic Model

We now formalize this story. The simplest model of capacity has a firm with constant marginal costs up to the capacity limit, giving a backwards 'L'-shaped marginal cost curve. Such a model typically yields a corner solution for output, since the solution to the first-order conditions may be greater than capacity before imposing the inequality constraint. To simplify the analysis we ensure interior solutions by assuming a hyperbolic marginal cost function for which the vertical asymptote can be thought of as the binding capacity constraint.[21]

The firm's marginal cost curve is given by:

$$MC = cx_s \frac{\phi}{\phi - x_s} ,$$

where x_s is the firm's output in season s, c is a fixed parameter, and ϕ is a parameter (the vertical asymptote) chosen *ex ante* by the firm at some cost per unit of "flexibility". Purchasing more ϕ lengthens the range over which the marginal cost curve is relatively flat and hence increases the firm's output response to demand shifts.

Suppose the firm chooses its technology once a year. During the year it produces for one high and one low season, after which the technology disintegrates. The inverse demand curve is linear,

$$p_s = a_s - \frac{b}{2} x_s ,$$

[21] The main points made in this section can be shown most simply in a model with linear marginal cost (MC) curves, with firms able to purchase *ex ante* the slope of the curve. The flatter is the curve, the greater is the output response to a demand shock. However, the simple linear MC model is not particularly interesting since almost all firms appear to operate sometimes in a region where MC turns up sharply. Moreover, linear marginal cost curves predict homoskedasticity in the growth rates of output across seasons whereas our model predicts heteroskedasticity. We discuss this implication below.

where $a_s = a + \delta\sigma + \tilde{\epsilon}$ with a fixed, $\tilde{\epsilon}$ is a white noise demand shock, $\delta = \{-1, 1\}$ in the low and high seasons respectively, and σ is the magnitude of the seasonal shift in demand.

If output decisions are made after the realization of the current period's shock, then given technology, ϕ, optimal output in a period s is

$$x_s^* = \frac{(a_s + [b+c]\phi) - \left[(a_s + [b+c]\phi)^2 - 4ba_s\phi\right]^{\frac{1}{2}}}{2b}$$

and maximized period profits are

$$\pi_s^* = (a_s - \frac{b}{2}x_s^*)x_s^* - c\phi[\phi \ln \phi - \phi \ln(\phi - x_s^*) - x_s^*].$$

We assume that both seasons are of the same length and that the firm does not discount across the two seasons. Then the firm's optimal *ex ante* capacity choice is obtained by maximizing the expected sum of period profits, minus the cost of purchasing capacity, $q\phi$. No explicit solution to this problem exists, so we solve the model numerically for a variety of parameter values.

For all parameter values tested, the model yields a positive correlation between the seasonal and non-seasonal standard deviations of output as the seasonal demand shift changes. Two typical sets of results are given in Tables 3a and 3b. The correlation coefficient between the standard deviations of the seasonal and non-seasonal components of output is greater than 0.9 in both cases. Thus, the model is consistent with the facts presented in Section 3.[22]

In order to make this explanation of the cross-sectional correlations convincing, we need to extend the model theoretically and test its empirical implications. At the theoretical level, the most important addition is to allow firms to hold inventories with which to smooth production. Since capacity and inventories play essentially the same role in our simple model, we ignore inventories

[22] We also constructed a model in which the firm fixes a single price at the beginning of the year and charges that price regardless of season or realization of the non-seasonal shock. Such behavior may be explained by high 'menu costs' of changing prices or by customer loyalty considerations. Thus, prices are not seasonal. We used the same marginal cost and demand curves as above and assumed that the firm sells either the quantity demanded at its pre-announced price or the quantity at which marginal cost is equal to price (whichever is smaller, and thus optimal, for the firm). This model generates the same result as above: there is a positive cross-sectional correlation between the standard deviations of seasonal and non-seasonal output as the seasonal demand shift changes. The other results discussed below also hold in our fixed-price model.

rather than deal with the added complication of a second state variable. In order to extensively test the model, however, we must account for the behavior of inventories. We would also like to consider entry and industry equilibrium, possibly with strategic competitive motives for holding excess capacity (*e.g.*, Spence (1979)) and inventories (*e.g.*, Rotemberg and Saloner (1986)). These features would make the model more complete in addition to suggesting tests of the relative importance of demand or cost fluctuations and strategic motives as determinants of capacity and inventory behavior.

5.2 Empirical Verification

Thorough empirical testing of our model is beyond the scope of this paper, in large part because the model is too preliminary to withstand detailed scrutiny. To illustrate the model's potential, however, we examine one simple implication that is likely robust to the theoretical extensions discussed above. The prediction is that output exhibits a particular form of seasonal heteroskedasticity.

Imagine non-seasonal stochastic shifts in the intercept of the demand curve in each season (see Figure 17). During the low season, there will be substantially more variation in realized output than during the high season because of the effective truncation of high season output by the capacity constraint as well as because of the greater slope of the MC curve up to the level of capacity. We should therefore see seasonal heteroskedasticity in the non-seasonal output residuals, *i.e.*, different non-seasonal variances in different seasons. The prediction is stronger than merely saying there will be seasonal heteroskedasticity; the model implies that the variance in the high season is *lower* than in the low season.

Testing this proposition is complicated when there is a unit root in production. For all seasons the theoretical variance of the level of output conditioned only on the season is infinite. Although the variance of growth rates is finite, the model does not predict a pattern relating heteroskedasticity in the growth rate variances to the seasonals in the growth rates. We do, however, expect the variance of the growth rates to be related to the seasonal in the *level* of output. Assume that the process for output is integrated because the process for demand is integrated. The firm adjusts output more in response to a shock to demand growth if capacity is slack than if capacity is tight because when capacity is slack MC is relatively flat. We therefore expect the non-seasonal output growth rate variance to be high when the level of output is low.

To verify this intuition, we constructed a 20-year simulation of our model in which the stochastic demand shock is integrated. This produces integration in production, and all of the results discussed above still hold. In particular there is seasonal heteroskedasticity in the log growth rate output variances, with the growth rate variances decreasing in the seasonal level of output.

We test the prediction of seasonal heteroskedasticity in our three measures of output: IP across countries, IP across U.S. manufacturing industries, and Y4 across U.S. manufacturing industries. We first calculate a White (1980) test for any form of seasonal heteroskedasticty. The results are presented in Table 4 under the column labeled *Heteroskedasticity.* At the 5 percent level, the data reject the null of no seasonal heteroskedasticity for eighteen of twenty countries (IP) and fourteen (IP) or seventeen (Y4) of twenty U.S. manufacturing industries. We also report test statistics for three U.S. industry aggregates. The results are consistent with those for the individual two-digit industries.

We next test whether the variance of the growth rate conditional on the month is negatively correlated with the level of production in that month. To calculate the seasonals in the level of production, we regress the log level of an industry's or country's production on twelve monthly dummies and a quadratic trend. Our estimates of the seasonal in the level of output are then the twelve coefficients on the monthly dummies. For each country and industry we calculate the Spearman rank correlation between the variance of the production growth rate in a month and the average level of production in that month. We also calculate the significance level for the one-sided alternative that the correlation is negative.[23]

The Spearman rank correlations are reported in Table 4 under the column headed *Pattern*. For all three production series, eighteen of the twenty countries or industries display negative correlations. For countries, with output measured by IP, ten of the correlations are significant at the 5 percent level and three more are significant at the 10 percent level. For industries, with output measured by IP, eight of the correlations are significant at 5 percent and two more are significant at 10 percent. For industries with output measured by Y4, four of the correlations are significantly negative at 5 percent and another two are significant at 10 percent. The percentage of negative rank correlations is substantially larger than under the null of no relationship. This conclusion applies even if countries or industries are correlated so that the observed seasonal variance-production level pairs are not independent observations.[24]

These results support the premise in our model that capacity constraints affect production more in high versus low demand seasons. They do not show that capacity constraints are chosen endogenously, as suggested above. We leave the investigation of this claim for future work.

6. Conclusions

In this paper we document a robust stylized fact, explain at a general level what factors are required in a model to accommodate the fact, and offer one specific model that is consistent with the empirical finding. The explanation we offer clearly requires significant further development at the theoretical level, as well as additional testing of its empirical implications. We leave these tasks for future work. We close with a discussion of some implications of our capacity story for understanding aggregate fluctuations.

The first and perhaps most important implication is that endogenous control of technological

[23] We have also calculated the Pearson correlation coefficients between the variance of the production growth rates and the level of production. The results are similar to those reported in the text.

[24] Under the null of independent observations, the probability of observing only two positive correlations out of twenty is .000. Under the null that there are only ten independent observations, the probability of observing one positive correlation is .011.

flexibility links seasonal cycles and business cycles so that it is not possible to correctly study the two types of fluctuations separately. In our model the amount of seasonal variation in demand is a crucial determinant of the firm's non-seasonal output variability, and the non-seasonal variation in demand partly determines the firm's seasonal pattern of production. Seasonal and non-seasonal fluctuations therefore interact and jointly determine the mechanisms by which both seasonal cycles and business cycles are propagated.

A corollary is that both anticipated and unanticipated shocks can have real effects, and these effects cannot always be sharply distinguished. Over horizons that matter, firms in our model respond similarly to all shifts in demand regardless of how well anticipated. The degree of flexibility chosen *ex ante* affects the *ex post* response to both anticipated and unanticipated shocks. Of course, if policymakers systematically attempted to exploit the medium-term fixity of technological flexibility, firms would adjust their choice of flexibility (the Lucas (1976) critique). Nevertheless, policies that smooth anticipated fluctuations have real effects.

A second implication of our model is that the technology is not something that can be treated as exogenously determined, as it is in the real business cycle models of Prescott (1986) and others. Instead, the degree of technological flexibility is chosen endogenously by firms in response to the degree of demand and cost variability. Of course exogenous technology shocks may be one source of aggregate fluctuations, but our model suggests that the path of technology should not be taken as something determined entirely outside the model. As long as there is more than one way to produce output, firms' choice of method is affected by the stochastic environment in which they operate, and this implies interactions between the nature of demand shocks and supply shocks.

Finally, our model is potentially consistent with the view (*e.g.*, De Long and Summers (1988), Ramey and Ramey (1991)) that the stabilization of output has first-order effects on welfare by raising the average level of output in addition to reducing its variance. Over fifty years ago Kuznets (1933) suggested this as a reason for stabilizing the seasonal cycle. Since we have not yet modeled the general equilibrium of the economy in which our firm resides, we cannot say whether it would improve welfare for policymakers to stabilize output; unused capacity is not equivalent to socially "excessive" capacity. It does follow, however, even in our simple model, that stabilizing demand—either seasonally or non-seasonally—would reduce the amount of resources invested in capacity and thus have a first-order effect on output.

ADDITIONAL ACKNOWLEDGEMENTS

Beaulieu acknowledges financial support from an NSF Graduate Fellowship; Mackie-Mason and Miron are grateful for financial support from NSF Grant SES-8921506, and Miron thanks the John M. Olin Foundation for a fellowship at the National Bureau of Economic Research.

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Table 1. Cross-Country Regressions: Non-Seasonal Standard Deviation on Seasonal Standard Deviation						
	Retail Sales	*Indus. Prod.*	*Money*	*Prices*	*Nom. Rate*	*Real Rate*
Coefficient	.22	.18	.51	1.91	2.27	.86
t-statistic	(2.36)	(2.42)	(2.93)	(4.74)	(3.83)	(3.18)
$\bar{R}^2$	.13	.34	.17	.66	.47	.52
Sample Size	18	20	23	21	11	10

Notes:

1. Weighted least squares regression results with weights equal to the fourth root of the sample length minus one, $(N-1)^{1/4}$.

Table 2. Cross-Industry Regressions: Non-Seasonal Standard Deviation on Seasonal Standard Deviation					
	Y4	*IP*	*Shipments*	*Inventories*	*Prod. Wrk. Hrs.*
Coefficient	.53	.32	.50	.76	.49
t-statistic	(2.55)	(9.50)	(2.05)	(25.85)	(7.39)
$\bar{R}^2$	.22	.60	.18	.91	.35
Sample Size	20	20	20	20	20
	Avg. Hours	*Prod. Workers*	*Total Emp.*	*Wages*	*Prices*
Coefficient	1.25	.42	.40	.70	.88
t-statistic	(8.00)	(5.45)	(6.39)	(28.19)	(1.34)
$\bar{R}^2$	.73	.20	.22	.86	.09
Sample Size	20	20	20	20	17

Notes:

1. OLS regression results except for prices, which is estimated by weighted least squares; see text for details.
2. Y4 is shipments plus the change in inventories.

Table 3a. Simulated Capacity Model					
Seas. Shift	Optimal "Capacity"	*Std. Dev. of Output*		*Non-seasonal Std. Dev. of Output*	
σ	ϕ^*	Seas.	Non-Seas.	Low Seas.	High Seas.
0.0	5.661	0.000	0.169	0.029	0.029
0.5	5.676	0.085	0.170	0.032	0.026
1.0	5.722	0.173	0.174	0.037	0.024
1.5	5.798	0.263	0.179	0.042	0.022
2.0	5.905	0.359	0.186	0.048	0.021
2.5	6.044	0.462	0.195	0.056	0.020
3.0	6.216	0.573	0.205	0.065	0.019
3.5	6.419	0.694	0.217	0.075	0.019
4.0	6.654	0.825	0.230	0.087	0.019
4.5	6.920	0.966	0.244	0.100	0.019
5.0	7.214	1.119	0.258	0.113	0.020
5.5	7.536	1.282	0.272	0.128	0.020
6.0	7.882	1.455	0.286	0.142	0.021
6.5	8.249	1.637	0.299	0.157	0.021
7.0	8.636	1.828	0.312	0.172	0.022
7.5	9.039	2.026	0.324	0.186	0.023
8.0	9.457	2.231	0.335	0.200	0.024
Correl.		.997			

Notes:

1. Each row contains the results from a different simulation, with the seasonal shift parameter indicated. For all simulations, the other parameter values are: $e = \pm 1$; $a = 10$; $b = 1$; $c = 1$; $\delta = .5$; $q = 1$.
2. ϕ^* is the optimal choice of the flexibility parameter ("capacity").
3. *Correl.* gives the correlation between the seasonal standard deviation of output and the non-seasonal standard deviation of output.

Table 3b. Simulated Capacity Model					
Seas. Shift	Optimal "Capacity"	*Std. Dev. of Output*		*Non-seasonal Std. Dev. of Output*	
σ	ϕ^*	Seas.	Non-Seas.	Low Seas.	High Seas.
0.0	2.475	0.000	0.051	0.003	0.003
0.5	2.480	0.027	0.053	0.004	0.002
1.0	2.494	0.055	0.057	0.005	0.002
1.5	2.518	0.087	0.065	0.007	0.001
2.0	2.554	0.124	0.077	0.011	0.001
2.5	2.604	0.170	0.093	0.016	0.001
3.0	2.670	0.226	0.112	0.024	0.001
3.5	2.754	0.296	0.133	0.035	0.001
4.0	2.858	0.382	0.156	0.048	0.001
4.5	2.982	0.484	0.177	0.062	0.001
5.0	3.123	0.602	0.195	0.076	0.001
5.5	3.277	0.734	0.210	0.088	0.001
6.0	3.443	0.876	0.222	0.098	0.001
6.5	3.615	1.025	0.231	0.106	0.001
7.0	3.794	1.181	0.238	0.112	0.001
7.5	3.976	1.340	0.244	0.117	0.002
8.0	4.161	1.502	0.248	0.122	0.002
Correl.		.945			

Notes:

1. Each row contains the results from a different simulation, with the seasonal shift parameter indicated. For all simulations, the other parameter values are: $e = \pm 1$; $a = 10$; $b = 2.5$; $c = .25$; $\delta = .5$; $q = 2.5$.
2. ϕ^* is the optimal choice of the flexibility parameter ("capacity").
3. *Correl.* gives the correlation between the seasonal standard deviation of output and the non-seasonal standard deviation of output.

Table 4a: Tests for Heteroskedasticity in Growth Rates – IP, OECD Countries									
Country	*Heteroskedasticity*		*Pattern*		*Country*	*Heteroskedasticity*		*Pattern*	
	χ^2_{11}	*p-value*	*Correl.*	*p-value*		χ^2_{11}	*p-value*	*Correl.*	*p-value*
Australia	9.83	.546	.420	.913	Japan	30.96	.001	-.538	.035
Austria	12.69	.314	-.147	.324	Luxembourg	140.33	.000	-.650	.011
Belgium	36.30	.000	-.734	.003	Netherlands	92.90	.000	-.280	.189
Canada	87.35	.000	-.469	.062	Norway	64.64	.000	-.685	.007
Finland	85.71	.000	-.650	.011	Portugal	52.38	.000	-.105	.373
France	77.14	.000	-.874	.000	Spain	86.55	.000	-.559	.029
Germany	58.54	.000	-.608	.018	Sweden	112.89	.000	-.455	.069
Greece	59.93	.000	.720	.996	United Kingdom	98.26	.000	-.161	.309
Ireland	20.52	.039	-.685	.007	United States	32.07	.001	-.580	.024
Italy	67.71	.000	-.413	.091	Yugoslavia	41.13	.000	-.329	.148

Table 4b: Tests for Heteroskedasticity in Growth Rates – IP, U.S. Manufacturing Industries									
Industry	*Heteroskedasticity*		*Pattern*		*Industry*	*Heteroskedasticity*		*Pattern*	
	χ^2_{11}	*p-value*	*Correl.*	*p-value*		χ^2_{11}	*p-value*	*Correl.*	*p-value*
Food	77.67	.000	-.154	.317	Stone, Clay, Glass	26.41	.006	-.713	.005
Tobacco	23.79	.014	-.287	.183	Primary Metals	14.60	.202	-.517	.042
Textiles	24.19	.012	-.776	.001	Fabricated Metals	10.77	.463	-.371	.118
Apparel	202.64	.000	-.685	.007	Machinery	11.31	.417	.063	.577
Lumber	26.64	.005	-.455	.069	Electrical Machinery	34.63	.000	-.385	.109
Furniture	27.85	.003	-.315	.160	Transportation Eqp.	59.71	.000	-.804	.001
Paper	31.50	.001	-.301	.171	Instruments	12.58	.321	-.154	.317
Printing	39.61	.000	.175	.707	Miscellaneous Mfg.	9.28	.596	-.587	.022
Chemicals	17.58	.092	-.448	.072					
Petroleum	25.23	.008	-.531	.038	Non–Durables	32.47	.001	-.007	.491
Rubber	21.05	.033	-.224	.242	Durables	66.01	.000	-.671	.008
Leather	45.30	.000	-.909	.000	Total Manufacturing	66.24	.000	-.573	.026

continued

Table 4c: Tests for Heteroskedasticity in Growth Rates – Y4, U.S. Manufacturing Industries									
Industry	*Heteroskedasticity*		*Pattern*		*Industry*	*Heteroskedasticity*		*Pattern*	
	χ^2_{11}	*p-value*	*Correl.*	*p-value*		χ^2_{11}	*p-value*	*Correl.*	*p-value*
Food	51.01	.000	-.294	.177	Stone, Clay, Glass	31.58	.001	-.392	.104
Tobacco	25.71	.007	-.154	.317	Primary Metals	29.34	.002	-.035	.457
Textiles	33.66	.000	.329	.852	Fabricated Metals	35.30	.000	-.734	.003
Apparel	15.40	.165	-.580	.024	Machinery	37.54	.000	-.357	.128
Lumber	49.94	.000	-.448	.072	Electrical Machinery	45.11	.000	-.329	.148
Furniture	11.03	.441	-.182	.286	Transportation Eqp.	28.19	.003	-.629	.014
Paper	47.63	.000	-.448	.072	Instruments	31.16	.001	-.028	.466
Printing	23.96	.013	-.357	.128	Miscellaneous Mfg.	38.03	.000	-.329	.148
Chemicals	35.02	.000	.070	.585					
Petroleum	16.14	.136	-.273	.196	Non–Durables	17.07	.106	-.175	.293
Rubber	34.69	.000	-.629	.014	Durables	42.73	.000	-.385	.109
Leather	28.49	.003	-.182	.286	Total Manufacturing	33.18	.000	-.343	.138

Notes for Tables 4a–4c:

1. χ^2_{11} are statistics for the hypothesis that all monthly variances are the same. *P–values* are the significance levels for the chi-square statistics.
2. *Correl.* gives the Spearman Rank Correlation between the montly variances of the growth rates and the average level of the series in that month. *P-values* are for test that the correlation ≤ 0 using a t-test approximation.
3. Y4 is shipments plus the change in inventories.

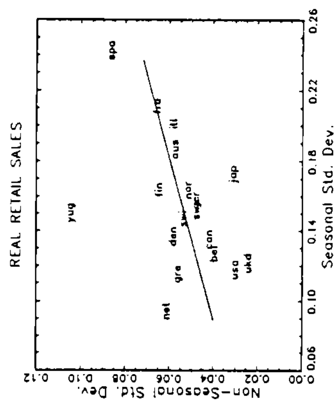


Figure 1

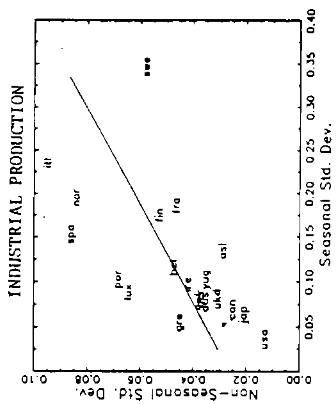


Figure 2

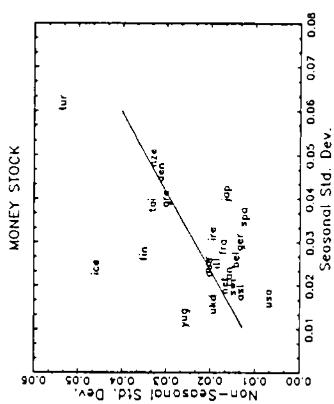


Figure 3

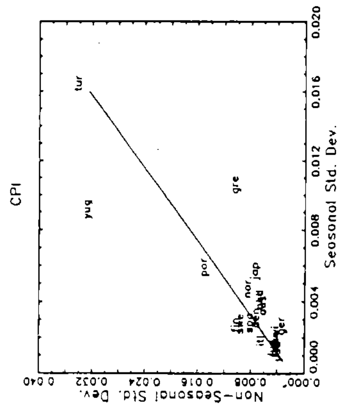


Figure 4

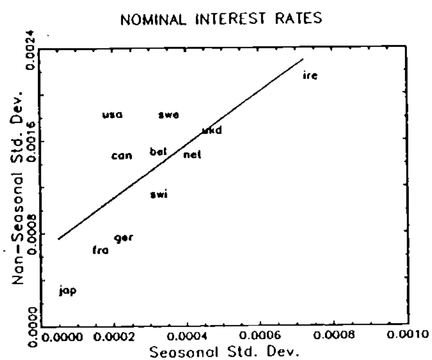


Figure 5

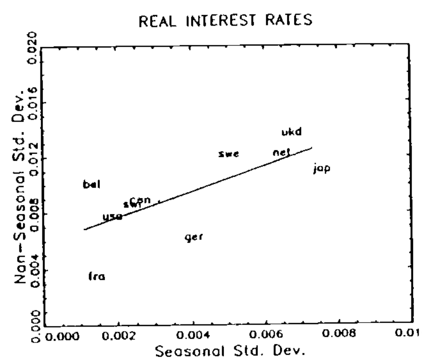
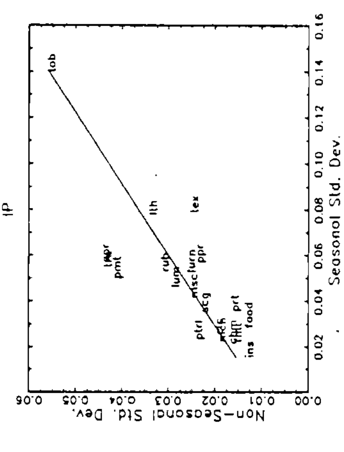


Figure 6



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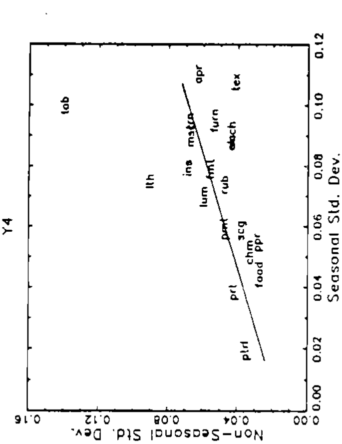


Figure 8

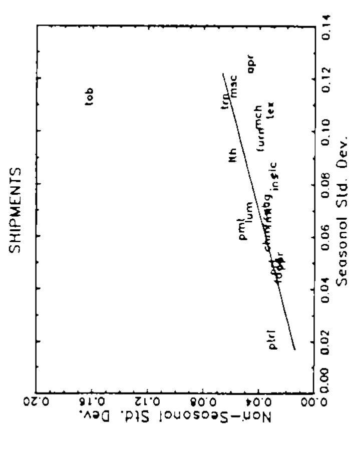


Figure 9

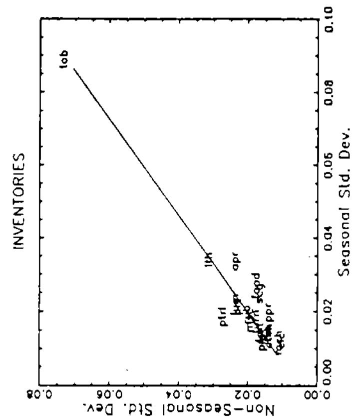


Figure 10

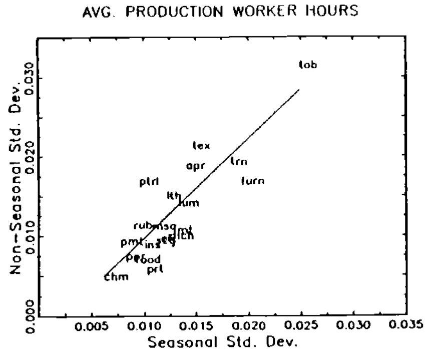


Figure 11

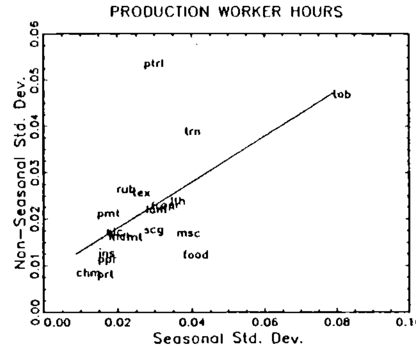


Figure 12

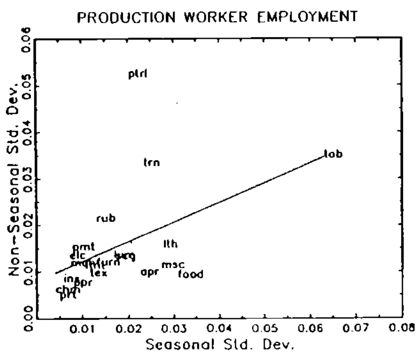


Figure 13

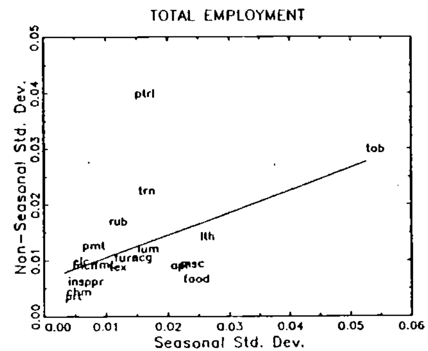


Figure 14

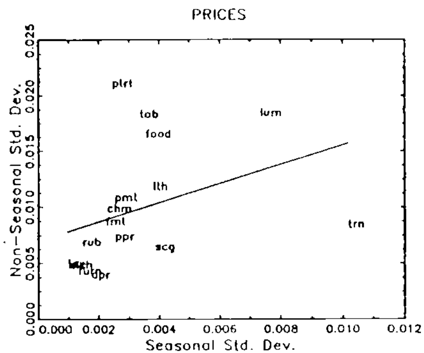


Figure 15

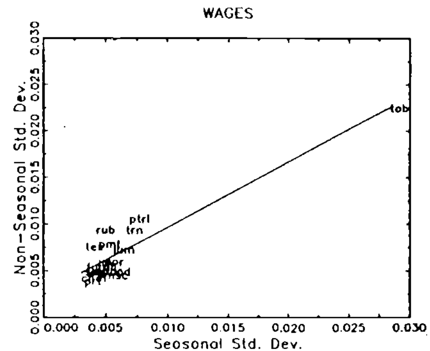
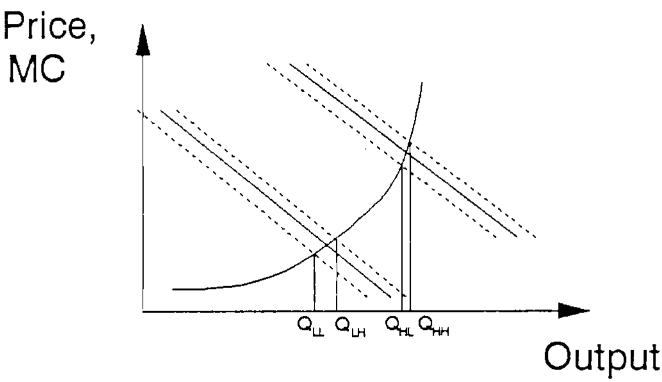


Figure 16

Figure 17: Fluctuations in Demand and Capacity Choice

Low Seasonal Variance



High Seasonal Variance

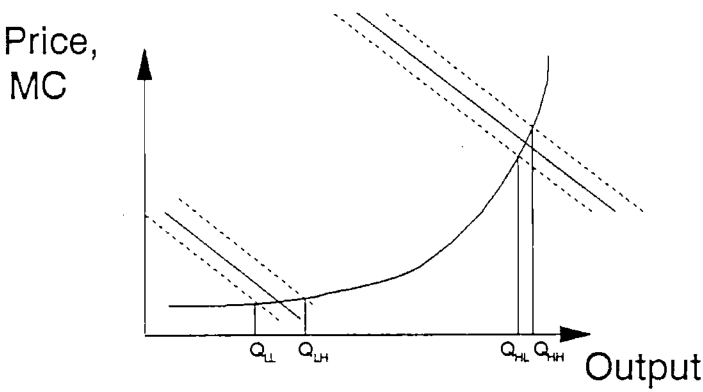


Table A1. Cross-Country Regressions: Non-Seasonal Standard Deviation on Seasonal Standard Deviation Selected Countries Excluded				
Excld. Countries	Spn, Yug	Swe	Ice, Tur	Gre, Tur, Yug
	Retail Sales	*Indus. Prod.*	*Money*	*Prices*
Coefficient	.15	.31	.38	1.37
T–Statistic	(1.39)	(5.37)	(2.42)	(3.11)
$\bar{R}^2$	.07	.54	.13	.43

Notes:

1. Weighted least squares regression results with weights equal to the fourth root of the sample length minus one, $(N-1)^{1/4}$.

Table A2. Cross-Industry Regressions: Non-Seasonal Standard Deviation on Seasonal Standard Deviation Selected Industries Excluded					
Excld. Industries	*Tobacco*				
	Y4	*IP*	*Shipments*	*Inventories*	*Prod. Wrk. Hrs.*
Coefficient	.35	.34	.25	.60	.53
t-statistic	(3.54)	(3.52)	(3.41)	(5.21)	(2.30)
$\bar{R}^2$	.23	.40	.30	.52	.14
	Avg. Hours	*Prod. Workers*	*Total Emp.*	*Wages*	*Prices*
Coefficient	1.07	.43	.32	1.21	.85
t-statistic	(5.49)	(1.58)	(1.75)	(5.18)	(1.38)
$\bar{R}^2$	.53	.05	.02	.42	.10
Excld. Industries	*Tobacco and Petroleum*			*Transp.*	*Lum. & Trn.*
	Prod. Wrk. Hrs.	*Prod. Workers*	*Total Emp.*	*Prices*	
Coefficient	.45	.27	.22	2.33	3.22
T–Statistic	(2.16)	(1.43)	(1.85)	(5.20)	(3.04)
$\bar{R}^2$	.26	.07	.07	.39	.32

Notes:

1. OLS regression results except for prices, which are weighted least squares; see text for details.

Table A3. Cross-Country Regressions with Country Characteristics Included: Non-Seasonal Standard Deviation on Seasonal Standard Deviation and Country Characteristics							
	Retail Sales	*Indus. Prod.*	*Money*	*CPI*	*Nom. Rate*	*Real Rate*	Controls
Coefficient	.18	.15	.42	1.88	2.86	.84	TGNP
t-statistic	(2.08)	(2.10)	(2.39)	(4.69)	(4.57)	(3.07)	
$\bar{R}^2$	.24	.39	.25	.65	.59	.47	
Coefficient	.22	.19	.19	1.49	3.03	.94	AG
t-statistic	(2.57)	(2.61)	(1.37)	(3.11)	(3.80)	(3.77)	
$\bar{R}^2$	.50	.34	.37	.65	.48	.50	
Coefficient	.30	.19	.67	1.54	1.69	1.01	MFG
t-statistic	(2.90)	(2.51)	(4.20)	(3.87)	(2.24)	(3.49)	
$\bar{R}^2$	.31	.33	.26	.72	.67	.65	
Coefficient	.14	.18	.39	1.57	3.08	.84	PCGNP
t-statistic	(1.62)	(2.78)	(2.68)	(4.86)	(4.45)	(2.33)	
$\bar{R}^2$	.39	.39	.16	.68	.56	.46	
Coefficient	.18	.16	.17	1.47	4.42	.92	TGNP, AG
t-statistic	(1.91)	(2.30)	(1.31)	(3.09)	(13.38)	(3.81)	& PCGNP
$\bar{R}^2$	.49	.34	.49	.62	.82	.34	
Coefficient	.25	.16	.58	1.52	3.54	.95	TGNP, MFG
t-statistic	(2.61)	(2.43)	(3.69)	(3.97)	(7.25)	(3.02)	& PCGNP
$\bar{R}^2$	.41	.36	.26	.68	.81	.53	

Notes:

1. Weighted least squares regression results with weights equal to the fourth root of the sample length minus one, $(N-1)^{1/4}$.
2. *TGNP* denotes the total GNP of the country in mid-1985 (dollars). *AG* denotes the share of GDP devoted to agriculture in 1985. *MFG* denotes the share of GDP devoted to manufacturing in 1985. *PCGNG* denotes the GNP per capita in 1985 (dollars).
3. The sample size varies according to the availability of data on the control variables.

Table A4. Cross-Industry Regressions with Industry Characteristics Included: Non-Seasonal Standard Deviation on Seasonal Standard Deviation and Industry Characteristics						
	Y4	*IP*	*Shipments*	*Inventories*	*Prod. Wrk. Hrs.*	Controls
Coefficient	.46	.30	.45	.77	.49	E7
t-statistic	(2.25)	(7.88)	(1.98)	(28.26)	(4.80)	
$\bar{R}^2$	.19	.59	.14	.91	.31	
Coefficient	.46	.30	.39	.76	.42	C4
t-statistic	(3.13)	(6.35)	(2.99)	(22.26)	(5.19)	
$\bar{R}^2$	.28	.63	.34	.91	.35	
Coefficient	.56	.30	.59	.76	.46	Union
t-statistic	(2.46)	(9.91)	(2.21)	(22.90)	(7.32)	
$\bar{R}^2$	.18	.69	.27	.91	.35	
Coefficient	.57	.32	.57	.75	.45	Stock
t-statistic	(2.40)	(8.17)	(2.00)	(17.96)	(4.43)	
$\bar{R}^2$	.21	.59	.25	.91	.34	
Coefficient	.57	.35	.56	.76	.48	Durb
t-statistic	(2.16)	(9.04)	(1.85)	(20.30)	(6.20)	
$\bar{R}^2$	.20	.62	.18	.91	.31	
Coefficient	.27	.37	.29	.51	.52	Union, C4 & Durb
t-statistic	(2.47)	(5.09)	(3.91)	(3.37)	(2.40)	
$\bar{R}^2$	.11	.52	.30	.47	.09	
Coefficient	.27	.37	.29	.51	.50	Union, C4 & Stock
t-statistic	(2.74)	(4.60)	(4.49)	(3.39)	(2.30)	
$\bar{R}^2$	.13	.52	.30	.47	.12	
Coefficient	.25	.25	.17	.53	.44	E7, C4 & Durb
t-statistic	(2.07)	(1.76)	(2.11)	(3.62)	(1.35)	
$\bar{R}^2$	.11	.45	.26	.47	.10	
Coefficient	.20	.29	.27	.57	.46	Union, E7 & Stock
t-statistic	(1.28)	(2.57)	(3.01)	(4.10)	(1.42)	
$\bar{R}^2$	.16	.50	.30	.44	.07	
Sample Size	20	20	20	20	20	

continued

Table A4. Cross-Industry Regressions with Industry Characteristics Included: Non-Seasonal Standard Deviation on Seasonal Standard Deviation and Industry Characteristics						
	Avg. Hours	*Prod. Workers*	*Total Emp.*	*Wages*	*Prices*	Controls
Coefficient	1.11	.49	.46	.69	.89	E7
t-statistic	(6.67)	(3.69)	(4.23)	(24.47)	(1.26)	
$\bar{R}^2$	.76	.19	.20	.86	.04	
Coefficient	1.21	.32	.33	.67	.87	C4
t-statistic	(7.45)	(3.30)	(5.05)	(19.07)	(1.34)	
$\bar{R}^2$	.72	.25	.26	.86	.02	
Coefficient	1.24	.36	.36	.68	.80	Union
t-statistic	(8.43)	(4.74)	(5.97)	(29.70)	(1.15)	
$\bar{R}^2$	.72	.25	.27	.86	.03	
Coefficient	1.25	.35	.33	.68	1.07	Stock
t-statistic	(10.76)	(2.94)	(3.10)	(15.78)	(1.75)	
$\bar{R}^2$	.78	.19	.22	.86	.28	
Coefficient	1.29	.42	.40	.69	1.11	Durb
t-statistic	(11.68)	(5.11)	(5.26)	(21.35)	(1.82)	
$\bar{R}^2$	.79	.15	.18	.85	.18	
Coefficient	1.27	.38	.33	1.11	1.20	Union, C4 & Durb
t-statistic	(7.36)	(1.71)	(1.98)	(4.41)	(2.95)	
$\bar{R}^2$	.58	.06	-.01	.35	.10	
Coefficient	1.23	.32	.29	1.07	1.22	Union, C4 & Stock
t-statistic	(6.51)	(1.49)	(1.69)	(4.17)	(3.17)	
$\bar{R}^2$	.53	.11	.04	.35	.18	
Coefficient	.99	.47	.38	1.00	1.58	E7, C4 & Durb
t-statistic	(9.56)	(1.30)	(1.21)	(3.36)	(3.82)	
$\bar{R}^2$	.74	.02	-.06	.45	.27	
Coefficient	1.01	.41	.32	1.03	1.00	Union, E7 & Stock
t-statistic	(5.20)	(1.23)	(1.08)	(3.49)	(1.48)	
$\bar{R}^2$	.66	.07	.01	.38	.07	
Sample Size	20	20	20	20	17	

Notes:

1. OLS regression results except for prices, which is estimated by weighted least squares; see text for details.
2. *E7* denotes the ratio of non-production workers to total employment in 1977. *Union* denotes the percentage of employees in unions in 1983. *C4* denotes a measure of concentration in each industry based on the Four-Firm Concentration Ratios reported in the 1977 Census. *Stock* denotes a dummy for the six production to stock industries, Food, Tobacco, Apparel, Chemicals, Petroleum, and Rubber. *Durb* denotes a dummy for the ten durable goods industries.

Table A5. Multivariate Cross-Country Regressions:
Non-Seasonal Standard Deviation on Seasonal Standard Deviation and Country Characteristics

	Retail Sales		*Indus. Prod.*		*Money*		*CPI*		*Nom. Rates*		*Real Rates*	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
SEASONAL	.19	1.90	.17	2.56	.29	2.27	1.19	2.81	3.33	9.90	1.20	4.53
	(.06)	(.62)	(.02)	(.38)	(.15)	(1.26)	(.47)	(1.21)	(.81)	(5.81)	(.21)	(1.67)
AREA	-.10	-1.18	-.16	2.07	-.10	-1.97	.00	.06	.01	2.24	-.01	-.30
	(.09)	(.92)	(.08)	(1.21)	(.06)	(1.01)	(.02)	(1.16)	(.00)	(1.21)	(.02)	(1.28)
POP	-.11	-2.45	-.06	-1.27	-.06	-3.02	-.01	-.93	.00	3.09	-.00	-.62
	(.03)	(.73)	(.03)	(.75)	(.02)	(1.16)	(.01)	(.73)	(.00)	(2.19)	(.01)	(1.62)
TOTGNP	-.61	-2.24	-.43	-1.78	-.36	-3.05	-.06	-.93	.01	4.39	-.02	-.41
	(.20)	(.73)	(.21)	(1.00)	(.11)	(1.29)	(.05)	(.78)	(.01)	(2.75)	(.05)	(1.55)
AGRSHR	.23	1.56	.04	.73	.10	2.39	.02	.43	-.00	-2.12	-.08	-.93
	(.16)	(.91)	(.08)	(.91)	(.04)	(.90)	(.04)	(.79)	(.01)	(2.33)	(.07)	(.93)
MFGSHR	-.08	-1.53	-.01	-.12	-.06	-2.30	-.00	-.20	-.00	-4.45	-.03	-2.76
	(.03)	(.41)	(.05)	(.61)	(.02)	(.57)	(.01)	(.76)	(.00)	(4.17)	(.01)	(.82)
INDSHR	.03	.17	.10	1.26	-.05	-1.83	.03	1.12	-.01	-6.30	-.05	-4.10
	(.05)	(.73)	(.03)	(.47)	(.02)	(.78)	(.01)	(.16)	(.00)	(2.70)	(.01)	(1.65)
SERSHR	-.09	-1.19	-.09	-1.39	.01	.40	-.04	-1.42	.00	5.00	.05	4.22
	(.07)	(.90)	(.03)	(.65)	(.03)	(1.10)	(.01)	(.27)	(.00)	(2.36)	(.01)	(1.60)
PCGNP	-.20	-1.91	-.08	-.54	.02	.25	-.03	-1.15	.01	2.82	-.03	-1.11
	(.07)	(.62)	(.04)	(.27)	(.07)	(1.08)	(.02)	(.66)	(.00)	(1.40)	(.03)	(1.05)
LIFE	-.05	-.25	-.02	-.20	-.10	-1.62	-.02	.32	-.00	-.89	-.10	-2.31
	(.22)	(1.01)	(.08)	(.46)	(.06)	(.97)	(.03)	(.46)	(.01)	(1.01)	(.03)	(1.13)
BIRTH	.26	1.17	-.42	-2.22	.15	3.35	.08	2.70	.00	.74	-.01	-.30
	(.19)	(.84)	(.10)	(.64)	(.04)	(1.19)	(.01)	(1.13)	(.01)	(1.46)	(.04)	(.86)
INFMOR	.20	2.76	.12	1.09	.03	4.85	.02	2.94	.00	.37	.05	1.40
	(.09)	(1.38)	(.15)	(1.33)	(.01)	(1.95)	(.00)	(1.72)	(.00)	(.35)	(.02)	(.77)
POPMD	-.35	-1.62	-.25	-.64	.17	3.31	.09	1.72	-.01	-1.49	-.00	-.04
	(.20)	(1.44)	(.19)	(.47)	(.05)	(1.10)	(.02)	(.87)	(.00)	(1.35)	(.03)	(.52)
CALOR	.23	1.84	.14	1.20	-.07	-.95	-.01	-.34	.00	1.16	.03	.93
	(.07)	(.21)	(.08)	(.68)	(.04)	(.55)	(.02)	(.53)	(.00)	(.48)	(.01)	(.24)
SCHOOL	.02	.43	-.07	-1.48	-.03	-1.30	.01	.87	.00	6.78	.00	.35
	(.04)	(.73)	(.02)	(.43)	(.02)	(.79)	(.01)	(.59)	(.00)	(3.16)	(.01)	(1.45)
LFAGR	.15	2.07	.05	.79	.04	3.03	.05	3.48	-.00	-1.60	-.05	-2.60
	(.06)	(.46)	(.04)	(.69)	(.03)	(1.99)	(.02)	(.57)	(.01)	(2.91)	(.01)	(.46)
URBAN	-.05	-1.55	-.02	-1.11	-.03	-2.83	-.01	-1.82	-.00	.14	.02	3.89
	(.02)	(.66)	(.01)	(.43)	(.01)	(.83)	(.00)	(.33)	(.00)	(2.20)	(.00)	(1.07)
$\bar{R}^2$	.42		.40		.42		.69		.80		.60	
	(.12)		(.05)		(.12)		(.06)		(.11)		(.15)	

continued

Notes:

1. The statistics are generated from regressions of the Non-Seasonal Standard Deviation times 100 on a constant, the Seasonal Standard Deviation times 100 and one variable from each of the three demarcated groups. The three groups measure the size of the country, the composition of GDP, and the level of economic development. The averages of all combinations are reported. Thus, SEASONAL reports the average coefficient on the Seasonal Standard Deviation from 108 regressions ($3 \times 4 \times 9$). AREA reports the average coefficient on the area variable from 36 regressions (4×9). The constant is not reported. Weighted least squares is used with weights equal to the fourth root of the sample length minus one, $(N-1)^{1/4}$.
2. Coeff is the average coefficient on that right-hand side variable for all regressions in which that variable is included. Standard deviations are in parentheses. Likewise, t–stat reports the average t–statistic.
3. *AREA*, is millions of square kilometers. *POP*, is total the population in hundred millions, mid–1985. *TOTGNP*, is the total GNP in billions of 1985 dollars. *AGRSHR*, is the share of agriculture in GDP, 1985. *MFGSHR*, is the share of manufacturing in GDP, 1985. *INDSHR*, is the share of industry in GDP, 1985. *SERSHR*, is the share of services in GDP, 1985. *PCGNP*, is GNP per capita in thousands of 1985 dollars. *LIFE*, is the life expectancy at birth as of 1985. *BIRTH*, is the crude birth rate per thousand population, 1985. *INFMOR*, is the infant mortality rate, 1985. *POPMD*, is the population per physician, ten thousands, 1981. *CALOR*, is the daily calorie supply per capita, ten thousands, 1985. *SCHOOL*, is the number of people enrolled in school as a percentage of age group, higher education, 1984. *LFAGR*, is the percent of labor force in agriculture, 1980. *URBAN*, is the percent of population in urban areas, 1985.

Table A6. Cross-Country Regressions: Non-Seasonal Standard Deviation on Seasonal Standard Deviation Various Robustness Checks							
	Retail Sales	*Indus. Prod.*	*M1*	*CPI*	*Nom. Rate*	*Real Rate*	*Type*
Coefficient	.30	.09	.43	1.87	—	—	First Half of
T-Statistic	(4.32)	(2.08)	(1.96)	(4.76)	—	—	time series
$\bar{R}^2$	.17	.21	.09	.65	—	—	sample
Coefficient	.10	.10	.52	1.16	2.70	.71	Second Half of
T-Statistic	(1.05)	(2.29)	(2.86)	(2.93)	(4.78)	(1.41)	time series
$\bar{R}^2$	.09	.19	.22	.44	.51	.13	sample
Coefficient	.19	.07	.56	1.92	—	—	EZ X-11
T-Statistic	(.84)	(2.63)	(.23)	(4.55)	—	—	
$\bar{R}^2$	-.05	.22	-.07	.66	—	—	
Coefficient	.62	.04	.61	9.99	4.13	—	Detrended
T-Statistic	(2.19)	(1.02)	(.53)	(4.11)	(2.38)	—	Levels
$\bar{R}^2$	.39	.02	.08	.50	.29	—	

Notes:

1. Weighted least squares regression results with weights equal to the fourth root of the sample length minus one, $(N-1)^{1/4}$.
2. The first half of the split sample is the longest possible subsample of the period 1960:2–1973:12. The second half is 1974:1–1987:12.
3. EZX–11 uses the EZX–11 data program (Doan, 1989) with default values for outliers (Outlier limit = 2.5; Graduate extremes, lower = 1.5, upper = 2.5). It also adjusts for Easter, Thanksgiving and Labor Day. It does not adjust for trading days. M1 is missing data for Australia and Belgium.
4. Detrended levels means the data were detrended using a quadratic trend.

Table A7. Cross Industry Regressions: Non-Seasonal Standard Deviation on Seasonal Standard Deviation Various Robustness Checks						
	Y4	*IP*	*Shipments*	*Inventories*	*Prod. Wrk. Hrs.*	*Type*
Coefficient	.41	.28	.20	.73	.42	First Half of
T-Statistic	(3.52)	(7.43)	(1.55)	(16.57)	(5.27)	time series
$\bar{R}^2$	.28	.51	.11	.89	.31	sample
Coefficient	.71	.32	.64	.56	.49	Second Half of
T-Statistic	(2.62)	(10.46)	(2.33)	(30.80)	(6.97)	time series
$\bar{R}^2$	.50	.70	.52	.88	.33	sample
Coefficient	.43	.31	.28	.60	.57	First Half,
T-Statistic	(3.78)	(4.35)	(2.56)	(7.96)	(2.07)	No Tobacco
$\bar{R}^2$	.34	.42	.26	.65	.19	
Coefficient	.31	.26	.19	.43	.52	Second Half,
T-Statistic	(3.54)	(3.52)	(3.57)	(3.55)	(2.76)	No Tobacco
$\bar{R}^2$	.23	.32	.29	.30	.17	
Coefficient	.43	.25	.26	.53	-.11	Census X-11
T-Statistic	(2.96)	(10.40)	(2.27)	(34.80)	(-.97)	adjusted
$\bar{R}^2$	.25	.57	.18	.88	-.02	data
Coefficient	.43	.25	.26	.55	.42	EZ X-11
T-Statistic	(2.74)	(8.62)	(2.21)	(33.41)	(5.73)	adjusted
$\bar{R}^2$	.23	.52	.17	.89	.25	data
Coefficient	.80	-.07	.45	.51	-.14	Detrended
T-Statistic	(3.05)	(-.31)	(1.93)	(1.66)	(-.78)	Levels
$\bar{R}^2$	.30	-.05	.14	.21	-.03	
Coefficient	.64	.21	.29	-.29	.43	Detrended
T-Statistic	(2.25)	(.56)	(1.43)	(-1.88)	(1.11)	Levels, No
$\bar{R}^2$	.20	-.04	.05	.01	.00	Food or Tobacco

continued

Table A7. Cross Industry Regressions: Non-Seasonal Standard Deviation on Seasonal Standard Deviation Various Robustness Checks (continued)						
	Avg. Hours	*Prod. Workers*	*Total Emp.*	*Wages*	*Prices*	*Type*
Coefficient	1.21	.38	.35	.56	1.44	First Half of
T-Statistic	(4.15)	(3.83)	(5.26)	(11.69)	(5.87)	time series
$\bar{R}^2$	.72	.22	.21	.69	.52	sample
Coefficient	1.19	.36	.31	.65	.80	Second Half of
T-Statistic	(8.42)	(3.48)	(4.66)	(37.88)	(1.17)	time series
$\bar{R}^2$	.65	.15	.17	.93	.09	sample
Coefficient	.77	.59	.48	1.43	1.41	First Half,
T-Statistic	(5.38)	(1.62)	(1.57)	(4.88)	(5.62)	No Tobacco
$\bar{R}^2$	.58	.15	.10	.52	.50	
Coefficient	1.35	.40	.29	1.02	.56	Second Half,
T-Statistic	(4.81)	(1.61)	(2.14)	(4.14)	(1.09)	No Tobacco
$\bar{R}^2$	.54	.08	.07	.60	.02	
Coefficient	1.19	.32	.28	—	—	Census X-11
T-Statistic	(6.14)	(4.22)	(4.87)	—	—	adjusted
$\bar{R}^2$	.65	.11	.09	—	—	data
Coefficient	1.15	.31	.26	.52	.73	EZ X-11
T-Statistic	(9.58)	(3.79)	(4.68)	(18.90)	(1.12)	adjusted
$\bar{R}^2$	.70	.09	.08	.75	.05	data
Coefficient	.87	-.14	-.09	.01	8.87	Detrended
T-Statistic	(3.32)	(-.84)	(-.50)	(.14)	(1.63)	Levels
$\bar{R}^2$	.23	-.03	-.05	-.06	.25	
Coefficient	.96	.35	.32	1.02	8.82	Detrended
T-Statistic	(1.83)	(.95)	(.74)	(.92)	(1.62)	Levels, No
$\bar{R}^2$	.14	-.02	-.03	-.00	.24	Food or Tobacco

Notes:

1. OLS regression results except for prices, which are weighted least squares; see text for details.
2. The first half of the split sample is 1967:5–1977:9; the second half is 1977:10–1987:12.
3. Census X–11 uses actual seasonally adjusted data. Seasonally adjusted data for Tobacco, Petroleum and Miscellaneous Manufacturing is unavailable for average hours and production worker hours.
4. EZX–11 uses the EZX–11 data program (Doan, 1989) with default values for outliers (Outlier limit = 2.5; Graduate extremes, lower = 1.5, upper = 2.5). It also adjusts for Easter, Thanksgiving and Labor Day. It does not adjust for trading days.
4. Detrended levels means the data were detrended using a quadratic trend.