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Market Structure, Technology and the Cyclicality of Output*

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Abstract

This paper examines a broad spectrum of technological and market structure characteristics to assess which factors may be important determinants of the relative cyclicality across industries. Utilizing a panel of 296 manufacturing industries, we find that the durability of output is fundamental to the cyclical behavior of manufacturing. Within durable goods industries, the factor intensities of raw materials, energy, and production workers are all positively associated with industry cyclicality. Industry concentration and the degree of labor hoarding, but not unionization, are also strongly associated with cyclicality. These results have implications for both Keynesian and RBC style models of the business cycle.

I. Introduction

Fundamental to current research on business cycles is the interaction between the microeconomic structure of the economy and macroeconomic behavior. For example, modern Keynesian models utilize price rigidities arising from imperfect competition in input and output markets, while RBC models link technical aspects of the production process to business cycle dynamics. For research on the business cycle to proceed effectively, it is important to sort out which elements of market structure and technological conditions appear to be most strongly associated with cyclical fluctuations in output. While there is considerable empirical evidence on the relationship of microeconomic structure and cross-sectional variation in cyclical output across industries, most of the evidence analyzes specific aspects of market structure in isolation, making it very difficult to draw conclusions about their relative importance.

In this paper, we utilize a panel data base of 296 industries covering the time period 1958 to 1986 to examine the relationship between a broad spectrum of technological and market structure variables and industry cyclicality. The variables considered include: the durability of output, the factor intensity of the mix of variable and fixed factors of production, inventory usage, labor hoarding activity, market concentration and unionization. For many, but not all of these variables, economic theory suggests how they should affect the cyclicality of industries. Our goal is to provide new evidence, in a multivariate regression setting, of the empirical importance of these potential determinants of why cyclicality varies extensively across industries in manufacturing.

A number of findings are reported in the paper and are briefly summarized below.

i) The durability of output appears to be fundamental to explaining the cyclicality of the manufacturing sector. Durable goods industries, on average, are three times more cyclical than nondurable goods industries. While the durable goods sector has long been known to be more cyclical, this phenomena has apparently not been explored with highly disaggregated industry data. *ii*) It is only for the durable goods industries that the technological and market structure variables explain a significant portion of the cross-sectional variation in industry cyclicality. *iii*) Labor hoarding, an issue of growing importance in macroeconomics, appears to be strongly associated (negatively) with industry cyclicality for both durable and nondurable goods industries. *iv*) Market concentration is positively associated with cyclicality in durable goods industries, providing new evidence of the importance of imperfect competition for explaining output fluctuations. In contrast, unionization, while strongly related to cyclicality when analyzed in isolation, is statistically insignificant when examined in the full specification. This last result demonstrates the importance of examining the potential determinants of cyclicality with a multivariate approach.

II. Technological and Market Structure Conditions

Industrial organization economists have traditionally argued that the performance of an industry, including its macroeconomic performance, is partially determined by a long list of "basic" and "market structure" conditions (e.g. Scherer 1980, pg 3)[1]. Basic conditions include the determinants of supply and demand, such as the variability of costs, the ability to hold inventories, and product durability. Market structure conditions include such elements as the concentration of sellers and the unionization of the labor market. We briefly discuss below a set of key elements of technology and market structure that are thought to have a bearing on the cyclicality of an industry's output. We also describe the measures of these variables that will be employed in our regressions; some of these measures are admittedly imprecise proxies of the conditions we wish to consider. The predicted correlations are summarized in Table 1, at the end of this section.

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[1]Quite frequently, the labeling of what is a basic condition and what is an element of market structure is imprecise. This is not very important for this paper; we refer here to the traditional industrial organization paradigm because of its familiarity to much of the profession.

Variability of Inputs

The extent to which a firm's inputs are variable in the short-run should be an important determinant of its response to either a short-run demand or supply shock.[2] This point is well known and can be easily illustrated. Suppose a firm faces a short-run Cobb-Douglas production function of the form: $Y = X^{\gamma} K^{(1-\gamma)}$, where X is the variable factor(s), K is the fixed factor(s) and let w be the cost of X. Then the short-run marginal cost of production schedule an be expressed as:

$$\frac{w}{\gamma}(Y/K)^{\frac{(1-\gamma)}{\gamma}}$$

The greater is γ, the flatter is a firm's short-run marginal cost schedule. Thus, the greater the share of variable inputs in the production process, the greater the ability of the firm to alter both variable cost and output in response to a temporary *demand* shock. Likewise, it is clear from the marginal cost equation that the greater is γ, the greater is the shift in the short-run marginal cost schedule in response to a change in w, the cost of the variable input, X. Thus, other things equal, the greater an industry's fraction of variable costs to total costs, the more cyclical the industry should be in response to either demand or cost shocks.

In practice, firms employ multiple inputs that are classified as variable, depending on the time horizon involved. We consider three different categories of variable inputs: materials intensity, energy intensity, and production labor intensity. In addition, we also include a measure of overhead labor intensity[3]. It is important to distinguish between production labor and

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[2]In practice, the distinction between variable and fixed inputs is not always clear. But, in general, variable inputs such as materials are typically easier to adjust than variable labor inputs, and in turn, production worker inputs are probably more variable than the inputs of management.

[3] Physical capital is left out of the factor mix discussion because capital, whether defined narrowly as physical assets or broadly as including market position, patents, proprietary technology, etc., does not have annual factor payments in

overhead labor since the latter is typically viewed as a quasi-fixed factor of production. Factor intensities for each industry were calculated by dividing nominal payments to the factor by nominal industry sales for each year and then averaging across the data sample. Table 1 lists all input measures employed.

There is, of course, the possibility of reverse causation between cyclicality and the flexibility of inputs that firms choose. It is typically assumed that production functions are determined by technological conditions such as the extent of economies of scale and mass production techniques as well as opportunities for division of labor. However, it is not unreasonable that a firm's choice of production technology is affected by the inherent cyclicality of its industry. How much scope there is for substitution of variable for fixed inputs is not well known. Evidence presented later in the paper appears to indicate that reverse causation is not a serious problem for our work. In particular, while the durable goods industries are far more cyclical than the nondurable goods industries, they do not, on average, employ a higher mix of variable inputs, as would be expected if reverse causation was important. In addition, only durable goods industries display a significant relationship between factor mix and cyclicality, a result which does not appear to be consistent with a reverse causation interpretation[4].

Labor Hoarding

Many types of labor embody sunk, firm-specific investments such as training and search costs (Oi 1962, Becker 1962). This is obviously the case for management, engineers and accountants, which make up a large fraction of the work force of the modern corporation, but it

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the same sense as the other factors. In any case, if one takes the broad view of capital then by simple adding up, capital is already included as residual in the factor shares. In regressions which attempted to include an estimated capital share by dividing the estimated capital stock for each industry by sales, capital intensity was insignificant both statistically and quantitatively. This is not to say that capital intensity doesn't matter, but that the information was already included implicitly in the other factor shares variables and that an imperfect proxy did not contain any additional information.

[4]Recent work by Shea (1992) shows both how this problem might addressed through the use of input-output tables as well as the severe limitations of such attempts in the current context.

is often true for skilled production workers in many industries. When sunk training and search costs are large, firms are reluctant to lay off workers in times of low temporary demand or to hire (and train) new workers in response to temporary increases in demand, a practice which is known as labor hoarding. One implication is that in downturns, the marginal cost of output is lower than if no labor hoarding occurred, since workers are not being fully utilized; in booms, the marginal cost of output rises more steeply than if labor had no fixed, sunk cost component. One way of restating this is that the quasi-fixed cost component of labor raises K and decreases X in equation (1).

There is a growing body of evidence that labor hoarding is an important feature in the U.S. economy, including the business cycle[5]. Labor hoarding has obvious implications for the cyclical sensitivity of an industry. If firms retain workers in periods of low demand, their economic incentive to cut output is lower than for an industry which does not hoard labor. Likewise, if firms are reluctant to hire new workers in boom periods, their incentive to increase output is also less than industries which do not hoard labor. Thus, other things equal, the more labor hoarding a industry engages in, the less cyclical should be its fluctuations in output.

Measuring the conditions (training and search costs, the existence of firm specific capital, etc.) that should induce firms to hoard labor is recognized to be extremely difficult, and few empirical estimates exist. At best, any measure of the incentive to engage in labor hoarding must be very imprecise. We do not try to proxy these conditions. Rather, we propose the following (direct) measure of the degree of labor hoarding: the negative of the correlation between the change in materials usage (measured as materials expenditures deflated by an industry specific materials deflator) and the change in the number of labor hours. The idea is that if there is no

[5]Bernanke and Parkinson (1991) find that labor hoarding, together possibly with economies of scale, are the main explanations for the phenomenon of short-run increasing return to labor in the U.S. economy. Braun and Evans (1991) show that labor hording is necessary to explain seasonal variations in output and productivity. Burnside, Eichenbaum and Rebelo (1990) show that the inclusion of labor hording in an RBC model substantially improves its ability to fit the data.

labor hoarding then there should be rough proportionality between material usage and hours, indicating a correlation of 1. If the firm engages in labor hoarding then the correlation will be lower and the extent of labor hoarding should be a declining function of the correlation. By taking the negative of the correlation, we get the normal interpretation that the variable rises with the inferred level of labor hoarding[6]. The Appendix to this paper describes alternative measures of labor hoarding as well as the results, which turn out to be quite similar.

There are two identifying assumptions implicit in the use of our variable as a proxy for labor hoarding. First, materials usage must enter the production function with fixed coefficients, at least with respect to cyclical movements in output. This assumption appears to be reasonable since it is typically very difficult for firms to vary the amount of materials per unit of output in the short run. The second assumption is that labor hoarding must be predetermined with respect to cyclical adjustments. This also seems reasonable since the practice of labor hoarding can be viewed as a type of implicit contracting, where the employer does not lay off workers in recessions in order to keep workers during booms. Such an arrangement would surely be highly dependent on some form of credible pre-commitment.

Durability

Bernanke (1983) notes that "sharp swings in the production of durable goods are yet, as in Keynes's day, an important feature of the business cycle." There are numerous explanations why the production of durable goods is so cyclical. One longstanding explanation, captured in various "accelerator" models of investment, is that relatively small percentage changes in the desired stock of capital goods can lead to very large percentage changes in the current demand for additional consumer and producer durable goods. Other demand side explanations emphasize imperfections in financial markets. A number of empirical studies have indicated that demand

[6]In order to make sure our findings are not the result of some quirk of this particular specification, the appendix contains an alternate measure of labor hoarding based on workers rather than hours. This measure yields almost identical results. We also present a regression where labor hoarding is omitted entirely.

for consumer durables is strongly driven by fluctuations in liquidity (e.g. Mishkin 1976). More recently, studies have indicated that fluctuations in cash flow generate strongly cyclical demand fluctuations for investment goods as well[7]. Further, Bernanke (1983) argues that since durable purchases involve some irreversibilities, there is an option value to waiting to obtain new information about the economy, and this option value rises during downturns, further accentuating demand swings. In addition, purchases of durable goods can be postponed or pushed forward across time, therefore producers with market power might be adverse to cutting prices in busts, or "spoiling" the market. Thus, demand disturbances, in durable goods oligopolies, may be accentuated by the strategic pricing behavior of suppliers.

We do not attempt to measure differences in the degree of durability of goods across industries. Instead, we follow the conventional practice of dividing manufacturing into a durable goods and a nondurable goods sector. We follow Ornstein's (1975) classification of SIC 4-digit consumer industries into durable and nondurable goods and Domowitz, Hubbard and Petersen's (DHP 1988) classification for producer industries[8].

Inventory Usage

The ability of a firm to hold inventories varies a great deal across industries, depending on such technological factors as the rate of spoilage and obsolescence of the good as well as the cost of storage. The ability of an industry to maintain large stocks of finished goods inventories is potentially an important determinant of output cyclicality. Unlike the determinants already discussed, the effect of inventory usage on cyclicality depends crucially on the source of the shock. For demand shocks, and convex production costs, the ability of firms to utilize inventories enables the firm to smooth production (e.g. Blinder, 1986). In contrast, for short-run

[7]For a summary of the theory and evidence pertaining to capital market imperfections and investment, see Fazzari, Hubbard and Petersen (1988).

[8]DHP's classification was done at the SIC two digit level. We corrected a number of 4 digit misclassifications that resulted.

cost shocks, the ability of a firm to use inventories can accentuate output swings, since firms use inventories to bunch production in low cost periods (e.g. Eichenbaum, 1989).[9] We emphasize, as indicated in Table 1, that it is not possible to deduce a priori the role that inventories play in industry cyclicality.

The ability to hold inventories is proxied by the average finished-good inventory/sales ratio for each industry. The inventory/sales ratio was calculated by dividing the average finished goods inventory level for a given year by sales and then averaging across the data sample. An alternative was a classification variable developed by Belsley (1969) and refined by Paxton (1988) for build-to-stock verses build-to-order. As discussed latter in the paper, this alternative classification has no explanatory power.[10]

Market Power in Input and Output Markets

Price rigidities arising from imperfect competition in input and output markets is a central feature in modern Keynesian models of the business cycle. While the presence of unions has been argued to be a potentially important reason for wage rigidities in the U.S. economy, the link between unionization and the cyclicality of output is not at all clear. Blanchard and Fisher (1990) review conditions under which traditional static models lead to real wage rigidity and output fluctuations, but then argue that once dynamic considerations are introduced, bargaining between unions and firms may actually lead to more real wage flexibility and smaller fluctuations in employment and output than in competitive labor markets. Thus, the current state of economic

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[9]Further, even if the production smoothing story is accepted as more convincing, there still remains the potentially destabilizing effect of involuntary inventories arising from unanticipated demand fluctuations.

[10]We suspect that this has more to do with the difficulties in classifying industries than the importance of the build-to-stock verses build-to-order distinction. The key classification criterion used in the literature is that average level of back-orders relative to sales at the three digit sic code level must be greater than 5% or the industry is build-to-stock. This may have far more to do with "industry practice" than with any conceptual notion of build-to-order. For instance, within our data, the build-to-order industries actually have, on average, larger finished goods inventories than the build-to-stock industries. This is strong evidence that the normal method of classification does not match our conceptual notion very well, since one would expect that a build-to-order industry would have far smaller finished goods inventories. In general, we would view the average inventory/sales ratio as a better proxy of this property than the build-to-stock classification variable that have been used in the past. The build-to-stock results are included in the appendix.

theory is ambiguous on the role of unionization. We use the Freeman-Medoff (1979) measure of unionization, which measures the fraction of the labor force that is unionized. This measure exists only for 1972, which is near the midpoint of our panel. However, there are wide cross-sectional variations in unionization across industries, and these differences appear to be quite persistent for most industries in our study.

The effect of market concentration on output fluctuations is also a longstanding topic in economics. Dating back to Means (1935), arguments have been made that industries with market power may exhibit less flexible pricing practices than perfectly competitive industries. Carlton (1989) and Scherer (1980) contain excellent surveys of the evidence and current theory on price rigidity and market power. Carlton (1986) is one of the few studies to measure the degree of price rigidity using transactions prices. He finds that the degree of price rigidity in many industries is significant and that the level of industry concentration is strongly correlated with the rigidity of prices. Ongoing research described in Blinder (1991) also finds evidence of substantial price rigidities as well as support for the role of imperfect competition. Recently, game theory (e.g. Rotemberg and Saloner, 1986) has been utilized to provide formal dynamic models of oligopoly behavior that predict "sticky" prices over the business cycle[11]. We use the 4-firm concentration ratio, averaged over time, as our measure of market power. While this measure of market power has well-known shortcomings, it is the most commonly used proxy, particularly in large cross-sectional studies of market performance.

Other variables

Two control variables are also utilized in this study. A producer goods dummy from Ornstein (1975) is included. This could be viewed either as a measure of market power on the

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[11]While most arguments indicate that market power accentuates output fluctuations, there are arguments suggesting the opposite effect. In particular, cartels may break down during downturns in the economy, leading to sharp declines in price (Stigler, 1964). Thus, while it is commonly argued that imperfect competition leads to greater output cyclicality, economic theory is not entirely unambiguous on this issue.

buyer side of the market or as a proxy for differences in the variability of demand. The other control variable is average industry growth over the time period of the study. This controls for the possibility that strong trends in growth might obscure cyclical responses.

Table I Predicted Relationships

Non-energy materials intensity	+
Energy intensity	+
Production labor intensity	+
Overhead labor intensity	-
Labor Hoarding	-
Inventory Intensity	-(?)
4-firm concentration ratio	+
Percent unionized	?
Average Industry Growth	?
Producer Dummy	?

III. Methodology

The method used in this paper abstracts from the time variation in industry characteristics and focuses on the relationship between industry cyclicality and fundamental technological and market structure characteristics of those industries. Thus, conceptually, the problem is split between the time-series estimation of industry cyclicality and the cross-sectional explanation of the variance in observed cyclicality. By structuring the question as a cross-sectional analysis of differences in the estimated time series behavior of industries, we can focus on fundamental low frequency aspects of the data, such as long-run factor shares and concentration, and relate them to differences in business cycle behavior with far greater precision than can be accomplished in the usual time-series context. The gain in precision arises from the ability to pool the long-run information from 296 different industries while still being able to adjust for the precision of estimation within each industry and for correlation across industries, thus addressing in a serious way the arbitrariness of SIC code designations and potential data problems that sometimes arises in highly disaggregated data.

The cyclicality of an industry is defined as β_i in the following regression

(2) $$\Delta VAD_{it}=\alpha_i+\beta_i\Delta GNP_t+\mu_{it} ,$$

where Δ VAD is the percent change in real value added in industry i at time t and Δ GNP_t is the real growth rate in GNP at time t[12]. The μ_i's are assumed to be correlated with covariance matrix Σ_μ and serially uncorrelated. The βs are then analyzed in a cross-sectional regression of the form

(3) $$\beta_i=Z_i\gamma+\epsilon_i ,$$

where Z_i is the vector of cross-sectional variables described below. Regression results are presented for two-step OLS implementation of the above regressions in the results section. In addition, EGLS results are estimated taking direct account of the estimation error in the βs . This is precisely equivalent to simultaneous estimation of the cyclicality βs and γ by substituting

[12]Alternative measures of cyclicality were explored. Two primary concerns dictated the search: the potential inadequacy of the purely contemporaneous lag structure specification between industry growth and GNP and the possibility of extraneous noise in the industry specific price deflators.

The paucity of observations limited our ability to investigate alternate time-series representations. With only 28 annual observations, Beveridge-Nelson or Hodrick-Prescott detrending are clearly beyond the data; however, a variety of alternative specifications of β were tested, including ones based on a variety of different structures of leads and lags, and log level regressions using quadratic time trends. These alternative estimates of β produce qualitatively identical cross-sectional results. This should not be surprising since the cross-sectional variation displayed by the 296 industries analyzed far exceeds the types of changes one associates with changes in time-series techniques. The log levels regression with quadratic trend, which was the most different, is presented in the appendix.

Also, as noted above, there is some reason to believe that deflators at the 4 digit level are subject to substantial measurement error. Alternate specifications with broader indices perform slightly better than the reported regressions, but the gain was very small. These estimations are also included in the appendix. The industry specific deflators are used in the reported results since they are conceptually superior.

equation 2 into equation 1, resulting in

$$\Delta VAD_{it}=\alpha_i+\Delta GNP_t Z_i\gamma+\Delta GNP_t \epsilon_i+\mu_{it} \ .$$

The calculations are easier in the two-step case. They are carried out as follows: writing the cross-sectional regression as

$$\hat{\beta}_i=Z_i\gamma+(\hat{\beta}_i-\beta_i)+\epsilon_i$$

or

$$\hat{\beta}_i=Z_i\gamma+\nu_i \ ,$$

where

$$\nu_i=(\hat{\beta}_i-\beta_i)+\epsilon_i \ .$$

It follows that

$$\Sigma_\nu=\sigma_\epsilon^2 I+\Sigma_\beta$$

where σ_ε is the standard error of the cross-sectional regression estimated with the true βs. This holds as long as the estimation error in cyclical βs is independent of the εs. σ_ε and Σ_β can be estimated from the two-step OLS estimates (Amemiya, 1978, Hsiao, 1986) and then used to perform EGLS estimation using

$$\hat{\Sigma}_\nu=\hat{\sigma}_\epsilon^2 I+\hat{\Sigma}_\beta$$

as the estimated covariance matrix. These results are presented as EGLS estimates in the results section.

This EGLS procedure brings out the real strength of the cross-sectional approach in that the use of Σ_β in the EGLS procedure explicitly takes into account the precision of the time-series estimates of the cyclicality β by reducing the influence of poorly estimated industries. Further, by including the covariances across the cyclicality β's we account for some of the arbitrariness of industry definitions, in that the influence of highly correlated groups of industries is reduced.

To implement this methodology it is necessary to filter out the time-series variation in the cross-sectional industry data. This should not be a major loss. For example, while it is clear that factor shares vary systematically through the business cycle, one would not want to interpret this as a cyclically varying production function. Rather, it reflects the differences in the relative fixity of factors and differences in factor wage cyclicality. Thus, in the construction of the cross-sectional database discussed below, factor shares are taken as long-run averages, rather than as time-varying proportions. While it is likely that some of industries examined do undergo some meaningful time variation in terms of their fundamental technological and market characteristics, the potential to distill this information from 28 annual observations is clearly very limited, therefore it is unlikely that anything substantive is being lost by collapsing the time dimension in this application, though a great deal is gained in terms of clarity of analysis.

Data

The data used in this study are annual observations taken from the Census of Manufacturing and cover the time period 1958-1986. The final sample consists of 296 manufacturing industries defined at the 4-digit SIC code level. This set of industries covers 68% of the 4-digit manufacturing industries and accounts for approximately 80% of value added in manufacturing as of 1981. This represents those industries which have a continuously mappable SIC code definition for the entire sample period and for which we have a complete set of explanatory variables. Much of the original data comes from DHP (1986) and is supplemented by new data covering the period 1982-1986. In addition, the price indices for the individual industries are from Gray (1989). Gray's data is re-mapped to the SIC code definitions used in DHP (1986). This is supplemented by a number of cross-sectional variables described earlier.

IV. Results

In the course of the investigation, it became clear that durable goods industries exhibit far greater output movements than nondurable goods industries over the business cycle. In addition, it became apparent that while we could account for a great deal of the variation in cyclicality across durable-goods industries, this was not the case for nondurable goods industries. We therefore report all of our findings for the durable/nondurable split of the data as well as the pooled data.

Summary Statistics

Table 2A (durable goods industries), Table 2B (nondurable goods industries) and Table 2C (all industries) report the minimum, maximum, mean, standard deviation, and correlation (with β) for all variables. The first row reports our measure of cyclicality. The mean value of β for the durable goods industries is 2.95, which is nearly three times greater than the mean value for the nondurable goods industries. This implies that nondurable goods industries are no more cyclical on average than the rest of the economy. While this finding is certainly consistent with the discussion in Section 2, the magnitude of the difference is quite striking.

The next four rows in Tables 2A - 2C report the shares of different factor inputs in the production process. For durable goods industries, the means of non-energy material intensity, energy intensity, production labor intensity, and overhead intensity are 0.45, 0.02, 0.17 and .09;

for nondurable goods industries, the means of these shares are 0.52, 0.02, 0.14 and 0.06, respectively. The sum of these shares is approximately 3/4 for both categories of goods. The remainder of the shares is made up of capital inputs, including technological stocks and advertising, as well as central administration (non-plant level) overhead costs. For durable goods industries, the correlation of non-energy material intensity with β is positive, large, and highly significant[13]. The same is true of energy intensity, although the correlation is not as large. The correlation for production labor intensity is negative, which is somewhat surprising, but statistically insignificant. (This may reflect the importance of labor hoarding, as suggested by our regression results.) The correlation of overhead labor intensity with β is negative, large in absolute size, and highly significant, which is expected, given the quasi-fixed factor nature of this type of labor. In comparison, for the nondurable goods industries, the correlation of energy intensity is positive and significant as expected, but the other correlations are either insignificant or have the wrong expected sign.

Our labor hoarding measure is reported in the sixth row. The mean is -.78 for durable goods industries and -.55 for nondurable goods industries, indicating a correlation between labor hours and materials considerably less than unity for both sectors. Minimum values of this variable are close to -1 in both sectors, which is reassuring. (Recall that, since we are taking the negative of the correlation between materials and production workers, the value -1 indicates complete absence of labor hoarding.) The standard error of the variable indicates considerable heterogeneity across industries in both sectors. The correlation of the labor hoarding measure

[13]The p-values in the table do not take into account the estimation error in the βs and should be viewed as suggestive.

with β is negative as expected, large in absolute size, and highly significant for both durable and nondurable goods industries.

The seventh row of Tables 2A and 2B indicate that the inventory/sales ratio is about the same across durable and nondurable goods industries. However, the correlation of inventory/sales ratio with β is negative and significant for durable goods, but zero for nondurable goods industries. The next two rows deal with measures of market imperfections arising from unionization and firm concentration. The mean of the fraction of workers unionized and the four-firm concentration ratio are approximately the same in both sectors, with very large standard deviations. For durable goods industries, the correlations of these variables with β are both positive and significant, which is consistent with most theories on the role of market power. However, for nondurable goods industries, while the correlations are also positive, they are much smaller and insignificant. Finally, industry growth is, on average, nearly identical for both durable and nondurable goods industries, and basically uncorrelated with industry cyclicality.

Regression Results

Tables 3A and 3B report regression results for the durable/nondurable split of the data; OLS[14] estimates appear in Table 3A and EGLS estimates appear in Table 3B. The difference in the estimates between 3A and 3B are slight. For the sake of comparison, we also report estimates for a pooled regression of durable and nondurable goods in the last column of the two tables. Pooling is very strongly rejected. The F statistic is 13.1, which is significant at the limits of calculation. From a purely statistical point of view, this rejection is not surprising, given the

[14]The standard errors reported for the OLS parameter estimates are the usual OLS standard errors, calculated without any adjustment for the estimation error in β. Corrected standard errors were calculated and were very similar. The EGLS results show both the corrected estimates and corrected standard errors. The pure OLS results were presented uncorrected as a bench-mark.

differences in the correlations of the regressors with β for the durable and nondurable goods industries reported in Tables 2A and 2B. As will be seen below, every variable in the durable goods regression for which there was a definite prediction has the predicted sign and all but one is highly significant. This is definitely not the case for the nondurable goods regression.

In Table 3A, starting with the regression for the durable goods industries, all four of the factor input variables have the expected sign and the coefficients are highly significant. Note that the coefficient for production labor intensity is positive while the coefficient for overhead labor intensity is negative. The standardized coefficients in Table 4 show that nonenergy materials intensity is the most important variable in explaining cyclical sensitivity for the durable goods industries. The next variable, labor hoarding, is also statistically significant, and judging by its standardized coefficient, it also appears to play an important role in explaining cyclicality. The inventory/sales ratio is negative, consistent with production smoothing, but it is insignificant, which is not surprising for the reasons discussed in Section 2. Turning to the market imperfection variables, the coefficient for the concentration ratio is positive and statistically significant. The coefficient for unionization, however, is very nearly zero and insignificant. Thus, once other potential determinants of cyclicality are controlled for, the extent of unionization appears to have no explanatory power, even though it is highly correlated with output cyclicality. Finally, average industry growth is positive and significant. Overall, the regression accounts for a 41 percent of the variation in cyclicality across durable goods industries.

The regression results are very different for the nondurable goods industries. The overall explanatory power of the regression is much lower. Only the labor hoarding variable and the producer goods dummy are significant. The failure of technological and market structure elements to explain the pattern of cyclicality in the nondurable goods sector is puzzling. One explanation is that the business cycle is so largely concentrated in the durable goods sector that there is relatively little business cycle output movement to explain in the nondurable goods sector, consistent with the low average level of β for nondurable goods industries reported in Table 2. Another way of explaining this result is to split the notion of cyclicality into two parts: that part intrinsic to the industry based on its fundamental characteristics and that part which is independent. The independent part would contain such things as government demand management policies, complementarity to other goods, inherited cyclicality resulting from having a narrow customer base, and, in the context of this regression, the estimation error in determining the cyclicality. It is quite reasonable that the independent component would be similar across all industry types, but that the intrinsic part would be far larger for durable goods for all of the reasons discussed in Section 2.

The results for the pooled regression are reported in the final column of Tables 3A and 3B. The durable goods dummy is, of course, statistically very significant. A comparison of this regression with the durable goods regression is of interest. In the pooled regression, none of the four factor intensity variables are significant. This lack of results highlights the misleading conclusions that may arise from inappropriately pooling the durable and nondurable sectors of the economy.

Before concluding, we return to reverse causation, an issue raised in Section II of the paper. Two findings for the durable and nondurable goods industries suggest that reverse causation is of limited importance for the results reported in this paper. First, Tables 2A and 2B indicate that the durable goods industries, on average, employ nearly the same share of variable inputs as the nondurable goods industries. Tables 2A and 2B also indicate that durable goods industries are, on average, three times more cyclical than nondurable goods industries. One would expect that if reverse causation is an important issue, the durable goods industries would display a much greater use of variable inputs compared to the nondurable goods industries. A second finding is that our technical and market structure variables are significant only for the durable goods industries. If reverse causation were playing a major role than one would expect the durable and nondurable regressions to be at least similar. After all, durability is clearly exogenous and the endogeneous response to demand volatility should in no way depend on the nature of the good produced. However, the estimated parameter values for the nondurable goods regressions are insignificant, and often have the opposite sign. The one exception is the labor hoarding variable which is significant in both the nondurable and the durable regression. This leaves open the possibility that the willingness to hoard labor is determined by the level of cyclicality. We partially address this potential problem by dropping the labor hoarding variable from the regression. The results are reported in the Appendix. The estimated coefficients for the durable goods regression change very little, and remain statistically significant.

V. Conclusion

In this paper we explore the degree to which a set of technological conditions and elements of market structure may account for differences in the cyclicality of output across industries. Some of the variables in this study, such as market imperfections and the ability to hold inventories, have received considerable attention in the literature, although not in a multivariate study. Other variables, such as labor hoarding and the role of variable and fixed factor inputs, have not. Most of the main findings of the paper were summarized in the introduction.

The results in this paper suggest that macroeconomic models of the business cycle should account for durability, labor hoarding, imperfect competition, and adjustment costs in the factor mix. The durability of output appears to be absolutely fundamental to the business cycle, with durable goods industries, on average, being three times as cyclical as nondurable goods industries. Market concentration appears to be important only for durable goods industries, which is consistent with the view that durable goods oligopolists seek to avoid "spoiling the market" during downturns in demand. We also find strong supporting evidence for Bernanke and Parkinson (1991), Burnside, Eichenbaum and Rebelo (1990) and Braun and Evans (1992) that labor hoarding is an essential feature of the business cycle. In fact it is the only variable that is important for explaining differences in interindustry cyclicality in both durable and non durable goods industries.

Table 2A: Durable Goods Industries

	Minimum	Maximum	Mean	Std. Dev.	Corr. with β	P value for correlations
Cyclicality Beta	-1.1050	8.4860	2.9529	1.6368	1.0000	(0.0000)
Non-energy Materials Intensity	0.1538	0.7943	0.4497	0.1098	0.2643	(0.0010)
Energy Intensity	0.0037	0.2429	0.0239	0.0325	0.1729	(0.0332)
Production Labor Intensity	0.0513	0.4001	0.1746	0.0568	-0.0926	(0.2563)
Overhead Labor Intensity	0.0284	0.2207	0.0871	0.0339	-0.3792	(0.0001)
Labor Hoarding	-0.9618	-0.2052	-0.7642	0.1612	-0.3872	(0.0001)
Inventory Intensity	0.0055	0.1708	0.0619	0.0324	-0.1824	(0.0245)
4-Firm Concentration Ratio	0.0431	0.8879	0.3758	0.2022	0.1703	(0.0359)
Percent Unionized	0.0000	1.000	0.6343	0.2408	0.2648	(0.0010)
Average Industry Growth	-6.5960	24.3090	3.4103	3.1935	0.0595	(0.4658)
Producer Dummy	0.0000	1.0000	0.8092	0.3942	0.1226	(0.1323)

Table 2B: Nondurable Goods Industries

	Minimum	Maximum	Mean	Std. Dev.	Corr. with β	P value for correlations
Cyclicality Beta	-3.1373	4.7735	1.1079	1.3584	1.0000	(0.0000)
Non-energy Materials Intensity	0.1350	0.8939	0.5226	0.1434	-0.1741	(0.0368)
Energy Intensity	0.0023	0.1900	0.0208	0.0271	0.1846	(0.0267)
Production Labor Intensity	0.0152	0.4170	0.1387	0.0717	0.0839	(0.3177)
Overhead Labor Intensity	0.0083	0.1929	0.0613	0.0350	0.0616	(0.4634)
Labor Hoarding	-0.9354	0.1265	-0.5546	0.2271	-0.4049	(0.0001)
Inventory Intensity	0.0009	0.4422	0.0626	0.0513	0.0350	(0.6764)
4-Firm Concentration Ratio	0.0524	0.8575	0.3647	0.1804	0.1006	(0.2300)
Percent Unionized	0.0000	1.0000	0.5611	0.2194	0.0642	(0.4441)
Average Industry Growth	-3.9492	12.7733	3.1898	2.7306	0.0089	(0.9158)
Producer Dummy	0.0000	1.0000	0.6041	0.4907	0.2361	(0.0044)

Table 2C: All Industries

	Minimum	Maximum	Mean	Std. Dev.	Corr. with β	P value for correlations
Cyclicality Beta	-3.1373	8.4860	2.0553	1.7660	1.0000	(0.0000)
Non-energy Materials Intensity	0.1350	0.8939	0.4851	0.1321	-0.1108	(0.0568)
Energy Intensity	0.0023	0.2429	0.0224	0.0300	0.1784	(0.0021)
Production Labor Intensity	0.0152	0.4170	0.1571	0.0668	0.1367	(0.0186)
Overhead Labor Intensity	0.0083	0.2207	0.0746	0.0367	0.0400	(0.4928)
Labor Hoarding	-0.9618	0.1265	-0.6622	0.2221	-0.5349	(0.0001)
Inventory Intensity	0.0009	0.4422	0.0622	0.0426	-0.0545	(0.3499)
4-Firm Concentration Ratio	0.0431	0.8879	0.3704	0.1916	0.1358	(0.0194)
Percent Unionized	0.0000	1.000	0.5987	0.2331	0.2345	(0.0001)
Average Industry Growth	-6.5960	24.3090	3.3030	2.9743	0.0528	(0.3653)
Producer Dummy	0.0000	1.0000	0.7094	0.4548	0.2635	(0.0001)

Note: The p values make no correction for the estimation eror in β.

Table 3A: OLS Regression Results

	Durables	Nondurables	All
Non-energy Materials Intensity	6.7409	-1.6153	-0.5735
	(2.000)	(1.5117)	(1.4048)
Energy Intensity	11.1960	2.0443	2.1483
	(4.5868)	(5.1016)	(4.1377)
Production Labor Intensity	9.9434	-2.3571	1.0775
	(3.2515)	(2.3486)	(2.2301)
Overhead Labor Intensity	-10.4321	0.7250	4.3371
	(4.5470)	(5.2209)	(4.1578)
Labor Hoarding	-3.3616	-2.2571	-0.8662
	(0.6980)	(0.5029)	(0.4939)
Inventory Intensity	-2.1264	1.7887	1.4116
	(3.5702)	(2.1437)	(2.2324)
4-Firm Concentration Ratio	1.2706	0.0923	0.3358
	(0.6198)	(0.7269)	(0.5605)
Percent Unionized	0.0252	0.0796	0.2510
	(0.5202)	(0.5079)	(0.4328)
Average Industry Growth	0.1142	-0.0158	-0.0241
	(0.0399)	(0.0420)	(0.0346)
Producer Dummy	0.8866	0.4284	0.5549
	(0.3083)	(0.2414)	(0.2244)
Durable Goods Dummy	n.a.	n.a.	0.9655
			(0.2247)
R^2	0.41	0.22	0.24
Number of Observations	152	144	296
SSE	238.28	205.43	698.96

Table 3B: EGLS Regression Results

	Durables	Nondurables	All
Non-energy Materials Intensity	6.7983	-1.3919	0.2841
	(1.8673)	(1.3978)	(1.2554)
Energy Intensity	12.4882	3.7461	0.9182
	(4.6150)	(4.6576)	(3.7600)
Production Labor Intensity	8.8577	-2.7615	1.4034
	(3.0492)	(2.1821)	(1.9988)
Overhead Labor Intensity	-7.2820	-1.2313	5.0809
	(4.6787)	(4.8676)	(3.7222)
Labor Hoarding	-3.4889	-1.8864	-0.6519
	(0.6760)	(0.4711)	(0.4491)
Inventory Intensity	-2.1296	1.8673	3.0620
	(3.3969)	(2.0059)	(2.0213)
4-Firm Concentration Ratio	1.3145	-0.3161	0.0888
	(0.5728)	(0.6757)	(0.5046)
Percent Unionized	-0.3195	-0.08914	0.2669
	(0.5164)	(0.4649)	(0.3843)
Average Industry Growth	0.0488	-0.0148	-0.0263
	(0.0439)	(0.0432)	(0.0309)
Producer Dummy	0.6999	0.5526	0.6162
	(0.3019)	(0.2232)	(0.2031)
Durable Goods Dummy	n.a.	n.a.	0.6422
			(0.2093)

Note: Numbers in parenthesis are standard errors.

Table 4: OLS Regression Results, Durable Goods Industries

	Standardized Coefficient
Non-energy Materials Intensity	0.4520
Energy Intensity	0.2224
Production Labor Intensity	0.3451
Overhead Labor Intensity	-0.2160
Labor Hoarding	-0.3310
Inventory Intensity	-0.0421
4-Firm Concentration Ratio	0.1569
Percent Unionized	0.0037
Average Industry Growth	0.2229
Producer Dummy	0.2135

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Appendix:

As mentioned in the paper, a number of alternate specifications suggest themselves. A representative sample is presented below. As can be seen, none of these specifications are substantively different from those presented in the paper. In fact some of them are arguably stronger. We only present durable goods industry regressions. All of the nondurable regressions are virtually identical to those presented in the paper.

Capital intensity, which is measured as the ratio of the capital stock to sales [see Gray (1989) for a description of how the capital stock series were created], and a build-to-stock dummy variable are added to the specification in the first two regressions shown. As can be seen, neither variable provides much explanatory power. As stated in the paper, this probably has more to do with the inherent measurement problems than with the conceptual validity of the variables. A number of alternate specifications were attempted, including selective exclusion of other variables and interaction terms. In all cases these variables failed to provide any statistically significant information or have any substantive impact on any other coefficients.

The third and fourth regressions explore the impact of labor hoarding. The third regression replaces the primary labor hoarding measure with an alternate measure based on workers rather than hours, in case the rigidity was more worker- rather than hour-based. The results are almost identical. There is a slight drop in overall explanatory power, but the precision on the other coefficients actually goes up slightly. The fourth regression drops labor hoarding entirely. Eliminating labor hoarding reduces the overall explanatory power of the regression, but it has very little impact on the other coefficients.

We also investigated a number of alternative definitions of industry cyclicality, including various lag structures and methods of estimation. Overall this had very little impact except for adding some noise into the βs. We also tried a number of different deflating techniques. As a rule, we found that general deflators perform better than the industry specific ones. The fifth regression shown is an example in which the manufacturing deflator was used to deflate each industry's output rather than the industry's own deflator. This regression is qualitatively very similar to those preceding, but the overall precision is slightly higher. Finally, the last regression shows the results from βs estimated on log levels with a quadratic time trend included in the regression. These estimates are extremely close to those based on βs estimated from differenced data, but are less precise. The precision increases substantially in the EGLS case, coming very close to the differenced regression. We would interpret this as evidence that the quadratic time trend model is inadequate for some industries. In addition to those regressions shown, we also did some outlier analysis and discovered that eliminating outliers modestly increases precision without changing coefficient values.

Appendix:
OLS Regression Results--Durables

	Standard β				Alt. Deflator β	Log-Level β
Non-energy Materials Intensity	6.8895	7.3009	6.5020	7.3472	7.8377	6.3594
	(2.0147)	(2.0898)	(2.0287)	(2.1470)	(2.1114)	(2.6294)
Energy Intensity	9.0371	11.2776	12.0581	8.9098	9.7605	11.3590
	(5.4854)	(4.5898)	(4.6687)	(4.9071)	(4.8408)	(6.0293)
Production Labor Intensity	9.5608	10.1725	9.5116	10.8973	12.5165	5.9360
	(3.3000)	(3.2623)	(3.2978)	(3.4899)	(3.4315)	(4.2741)
Overhead Labor Intensity	-9.8128	-9.2225	-11.2232	-9.8890	-14.3129	-6.5667
	(4.6352)	(4.7306)	(4.6078)	(4.8879)	(4.7988)	(5.9770)
Labor Hoarding	-3.3370	-3.4842	n.a.	n.a.	-3.3400	-1.2940
	(0.7000)	(0.7107)			(0.7366)	(0.9176)
Inventory Intensity	-2.6820	-2.6929	-3.2279	-3.6624	-1.9933	-7.9593
	(3.6585)	(3.6231)	(3.5981)	(3.8237)	(3.7679)	(4.6930)
4-Firm Concentration Ratio	1.2254	1.3162	1.6612	1.6163	1.2329	1.3434
	(0.6241)	(0.6220)	(0.6228)	(0.6620)	(0.6542)	(0.8148)
Percent Unionized	0.0207	-0.0569	0.0218	0.6156	-0.5286	-0.3519
	(0.5211)	(0.5278)	(0.5287)	(0.5436)	(0.5490)	(0.6837)
Average Industry Growth	0.1159	0.1141	0.1148	0.1070	0.1553	0.0832
	(0.0400)	(0.0399)	(0.0404)	(0.0429)	(0.0421)	(0.0525)
Producer Dummy	0.8221	0.9905	0.8853	0.9064	0.9256	0.9411
	(0.3215)	(0.3280)	(0.3119)	(0.3315)	(0.3254)	(0.4053)
Alternative Labor Hoarding	n.a.	n.a.	2.8609	n.a.	n.a.	n.a.
			(0.6482)			
Build-to-Stock Dummy	n.a.	0.2540	n.a.	n.a.	n.a.	n.a.
		(0.2725)				
Capital Intensity	0.6165	n.a.	n.a.	n.a.	n.a.	n.a.
	(0.8558)					
R^2	0.4132	0.41	0.40	0.31	0.42	0.22
Number of Observations	152	152	152	152	152	152
SSE	237.39	236.81	243.79	277.47	265.40	411.71

EGLS Regression Results--Durables

	Standard β				Alt. Deflator β	Log-Level β
Non-energy Materials Intensity	6.8458	6.8896	6.2983	6.9880	7.9228	7.2682
	(1.8798)	(1.9341)	(1.8731)	(2.0319)	(1.9921)	(2.1554)
Energy Intensity	11.6703	12.4971	13.1897	9.5082	9.9851	13.0390
	(5.3636)	(4.6314)	(4.6352)	(4.9658)	(4.8242)	(5.1135)
Production Labor Intensity	8.6816	8.8849	8.0238	8.5380	11.3360	9.1503
	(3.1135)	(3.0631)	(3.0517)	(3.3164)	(3.1684)	(3.4908)
Overhead Labor Intensity	-7.0712	-7.0795	-7.9326	-7.0481	-10.0439	-6.7511
	(4.7447)	(4.8118)	(4.6830)	(5.0723)	(4.8196)	(5.3078)
Labor Hoarding	-3.4851	-3.5106	n.a.	n.a.	-3.2700	-3.1981
	(0.6784)	(0.6878)			(0.6794)	(0.7702)
Inventory Intensity	-2.4346	-2.2384	-3.4286	-4.0308	-1.6302	-2.8033
	(3.55360)	(3.4562)	(3.3809)	(3.6715)	(3.5000)	(3.8958)
4-Firm Concentration Ratio	1.2990	1.3209	1.6720	1.5853	1.2275	1.2674
	(0.5768)	(0.5757)	(0.5713)	(0.6212)	(0.5946)	(0.6629)
Percent Unionized	-0.3289	-0.3334	-0.3884	0.2526	-0.6620	-0.4096
	(0.5191)	(0.5232)	(0.5199)	(0.5483)	(0.5284)	(0.5799
Average Industry Growth	0.0489	0.0490	0.0451	0.0331	0.0842	0.1052
	(0.0441)	(0.0441)	(0.0439)	(0.0474)	(0.0440)	(0.0456)
Producer Dummy	0.6744	0.7187	0.6820	0.6699	0.6861	1.0410
	(0.3141)	(0.3192)	(0.3020)	(0.3282)	(0.3168)	(0.3393)
Alternative Labor Hoarding	n.a.	n.a.	-3.2096	n.a.	n.a.	n.a.
			(0.6240)			
Build-to-Stock Dummy	n.a.	0.0481	n.a.	n.a.	n.a.	n.a.
		(0.2533)				
Capital Intensity	0.2451	n.a.	n.a.	n.a.	n.a.	n.a.
	(0.8096)					

Note: Numbers in parenthesis are standard errors.