LABOR PRODUCTIVITY AND THE CYCLE

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ABSTRACT:
Using the NBER Manufacturing Productivity database, this paper investigates the relationship between labor productivity and real output for four hundred and fifty U.S. 4-digit manufacturing industries for the years 1958 to 1991. Labor productivity is significantly pro-cyclical in 63 per cent of industries and acyclical in 36 per cent. Furthermore, degrees of cyclicality are not random across manufacturing. For example, while labor productivity in chemical industries is predominantly pro-cyclical, it exhibits mainly acyclical behavior in industrial machinery industries. Such industrial clusters are examined systematically within cross-section regressions that seek to investigate the distribution of cyclicality across industries. The regression analysis attributes important roles to variations in materials costs, as a proxy for fluctuations in factor utilisation, as well as variations in inventory accumulation.

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1 Introduction

Empirical work has reached the stage where few researchers question the stylised fact that average labor productivity is pro-cyclical. Current research is concentrated primarily on discriminating among competing economic explanations of this phenomenon. Ever since the pioneering work of Oi (1962) and Becker (1964), the labor hoarding hypothesis has consistently led the field of contenders[1], although the roles of technology shocks and true increasing returns in production have featured prominently in more recent times. Despite the force of these explanations, it is likely that significant sectors of industry do not display pro-cyclical labor productivity. Labor hoarding and increasing returns do not constitute universal laws of the production process.

The view that recessions provide opportune times for firms to "clean-up" or rationalize labor and capital resources offers a potentially important source of counter-cyclical effect.[2] For example, Caballero and Hammour (1994) model the process whereby productivity is enhanced during recessions as firms scrap outdated capital and invest in the latest product and process innovations.[3] If these and other

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[1] See the discussion in Hart and Malley (1996). Some leading examples include Fair (1969 and 1985), Fay and Medoff (1985); Aizcorbe (1992), Bernanke and Parkinson (1991), and Marchetti (1994). The last two papers, in particular, evaluate empirically the relative strength of the hoarding hypothesis against alternative theories.

[2] Caballero and Hammour (1994) and Aghion and Saint-Paul (1991) stress technological and capital - related activities. Saint-Paul (1993) provides a review of these and other so-called "opportunity cost" models - i.e. models in which recessions serve to stimulate intertemporal substitution of capital and labor projects designed to enhance current and future productive performance - within a general modelling framework. Recent empirical work by Malley and Muscatelli (1996) provides strong evidence, using U.S. 2-digit total factor productivity and employment data, for the opportunity cost view of business cycle - productivity growth interaction.

[3] Stories of recessionary cleansing do not necessarily predict counter-cyclical productivity. Bean (1990) argues that during recessions firms may reallocate a larger part of their labor force towards human capital enhancing activities that do not directly add to current output while, during booms, they shift emphasis towards current production. Output per measured labor input will, accordingly, reduce during a recession and rise during a boom thereby giving a pro-cyclical pattern of measured

cleansing operations are important, then might counter-cyclical productivity behavior predominate in such industries? Based on calibrations from their vintage capital model, Caballero and Hammour suggest that the likely answer is no.

"*One objection to the view that recessions are times of cleansing is that it implies countercylical productivity, while average labor productivity is in fact procyclical. However, one can show that this effect on productivity is likely to be small and may be dwarfed by other factors (labor hoarding, externalities etc.) that make measured productivity procyclical.*" [Caballero and Hammour, 1994, p. 1365]

Interestingly, however, if recessions produce opportunity costs in many industries that favour substitution towards upgrading and replacing capital equipment and processing systems then, concomitantly, they lead directly to product demand in investment goods industries. Replacing the old with the new means purchasing industrial machinery, machine tools, conveyors, power transmission equipment, industrial control systems, industrial process furnaces etc. In other words, capital cleansing within the textile, chemical, printing and transport industries translates into orders for industrial machinery and equipment industries that supply the cleansing materials.

It follows that in some investment goods industries, significant new orders may accrue both during the upswings of the business cycle, as new firms are established and production expands, and towards the troughs of the cycle, as capital and processing renewal and upgrading are undertaken. Accordingly, this may help to iron-out cyclical peaks and troughs in these industries and to facilitate the ability to

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productivity. Davis and Haltiwanger (1989) and Gali and Hammour (1991) also emphasise labor-related cleansing activities, such as labor reallocation and training. Fay and Medoff (1985) provide direct evidence of alternative work scheduling during recessionary periods.

undertake long-term output planning and production scheduling. Cyclical movements in labor productivity may be less apparent because contributory factors, such as labor hoarding or shifts in production requirements, are not important features.

Of course, outside of these arguments, for structural and other reasons pro-cyclical labor productivity may not be a predominant industrial feature. In the first instance, the demand for certain industrial products is unlikely to follow typical cyclical patterns. The manufacture of medicinal chemicals and burial caskets provide two examples.[4] Secondly, industries with low set-up and other fixed capital and labor costs, may feel better able to vary short-run factor inputs so as to attain relatively stable labor productivity growth paths.

These lines of reasoning point to the possibility that significant instances of counter-cyclical and acyclical productivity behavior have not been observed because studies to date have failed to disaggregate the industrial data sufficiently. Utilizing the full detail of the NBER Manufacturing Productivity (MP) database, this paper attempts to remedy this deficiency. It analyses relationships between labor productivity and the cycle for four hundred and fifty U.S. manufacturing four-digit industries between 1958 and 1991. It finds that labor productivity in 63 per cent of these industries is significantly pro-cyclical while it is acyclical in 36 per cent and significantly counter-cyclical in 1 per cent. Moreover, the degrees of cyclicality across industries is by no means random. At one end of the spectrum, 89 per cent of chemical industries exhibit pro-cylical labor productivity. At the other, 74 per cent of industrial machinery

[4] These two industries are included in the empirical work of this paper.

and equipment industries display either acyclical or (in two cases) counter-cyclical labor productivity.

Via a series of exploratory cross-sectional regression models, the paper then proceeds to examine a number of key influences that help to explain the distribution of 4-digit industry productivity/output correlations. The central hypothesis is that unobserved variations of labor and capital utlilization play a key role in determining the productivity patterns. Following the approach by Basu (1996), we use variations in materials costs to capture such factor utilization movements while also controlling for variations in inventory accumulation. These arguments enter with the expected signs and prove to be very robust to progressive extension of the conditioning set to control for industry specific and other economic factors.

2 The stylized fact revisted

Without attempting to provide an exhaustive overview, Table 1 summarises the findings of well-known U.S. and other studies that have provided economy-wide correlations between labor productivity and an output/GNP measure of the business cycle. They are all supportive of the view that labor productivity is pro-cyclical and serve to underpin theoretical and empirical macroeconomic studies that incorporate this property. Extreme caution is warranted over the interpretation of this evidence, however. The studies are not necessarily inconsistent with the possibility that significant sectors/industries within these economies experience acyclical or even counter-cyclical productivity. At best, they represent the net outcomes of countervailing forces. At worst, they suffer unavoidably from serious interpretational problems of data aggregation (see, for example, Stoker, 1993). For example, the necessary inclusion of hours of work within measures of labor productivity[5] is particularly fraught with interpretational difficulty when aggregating across the full breadth of industrial and service activity. The gap between measured hours and those effectively worked - a problem at the core of understanding pro-cyclical productivity - is difficult to handle within relatively homogeneous manufacturing sectors. Aggregating hours across such diverse sectors as insurance offices, superstores, chemical plants and machine tool makers poses an especially difficult challenge.[6]

As an initial benchmark exercise, we investigated the cyclicality of labor productivity at the aggregate manufacturing level using the NBER MP database. We correlated detrended total manufacturing aggregate productivity (pr) and equivalent detrended real output (y) since we are interested in the comovement of the cyclical components of these series. An additional motivation for detrending prior to examining the correlations is to avoid the potential problem of nonsense or spurious correlation (see Granger and Newbold (1974) and Phillips (1986))[7] when dealing with non-

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[5] Actually, several of the studies cited in Table 1 measure labor productivity without regards to the hours dimension of the labor input. This presumably reflects the fact that comparable international hours data are not available. It is interesting to note that omitting hours tends to produce higher estimates of pro-cyclical labor productivity. This may mean that hours are relatively more responsive than employment (i.e. numbers of workers) to cyclical changes in output.

[6] The problem of measuring the gap between effective and actual worked hours is a key element in the notion of labor hoarding. Accounting for this gap involves attempts to proxy factor utilization rates. On current methodology and data availability, this cannot realistically be achieved across all non-agricultural industries.

[7] When Y and X are generated by fairly general non-stationary/non-cointegrated ARIMA processes, Phillips (1986) shows, in the context of the simple regression model $Y = \alpha + \beta X + \mu$, that (i) the distribution of t_β diverges as $T\uparrow\infty$ and (ii) $\hat{\beta}$ has a non-degenerate limiting distribution. Both of these finding are directly relevant to our interest in bivariate correlations and imply (i) that asymptotically correct critical values for t_ρ cannot be obtained and (ii) that r is inconsistent. The first implication follows since the t-test for H_0:β=0 vs. H_1:$\beta\neq0$ is equivalent to the t-test for H_0:ρ=0 vs. H_1:$\rho\neq0$, i.e. $t=\hat{\beta} / se_{\hat{\beta}} \equiv r\{(n-2)/(1-r^2)\}^{0.5}$. The second implication follows since the sample correlation can be reexpressed as a function of $\hat{\beta}$, e.g. $r=\hat{\beta}\{Var(X)/Var(Y)\}^{0.5}$.

stationary data. Although we ultimately concentrate our analysis on correlations based on deviations from a Hodrick-Prescott trend, several other *ad hoc* methods for removing low frequency fluctuations are presented. These include: (i) stochastic detrending using logged first-differences and (ii) deterministic detrending using deviations from a linear trend. [8] While far from being exhaustive, these *ad hoc* filters have all been applied widely in the relevant literature, with the HP-filter being the most popular in recent years.[9] However, since it is well known that the HP-filter may induce spurious correlations and since there is no way of knowing if too little or too much of the low frequency movement in the series is being removed (see, for example, Maravall, 1995), the latter two filters are presented as benchmarks for comparison.

Correlations were first carried out for the whole sample period and then for the somewhat more volatile period, 1974-91, that followed the first OPEC supply shock. Based on two-tailed t-tests, Table 2 reveals that regardless of time period and detrending method, the correlations are not significantly different from zero. The one potential exception is in the linear detrended case which is nearly significant at the 5% level for the 1958-91. At the aggregate U.S. manufacturing level, unlike the whole economy findings in Table 1, the stylised fact of pro-cyclical labor productivity

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[8] *Ad hoc* univariate fixed filters for unobserved component estimation have well known pitfalls and limitations (see for example, Maravall, 1995). However, we apply them here since alternatives, such as structural time series analysis (see, for example, Harvey, 1989) are simply not practical when dealing with four hundred and fifty industries.

[9] King and Rebelo (1989) find that the HP-Filter is able to render stationary, series that are integrated up to fourth order. Abraham and Haltiwanger (1995) report that the above three filters tend to produce a range of results that are similar to and/or encompass some obvious univariate alternatives, e.g. "*Use of a quadratic deterministic trend yields results that mostly lie between those generated with linear detrending and those using the HP-filter*" [p. 1228]. They also report that, "I*n practice, HP-filtered series exhibit properties very similar to the deviations from a high order moving average centered on the current period*' [p. 1228].

Table 1
Correlation between HP-detrended Output & Productivity: Economy Wide Studies

Study (Country)	Data (Estimation Period)	Correlation	
Kydland and Prescott, (U.S.) 1982 Econometrica	GNP & GNP/hours worked (1950.1-1979.2)	0.10	
Hansen, (U.S.) 1985 Journal of Monetary Economics	GNP & GNP/hours worked (1955.3-1984.1)	0.42	
Prescott, (U.S.) 1986 FRB Minneapolis Quarterly Review	GNP & GNP/hours worked (1954.1-1982.4)	0.34	
Kydland and Prescott, (U.S.) 1990 FRB Minneapolis Quarterly Review	GNP & GNP/hours worked (1954.1-1984.2)		
	• household survey	0.51	
	• establishment survey		0.31
McCallum, (U.S.) 1989 Ch. in Barro (ed.)	GNP & GNP/hours worked (1955.3-1984.1)	0.42	
Benhabib, *et al.*, (U.S.) 1991 Journal of Political Economy	GNP & GNP/hours worked (1954.1-1988.2)	0.51	
Hansen and Wright, (U.S.) 1992 FRB Minneapolis Quarterly Review	GNP & GNP/hours worked (1947.1-1991.3)		
	• household survey	0.63	
	• establishment survey		0.31
Bencivenga, (U.S.) 1992 International Economic Review	GNP & GNP/hours worked (1954.1-1985.2)	0.44	
Fiorito and Kollintzas, (G-7) 1994 European Economic Review	GNP & GNP/employment (1960.1-1989.4)		
	• USA	0.83	
	• Canada	0.52	
	• Japan	0.90	
	• Germany	0.61	
	• France	0.78	
	• UK	0.76	
	• Italy	0.85	
Christodoulakis *et al.*, (EC) 1995 Economica	GDP & GDP/employment (1960-90)		
	• Belgium	0.82	
	• Denmark	0.53	
	• France	0.84	
	• Germany	0.31	
	• Greece	0.93	
	• Ireland	0.67	
	• Italy	0.91	
	• Luxembourg	0.65	
	• Netherlands	0.55	
	• Portugal	0.85	
	• Spain	0.39	
	• United Kingdom	0.56	

does not appear to hold. As with the economy-wide findings, however, we do not believe that the results shown in Table 2 provide a useful summary of productivity-output relationships. Even though measurement problems with hours of work and the other variables are greatly reduced at this narrower level, the results do not reflect a stylised relationship within U.S. manufacturing.

TABLE 2
Cyclicality of Aggregate Manufacturing Labor Productivity:
Sensitivity to Detrending Method and Time Period

Bivariate Correlations

	1958-91			1974-91		
	hp(y)	*d*(y)	*t*(y)	*hp*(y)	*d*(y)	*t*(y)
hp(pr)	0.041			0.104		
	[0.233]			[0.417]		
d(pr)		0.019			-0.062	
		[0.107]			[-0.247]	
t(pr)			0.330			0.231
			[1.98]			[1.06]

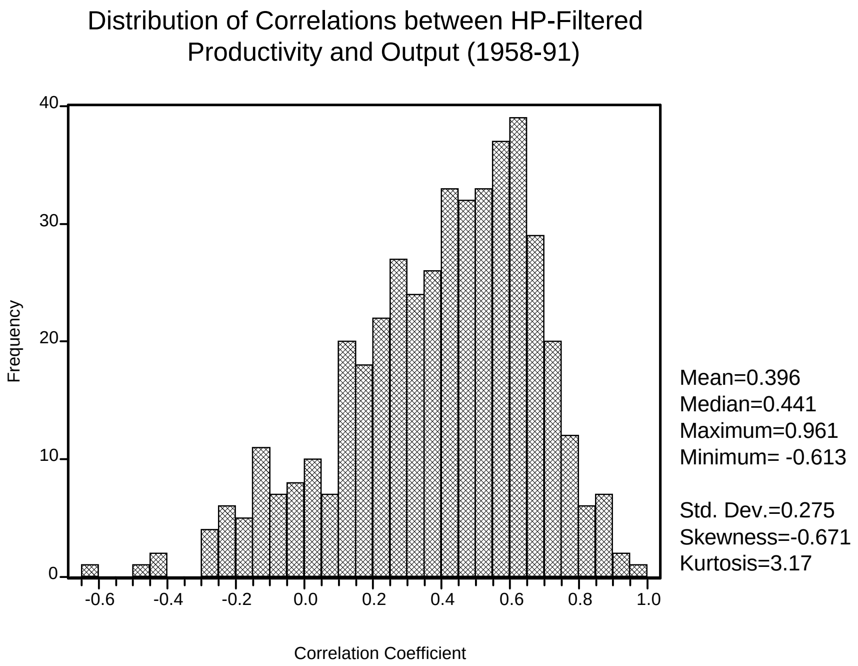
Notes: (i) the data reported in the first part of the table refer to the correlation coefficient between detrended aggregate manufacturing productivity (i.e. real output per hours worked) and real output; (ii) all variables are in logs; (iii) *hp* denotes the deviation of a logged series from a Hodrick-Prescott (HP) trend (i.e. $\ln y_t - \tau_t$). The HP trend, τ_t is obtained as the solution to the following optimisation problem: $\min_{\{\tau_t\}} \sum_{t=1}^{T} (\ln y_t - \tau_t)^2 + 100 \sum_{t=2}^{T-1} [(\tau_{t+1} - \tau_t) - (\tau_t - \tau_{t-1})]^2$; (iv) *d* refers to the first difference operator; (v) *t* denotes deviations from a linear trend; (vii) t-values are reported in brackets;

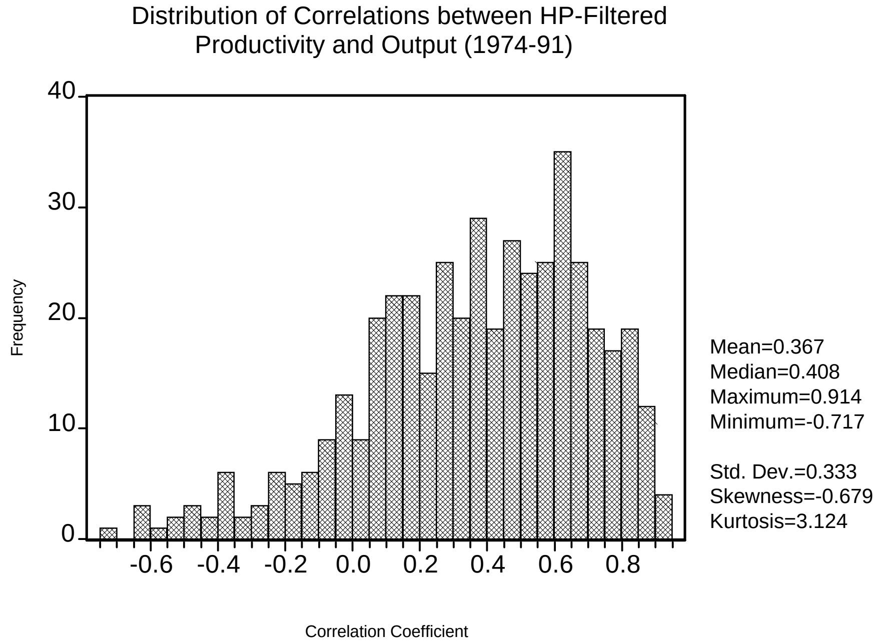
3 Industrial labor productivity patterns

In order to portray succinctly the coverage of the NBER MP database, Table 3 lists the SIC 2-digit manufacturing headings together with the count of 4-digit industries under each heading. We repeated the estimations contained in Table 2 at the 4-digit level.

Figure 1 summarises the distributions of the correlations between HP-filtered labor productivity and output for the full period 1958-91 and the sub-period 1974-91. It reveals that 90% (i.e. four hundred) of the industries record positive correlations, while 10% (forty-five) record negative correlation. For the whole period, the mean correlation is 0.396. Comparing the two time periods, we obtained similar measures

Figure 1 - Industry Bivariate Correlations: Sensitivity to Time Periods





of central tendency and of higher moments of the distributions.[10] We next tested whether or not the individual correlation coefficients were significantly different from zero. With respect to labor productivity in the full period, four industries (0.89 per cent of the total) were significantly counter-cyclical, one hundred and sixty four (36.44 per cent) were acyclical and two hundred and eighty two (62.67 per cent) were significantly pro-cyclical. Proportions of significantly pro-cyclical industries under each 2-digit SIC heading are reported in Table 3.

Table 3
NBER Manufacturing Industry Classification

2-digit SIC Number	Industry	No. of 4-digit industries	Prop. pro-cyclical labor productivity
20	Food and Kindred Products	47	0.77
21	Tobacco Products	4	0.25
22	Textile Mill Production	30	0.57
23	Apparel and Other Textile	33	0.79
24	Lumber and Wood Products	17	0.53

[10] Our other two detrending methods - (a) logged first differences and (b) deviations from a linear trend - produced distibutions very similar to those in Figure 1. For the full period their respective mean correlations and standard deviations were (a) 0.406 and 0.260 and (b) 0.435 and 0.346. For the shorter sub-period, these first and second moments were even closer to their respective measures using the HP-filter.

25	Furniture and Fixtures	13	0.38
26	Paper and Allied Products	17	0.65
27	Printing and Publishing	17	0.53
28	Chemicals and Allied Products	28	0.89
29	Petroleum and Coal Products	5	0.80
30	Rubber and Miscellaneous Plastic Products	6	0.33
31	Leather and Leather Products	11	0.55
32	Stone, Clay and Glass Products	27	0.59
33	Primary Metals	26	0.69
34	Fabricated Metals	36	0.72
35	Industrial Machinery and Equipment	44	0.36
36	Electronics and Other Electrical Equipment	39	0.64
37	Transportation Equipment	17	0.65
38	Instruments and Related Products	13	0.62
39	Miscellaneous Manufacturing Industries	20	0.55
	All 4-digit industries	450	0.63

Note: the last column consists of numbers of industries under each SIC heading exhibiting cyclical labor productivity that is statistically significantly greater than zero (two-tailed t test).

At the disaggregated level, the economy-wide stylised fact of pro-cyclical labor productivity survives in the sense that a majority (i.e. 63 percent) of industries exhibit significant degrees of pro-cyclical labor productivity. However, there are enough exceptional cases to warrant caution over its unselective background application to economic analysis. This is particularly the case when further investigation reveals that many of the exceptions follow systematic patterns.

Table 4 shows the frequencies at which negative, low (< 0.3) and high (> 0.6) correlations of detrended labor productivity and output occur under each of the 2-digit SIC headings listed in Table 3. Of the negative correlations, by far the largest cluster occurs at SIC 35, Industrial Machinery and Equipment. Twelve of forty-five industries with negative correlations occur in SIC 35; it also has the highest frequency (26) of industries with correlations < 0.3. In fact, of the forty-four 4-digit industries within SIC 35, only sixteen, or 36 per cent, exhibit significantly pro-cyclical productivity. Two of the remainder, SIC 3563 (Air and Gas Compressors) and SIC 3586 (Measuring and Dispensing Pumps) make up half of the four significantly counter-cyclical industries within the entire NBER database. The remaining twenty six-industries display acyclical productivity. Appendix 1 lists each of forty-four industries and its correlation status. It is quite clear that if many industries do take advantage of recessions to replace and upgrade their production and processing system, then industries under SIC 35 would be among the main investment goods suppliers.

The evidence that industrial machinery suppliers experience generally different cyclical labor productivity from most other industries is apparently contradicted by the fact that 64% of industries under SIC 36 (Electronics Equipment) exhibit pro-cyclical productivity. This industry is also a major industrial machinery supplier. Interestingly, however, more detailed observation of this industry reveals a picture that is not altogether at odds with the results pertaining to non-electrical machinery. The pro-cyclical industries under SIC 36 are completely dominant within industries that supply electronic equipment to households as well as relatively small scale electonic components; these can be summarised under their 3-digit headings as Household Appliances (SIC 363), Electrical Lighting and Wiring Equipment (SIC 364), Radio and Television Receiving. Equipment (SIC 365), Electronic Components and Accessories (SIC 367)[11], Miscellaneous Electrical Machinery, Equipment and Supplies (SIC 369)[12]. By contrast, under Electrical Industrial

[11] SIC 367 incorporates radio and television tubes, transmitting electronic tubes, semiconductors, electronic capacitors, resistors, electronic coils, connectors for electronic applications.

[12] SIC 369 covers storage batteries, primary dry and wet batteries, X-ray apparatus and electromedical apparatus, electrical equipment for internal combustion engines, and electrical machinery, equipment and supplies n.e.s.

Apparatus (SIC 362), four out of five industries display acyclical productivity.[13] Further both industries under Electrical Transmission and Distribution Equipment (SIC 361) and both industries under Communication Equipment (SIC 366) exhibit acyclical productivity. The installation of machines from this latter group of industries is likely to require more down-time and periods of major disruption to normal production processes.[14]

What about instances of acyclical labor productivity unconnected with machinery supply? We limit discussion to two ad hoc examples. First, three of the four industries within Tobacco Manufactures (SIC 21) fall into this category.[15] It is perhaps not surprising that the addictive demand for tobacco products does not bear relation to business cycle trends. Second, while the Chemicals and Allied Products (SIC 28) is the most predominantly pro-cyclical - with seventeen industries (see Table 4) with correlations > 0.6 - its three (from twenty eight) exceptions are worth noting. One of these, medicinal chemicals and botanical products (SIC 2833)

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[13] These are motors and generators (SIC 3621), industrial controls (SIC 3622), carbon and graphite products (SIC 3624) and electrical industrial apparatus n.e.s. (SIC 3629. The exceptional (pro-cyclical industry) is electric welding apparatus (SIC 3623).

[14] This latter point is worth emphasising. Arguments supporting the view that recessions may be times when industries perceive opportunity cost advantages in upgrading capital equipment are necessarily predicated on the notion that these activities will serve to disrupt normal production scheduling. In many instances, the installation of new equipment may be undertaken in parallel with normal production activities without serious effect. For example, small items of equipment that are integral to production processes may be relatively easily replaced during regular daily or weekly down-time periods. Even where capital re-stocking involves large units of equipment, replacements and upgrades may be introduced during any phase of the business cycle without seriously affecting the supply of output or services. This is likely to be the case, for example, with respect to transportation equipment (SIC 37), that inputs into motor vehicles, aircraft, railways, ships and boats, as well as guided missile and space vehicles. Typical firms within these industries are likely to have many substitute modes of transport thereby enabling continual upgrading of part of their overall stock.

[15] The three acyclical industries are cigarettes (SIC 2111), cigars (SIC 2121), and tobacco (chewing and smoking) and snuff (SIC 2131). The pro-cyclical industry is tobacco stemming and redrying (SIC 2141).

provides a rare example of an industry with significantly counter-cyclical labor productivity. Perhaps this industry also might not be expected to follow convential cyclical influences. The two instances of acyclical behaviour are nitrogenous fertilisers (SIC 2873) and explosives (SIC 2892).

TABLE 4
Frequency of Negative, Low and High Correlations at the 2-Digit Level

Correlations < 0

SIC	Frequency	SIC	Frequency	SIC	Frequency
20	0	27	1	34	1
21	0	28	2	35	12
22	2	29	0	36	4
23	1	30	1	37	2
24	4	31	0	38	4
25	3	32	1	39	3
26	2	33	2	Total	45

Correlations < 0.3

SIC	Frequency	SIC	Frequency	SIC	Frequency
20	6	27	6	34	9
21	3	28	2	35	26
22	12	29	1	36	14
23	6	30	4	37	6
24	8	31	5	38	5
25	8	32	8	39	8
26	5	33	7	Total	149

Correlations > 0.6

SIC	Frequency	SIC	Frequency	SIC	Frequency
20	26	27	2	34	8
21	0	28	17	35	6
22	6	29	2	36	7
23	7	30	1	37	2
24	2	31	1	38	3
25	3	32	7	39	4
26	6	33	6	Total	115

Note: (i) the correlations are calculated using the HP-filtered series over the period 1958-91.

4 Distribution of industry correlations and labor utilization

Our correlations of HP-filtered productivity and output for 4-digit industries between 1958 and 1991 lie in the range 0.961 to -0.613 (see Figure 1). In this section, we explore potential explanations of this distribution. Our central hypothesis is that variations in factor utilization play a major role. Firms experiencing high short-run fixed costs of organisational and physical capital and/or specific labor investments will display more sluggish factor adjustment responses to cyclical fluctuations in demand. In a labor market bargaining context, firm-specific human and organisational capital - deriving from specialised training, co-operative team effort, and acquired organizational know-how - produce joint rents that both management and workforce will strive to preserve during difficult economic conditions.[16] As long as joint rent remains positive, the parties will endeavour to maintain their employment relationship during recessionary periods.[17] In such situations, labor input will be varied, in part, through cyclical changes in effort. Labor productivity will fall with output during downswings of the cycle (labor hoarding) and rise with output during upswings (labor dishoarding).

This tendency towards pro-cyclical labor productivity will be mitigated in the event of (at least) three, non-mutually exclusive, scenarios. First, firms with low fixed factor costs are more likely to vary labor requirements directly with output fluctuations. Second, firms with higher worker-management transaction costs will face higher

[16] This response will be particularly apparent where the transaction costs of communicating and verifying information between the parties is relatively low (Hashimoto, 1979; Hashimoto and Yu, 1980).

[17] This may even be the reaction in the face of short-run negative joint rent. As long as the parties agree to the likelihood of net positive rent over the longer-term employment relationship, they will endeavour to preserve specific investments.

probabilities of separations[18] during recessionary periods. Third, firms that face more dampened output cycles will be more inclined to risk longer-term production scheduling.

When viewed in the context of relative variations in factor utilization, the observation of pro-cyclical productivity reduces essentially to a measurement-related phenomenon. On the labor front, hoarding represents a gap between measured, or paid-for, and effectively-worked total hours. During the upturn (downturn) of the cycle, output per measured hour may appear relatively high (low) because of unobserved increases (decreases) in hourly effort. As a consequence, output will fluctuate more than proportionately to total hours, reflecting pro-cyclical variations in effort. How might we proxy this latter unobserved effect? Based on the arguments of Basu (1996), we might expect that variations in materials costs will serve to capture this process. If labor effort, as well as capital intensity, fluctuate over the cycle then this will show up, *ceteris paribus,* in variations of raw materials, parts and other supplies that define materials inputs. In other words, while cyclical changes in effort will not be fully reflected by changes in total measured hours of work, they will directly relate to changes in materials costs.

There is a complication, however. Labor productivity is the ratio of the value of shipments (not including inventories) to measured total hours. During a boom, if output rises more than proportionately to total hours due to dishoarding, then this will be “captured” directly by observed rises in materials costs. In general, variations in materials costs would be expected to be positively related to variations in labor

[18] Because of an increased likelihood of separations occuring despite positive joint rents.

productivity. But the association of materials costs and labor productivity will not be solely confined to this route. Variations in materials costs will also directly relate to variations in inventory stocks of finished and partly finished goods. For *given* effort, inventory fluctuations will be negatively associated with the cylicality of labor productivity since an increase in labor input will leave shipments unaffected. In other words, in order to argue that variations in materials costs are capturing variations in labor and capital utilization, it is necessary additionally to control for inventory fluctuations.[19]

Following these arguments, our basic cross-section regression Model 1

$$\begin{aligned} &\mathbf{y} = \mathbf{X}\beta + \mathbf{u} \\ &\mathbf{u} \sim N(0,\sigma^2\mathbf{I}) \\ &\rho(\mathbf{X}) = k \end{aligned} \qquad (1)$$

concentrates on assessing the separate influences of materials inputs and inventories on the observed four hundred and fifty correlations of HP-filtered hourly productivity and output, r_i between 1958 and 1991. The (450x1) column vector **y** is comprised of transformed correlation coefficients, i.e. $z_i = 0.5\ \ln\left[(1+r_i)/(1-r_i)\right]$. This variance stabilising transformation is undertaken since valid application of regression requires that the response variable be unbounded (see Stuart and Ord, 1991, 1994). The (450*x*k) **X** matrix is comprised of a column of units to allow for a constant term, and initially, two more columns to represent relative propensity to vary factor inventory stock holdings and utilization rates. These are measured, respectively, as the logged variance of inventories, $\ln(s^2_{I_i})$ and the logged variance of

[19] In a regression context, the above argument implies that excluding inventory fluctuations from a regression of the distribution of correlations on the variation in material costs would lead to a downward biased estimate of the effort effect .

materials costs, $\ln(s^2_{mc_i})$. A complete description of the raw data and transformations is given in Appendix 2.

Results for Model 1 and diagnostic tests relevant to the assumptions in (1) are presented in Table 4. The residual based diagnostics pertaining to the distribution of **u** and its variance are given by the (JB)[20] and (H)[21] statistics respectively. In addition, the RESET[22] test for general misspecification is also reported. Tests pertaining to the rank of **X** i.e., $\rho(\mathbf{X})$ are given by the condition index (CI) and the variance inflation factor (VIF) for each column of **X**. The condition index (CI) is calculated as the square root of the ratio of the largest to smallest eigenvalue of the **C'C** matrix. The elements of **C** are comprised of the regressors normalised to unit length, i.e.

$$\mathbf{x}^n_{tk} = \frac{\mathbf{x}_{tk}}{\sqrt{(\mathbf{x}'_k \mathbf{x}_k)}}, \qquad (2)$$

where $\mathbf{x}_{tk}$ is the t[th] observation on the k[th] explanatory variable and $\mathbf{x}_k$ is the k[th] column of **X.** Belsley *et al.*, 1980 argue that a CI of 30 or greater is indicative of extreme multicollinearity. The variance inflation factor (VIF) indicates the effect the other conditioning variables have on the variance of a regression coefficient. The VIF's are the diagonal elements of $(\mathbf{R}'\mathbf{R})^{-1}$, where the **R** matrix is comprised of

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[20] JB is the Jarque-Bera (1980) test for normality of the errors and is distributed χ^2 with 2 df.

[21] The diagnostic statistic for heteroskedasticity is based on the test developed by Ramsey, 1969 and is conducted by regressing the squared residuals on powers of the predicted dependent variable, z, and then testing the null hypothesis that the powers of z are equal to zero. The test statistic is distributed χ^2 with q df where, q refers to the number of restrictions in the auxiliary regression.

[22] The RESET test (see Ramsey, 1969) is conducted by running an auxiliary regression of the dependent variable, z on all of the explanatory variables plus powers of predicted z and testing the null hypothesis that the powers of predicted z are equal to zero. The χ^2 distribution with q df is again used.

the correlation matrix of standardized (i.e. in z-score form) regressors. For example, if VIF=1 for a particular variable then it is orthogonal to the other regressors. VIF's of 5 or greater may be indicative of severe multicollinearity (see, Marquardt and Snee (1975)).

Examination of Table 5 indicates that the explanatory variables enter significantly with the expected signs, i.e. the z_i's associate positively with variations in materials costs and negatively with variations in inventories. As expected, the estimated coefficient attached to $\ln(s^2_{mc_i})$ is lower when $\ln(s^2_{i_i})$ is excluded from the regression (i.e. normalized $\hat{\beta}_2 = 0.121,\ t = 2.58$). Finally, Model 1 appears to perform well on the diagnostic tests except normality.

TABLE 5
Determinants of Cross-Industry Cyclical Differences in Productivity:
Model 1: $z_i=\beta_1+\beta_2\ln(s^2_{i_i}) + \beta_3\ln(s^2_{mc_i}) + u_i$

Summary of Model Fit

R	R^2	$\bar{R}^2$	F-statistic	S.E. of the Estimate	Condition Index
0.226	0.051	0.047	12.058**	0.151	19.55

Coefficient Estimates

	Unstandardised Coefficients	Standardised Coefficients	t-statistic	VIF
$\hat{\beta}_1$	0.109		3.250**	
$\hat{\beta}_2$	-0.024	-0.366	-4.152**	3.656
$\hat{\beta}_3$	0.027	0.433	4.910**	3.656

Residual Based Diagnostic Tests

H(1)	H(2)	H(3)	RESET(1)	RESET(2)	RESET(3)	JB
0.016	0.303	2.313	0.696	1.378	3.281	5.84*

Notes: (i) in Tables 5 through 6 **, and * refer to significance at the 1 and 5 percent levels respectively; (ii) the standardized regression coefficients, are the regression coefficients when all variables are expressed in z-score form.

In Section 3, we reported that the incidences of pro-cyclical and a cyclical labor productivity were not evenly distributed across 2-digit groupings. Food and chemical industries, for example, are predominantly pro-cyclical while industrial machinery and tobacco product industries are mainly acyclical. Economic, technological and organizational affinities within coherent broadly-based groups of industries could well have some bearing on an individual group member's productivity patterns. Intra-group trade, joint ventures and information exchange may result in systematic patterns of behavior among members of the group. In some instances, co-operative intra-group activities may produce positive externalities[23] and these may act to enhance the tendency to pro-cyclical productivity (Vecchi, 1996). Accordingly, our next two regression models are designed to capture systematic group effects.

Using a step-wise regression procedure, Model 2 extends Model 1 by additionally testing for the effects of 2-digit industry controls. The stepwise search algorithm proceeds through a combination of forward and backward variable selection. For example, the routine first fits a simple regression model for k-1 columns of **X** and obtains F statistics for each, e.g.

$$F_k^* = \frac{MSR(\mathbf{x}_k)}{MSE(\mathbf{x}_k)},\ F^* \sim F(k-1,\ n-k) \qquad (3)$$

where, MSR is the mean square regression, and MSE is the mean square error. The **x** variable with the largest F^* value is added to the equation if the predetermined probability value for F-to-enter is achieved. Assuming an **x** is entered at stage-

[23] For example, coherent industrial groups might be better able to disseminate and exchange information across the range of activities so that better advantage can be taken of opportunities arising during cyclical expansions.

1(denoted $\mathbf{x}_{k1}$) the procedure next fits all regression with two **x** variables. For each regression model in stage-2 a partial F-test statistic is calculated, e.g.

$$F_k^e = \frac{MSR(\mathbf{x}_k|\mathbf{x}_{k1})}{MSE(\mathbf{x}_{k1,}\mathbf{x}_k)},\ F^e \sim F(1,\ n-k). \quad (4)$$

Again, the **x** variable with the largest F^e value is added to the equation if the predetermined probability value for F-to-enter is achieved. Assuming another **x** is added at stage-2, (denoted $\mathbf{x}_{k2}$) the algorithm next tests whether any of the **x** variables previously entered should be dropped, e.g.

$$F_k^d = \frac{MSR(\mathbf{x}_{k1}|\mathbf{x}_{k2})}{MSE(\mathbf{x}_{k1},\mathbf{x}_{k2})},\ \ F^d \sim F(1,\ n-k). \quad (5)$$

This cycle is repeated until no further **x**=s can be either added or deleted. The results for the "final equation" are reported in Table 6.[24] Four of the twenty 2-digit industries entered significantly; these are SICs 24, 25, and 35 which enter negatively and SIC 28 which is positive. Inspection of Table 1 reveals that the first three industries display largely acyclical labor productivity while the last industry is overwhelmingly pro-cyclical. Inventory and materials costs variables remain significant in Model 2 with little qualitative change in their coefficient estimates compared to Model 1. The inclusion of the 2-digit controls improves the overall model fit. Again, the model performs satisfactorily on all diagnostic tests, except the normality test.

Model 3 extends the methodology of Model 2 by substituting one hundred and forty one 3-digit for the twenty 2-digit controls. Results are shown in Table 7. The same

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[24] Note that application of separate specific-to-general (based on F-to-add) and general-to-specific (based on F-to-delete) selection strategies as well as altering the selection criteria in the stepwise routine produced the same final set of conditioning variables.

stepwise procedure is adopted. Four groups of industries exert a significant negative influence on the z_i's. Three of these are within the non-electrical machinery industry (SIC 35 - see Appendix A1); these are general industrial machinery and equipment (SIC 356), refrigeration and service industry machinery (SIC 358), and miscellaneous machinery (SIC 360). Nineteen industries display a significant positive influence. In general, these group effects tend to correspond more with pro-cyclical than with acyclical labor productivity. Incorporating 3-digit controls provides an additional improvement in results with respect to both overall fit and diagnostic tests. Model 3 passes all diagnostic tests, including normality. Further, the materials costs and inventories variables remain robust - surviving the selection criteria of the stepwise regressions - despite a considerable expansion of the industry controls.

TABLE 6

Determinants of Cross-Industry Cyclical Differences in Productivity:

Model 2: $z_i=\beta_1+\beta_2\ln(s^2_{l_i}) + \beta_3\ln(s^2_{mc_i}) + \sum \gamma_i SIC_{i,2-digit} + u_i$

Summary of Model Fit

R	R^2	$\bar{R}^2$	F-statistic	S.E. of the Estimate	Condition Index
0.344	0.118	0.106	9.902**	0.147	21.366

Coefficient Estimates

	Unstandardised Coefficients	Standardised Coefficients	t-statistic	VIF
$\hat{\beta}_1$	0.127		3.903**	
$\hat{\beta}_2$	-0.023	-0.306	-3.440**	3.988
$\hat{\beta}_3$	0.020	0.370	4.190**	3.913

Residual Based Diagnostic Tests

H(1)	H(2)	H(3)	RESET(1)	RESET(2)	RESET(3)	JB
1.136	1.621	2.701	0.041	0.462	0.585	9.36**

Note: the stepwise search algorithm was used to select from industry controls (SIC21 to SIC39 inclusive) plus $\ln(s^2_{l_i})$ and $\ln(s^2_{mc_i})$ since the alternative of examining all possible regressions, i.e. 2^{21}-1 was not practical. The criteria used in the stepwise search was probability-of-F-to-enter<=0.050, and probability-of-F-to-remove<=0.010.

TABLE 7
Determinants of Cross-Industry Cyclical Differences in Productivity:
Model 3: $z_i=\beta_1+\beta_2\ln(s^2_{i_i})+\beta_3\ln(s^2_{mc_i})+\sum\gamma_i SIC_{i,3-digit}+u_i$

Summary of Model Fit

R	R^2	$\overline{R}^2$	F-statistic	S.E. of the Estimate	Condition Index
0.525	0.275	0.232	6.437**	0.136	21.961

Coefficient Estimates

	Unstandardised Coefficients	Standardised Coefficients	t-statistic	VIF
$\hat{\beta}_1$	0.102		3.301**	
$\hat{\beta}_2$	-0.018	-0.277	-3.269**	4.203
$\hat{\beta}_3$	0.021	0.327	3.913**	4.093

Residual Based Diagnostic Tests

H(1)	H(2)	H(3)	RESET(1)	RESET(2)	RESET(3)	JB
0.470	0.525	1.861	0.102	0.111	5.931	2.409

Notes: (i) a stepwise search algorithm was again used to select from the 141, 3-digit SIC industry controls plus the inventory and material costs variables; (ii) the 3-digit industry controls which entered significantly negative include: SIC's 254, 356, 358, 359; (iii) the significant positive industry controls include: SIC's 203, 204, 206, 207, 209, 229, 239, 264, 281, 282, 284, 286, 289, 339, 344, 346, 367, 384, 387 .

As a final specification, we extended Model 3 to include additional economic and structural variables that plausibly relate to the z_i's. These are intended to capture fluctuations in effort and labor's fixity.

Despite the generality of the materials costs variable, we examined two arguments that have been used in the existing literature to capture effort fluctuations. Shea (1992) uses industrial injury rates as a proxy for effort and finds that they add significantly to production function estimates. He finds that accident rates correlate with average overtime hours and the ratio of production and total workers. Given a lack of accident data, Caballero and Lyons (1992) and Marchetti (1994) use the latter two variables as effort proxies in their studies.[25] In our context, an industry with relatively high variance in (a) average hours per worker, $s^2_{hnp_i}$ and/or (b) the ratio of production to total workers, $s^2_{npn_i}$ will be those industries which are the most prone to effort fluctuation. Our remaining variables relate, albeit somewhat indirectly, to specific human capital and labor's fixity. In general, we might expect that a firms which are relatively highly capitalized will employ higher proportions of skilled labor requiring higher levels of specific training. We included, therefore, the mean capital to labor ratio, $\overline{k}n_i$ in the i'th industry. Further, industries with the highest growth rates in capital to labor may find it particularly necessary to instigate more re-training programmes and on-the-job training schemes in order to update the skills of their workers. To capture this possibility, we also incuded the variable $\ln\left[kn_{iT} / kn_{i1}\right] / T$, the average exponential growth of capital to labor in the i'th industry.

The stepwise search procedure on this extended model[26] produced the same results as Model 3, Table 6. The additional variables, some of which have proved important additions in the existing literature, did not add significantly to our existing formulation. In particular, they did not supplant or add-to the materials costs and inventory variables.

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[25] Actually, they use average total hours rather than overtime - the two variables are very highly correlated.

[26] The final regression takes the form: Model 3: $z_i=\beta_1+\beta_2\ln(s^2_{i_i}) + \beta_3\ln(s^2_{mc_i}) + \beta_4\ln(s^2_{hnp_i}) + \beta_5\ln(s^2_{npn_i}) + \beta_6\overline{k}n_i + \beta_7\ln\left[kn_{iT} / kn_{i1}\right] / T + \sum \gamma_i SIC_{i,3-digit} + u_i$

5 Concluding comments

At one end of the spectrum, problems of aggregation are greatest in the search for stylised facts on labor productivity at the level of an entire economy. At the other, aggregation ceases to be a serious concern for empirical studies undertaken at the level of the individual plant or business premise or government department. Of course, moving from broad to narrow involves a trade-off. Substituting detailed micro for macro information provides more precision in estimation at the expense of obtaining a more limited, and perhaps more *ad hoc*, picture of the wider economy. It is not our intention in this paper to undervalue the usefulness of aggregate information on labor (or other) market phenomena, especially if this helps towards the formulation of models of macroeconomic behavior. We have purposely chosen a broad canvas, covering total U.S. manufacturing industry. Compared to much of the previous work, however, we have tried to balance the benefits of aggregated summary and dis-aggregated empirics.

The “loss” resulting from this exercise is that it forces us to conclude that it is unsafe to characterise U.S. manufacturing industry, let alone the entire economy, as being generally represented by pro-cyclical labor productivity. On our evidence, labor productivity in roughly two-thirds of 4-digit industries is pro-cyclical while it is acyclical in one-third. The “gain” is the finding that these two productivity traits are not randomly disbursed but appear to cluster within coherent higher-order industries. The observed systematic patterns may themselves provide useful insights at the level of macroeconomic modelling. For instance, we suggest that the observation of an above-average tendency towards acylical labor productivity in investment goods industries may link to the growing literature on industrial cleansing during recessions. The importance of industrial clusters of common cyclical behavior carries over into our cross-sectional regression analysis. This framework also provides a fresh perspective on the analysis of the role of variations in factor utilization on cyclical labor productivity. As in a number of previous studies, we find support for continued exploration down this avenue.

Appendix A1: SIC 35

TABLE A1
Cyclicality of Labor Productivity:
SIC 35 (Machinery Except Electrical)

SIC code	Industry	Cyclicality
3511	Steam, gas, and hydraulic turbines, and turbine generator set units	pro-
3519	Internal combustion engines, not elsewhere specified (n.e.s)	acyclical
3523	Farm machinery and equipment	pro-
3524	Garden tractors and lawn and garden equipment	pro-
3523	Construction machinery and equipment	acyclical
3532	Mining machinery and equipment, except oil fields	acyclical
3533	Oil field machinery and equipment	acyclical
3534	Elevators and moving stairways	pro-
3535	Conveyors and conveying equipment	acyclical
3536	Hoists, industrial cranes, and monorail systems	acyclical
3537	Industrial trucks, tractors, trailers, and stackers	pro-
3541	Machine tools, metal cutting types	acyclical
3542	Machine tools, metal forming types	acyclical
3544	Special dies and tools, die sets, jigs and fixtures, and industrial molds	pro-
3545	Machine tool accessories and measuring devices	pro-
3546	Power driven hand tools	pro-
3547	Rolling mill machinery and equipment	pro-
3549	Metalworking machinery, n.e.s.	acyclical
3551	Food products machinery	acyclical
3552	Textile machinery	pro-
3553	Woodworking machinery	acyclical
3554	Paper industries machinery	acyclical
3555	Printing trades machinery and equipment	acyclical
3559	Special industry machinery, n.e.s.	pro-
3561	Pumps and pumping equipment	acyclical
3562	Ban and roller bearing	pro-
3563	Air and gas compressors	counter-
3564	Blowers and exhaust and ventilation fans	acyclical
3565	Industrial patterns	pro-
3566	Speed changes, industrial high speed drives, and gears	acyclical
3567	Industrial process furnaces and ovens	acyclical
3568	Mechanical power transmission equipment, n.e.s.	acyclical
3569	General industrial machinery and equipment, n.e.s.	acyclical
3572	Typewriters	pro-
3573	Electonic computing equipment	acyclical
3574	Calculating and accounting machines	pro-

(Table A1 continued)

3576	Scales and balances, except laboratory	acyclical
3579	Office machines, n.e.s.	acyclical
3581	Automatic merchandising machines	acyclical
3582	Commercial laundry, dry cleaning, and pressing machines	acyclical
3585	Air conditioning and warm air heating equipment and commercial and industrial refrigeration equipment	acyclical
3586	Measuring and dispensing pumps	counter-
3589	Service industry machines, n.e.s.	pro-
3592	Carburetors, pistons, piston rings and valves	acyclical
3599	Machinery, except electrical, n.e.s.	acyclical

Appendix A2: Data

The data used to construct the variables employed in this study are from the NBER productivity database compiled by Eric J. Bartelsman and Wayne B. Gray.[27] This database contains annual U.S. production and cost data for 450 manufacturing industries from 1958 to 1991 and is based on the 1972 Standard Industrial Classification. The particular variables used from this database, and the corresponding notation employed in the paper (in brackets), definitions and transformations are as follows:

Variable	Description
CAP (=k)	real capital stock (millions of 1987 dollars)
EMP (=n)	number of employees (in 1,000s)
INVENT (=in)	end-of-year inventories (millions of dollars)
MATCOST (=mcn)	cost of materials (millions of dollars)
PRODE (=np)	number of production workers (in 1,000s)
PRODH (=h)	number of production worker hours (in millions of hours)
PIMAT (=pmc)	price deflator for materials (equals 1 in 1987)
PISHIP (=p)	price deflator for value of shipments (equals 1 in 1987)
VSHIP (=yn)	value of industry shipments (millions of dollars)

Transformations	Description
hnp=h/np	average hours per production worker
i=in/p	real inventories
kn=k/n	capital to labor ratio
mc=mcn/pmc	real material costs
npn=np/n	production to total employment
pr=y/h	hourly productivity
y=yn/p	real shipments

[27] The version of the data employed was received in February 1996 and was last updated by NBER on September 23, 1994. Other researchers should note that this data set can be obtained by using the FTP address "nber.harvard.edu". Bartelsman and Gray provide detailed documentation further describing the data sources and methods in the readme.doc and nberprod.doc files.

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