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Do Inventories Moderate Fluctuations in Output?

Donald S. Allen

The movement of aggregate inventory investment appears to play a major role in business-cycle dynamics. Economists continue to explore the idea that large unexpected slowdowns in demand may cause an excessive amount of inventory to build up, causing a slowdown in output as firms cut back on production until inventories return to normal. A previous article in this publication (Allen, 1995) discusses the potential impact of changing inventory management methods on the frequency and depth of recessions. Although the findings are inconclusive, the potential effect of inventory movement on the business cycle warrants continued research. In addition, some authors argue that monetary policy has its primary impact through an effect on inventory investment. If this is the case, then it is important for monetary policymakers to understand how the decisions on inventory investment—that is, periodic changes in inventory—are made.

In spite of the large amount of research on inventories, many questions remain. This article tries to answer two of several open questions identified by Lovell (1994): First, do firms use inventories to schedule production efficiently? Specifically, do firms use inventories to smooth production in the face of uncertain demand? Second, are problems of aggregation important? More directly, do problems of aggregation account for economists' failure to confirm smoothing by analyzing aggregate inventory data?

Inventories allow firms to supply unexpected demand without having to adjust output immediately. When firms face increasing marginal costs of production, using inventory to smooth production is efficient, as long as the savings from not adjusting production exceed the cost of holding inventory. Inventory acts as a buffer stock, absorbing increases or decreases in demand while production remains relatively steady. If firms are smoothing production, then we would expect sales to vary more than production: The variance of production should be less than the variance of sales. If inventories are used as a buffer stock, then high-frequency changes in inventory should be in the opposite direction to sales. Empirical research using aggregate data does not confirm this intuition. Inventory researchers (Blinder, 1986, for example) have found that production varies more than sales and that the covariance of changes in inventory and sales is actually positive. These stylized facts imply that either the production-smoothing, buffer stock model is incorrect,[1] or there are other factors that prevent empirical confirmation of the smoothing effect.

Most of the research that finds contradictions of production smoothing uses seasonally adjusted aggregate data of inventory and sales. It is possible that firms actually do use inventory to smooth production and that the empirical research has failed to detect the signs of this activity because the data are too highly aggregated over many firms. This article uses firm-level data from COMPUSTAT to test whether the stylized facts hold at the firm level and at the aggregate level over firms in the same 2-digit SIC code. The data are for publicly traded firms in a variety of SIC codes. The results are still negative for the production-smoothing model, however. Statistical tests in which the ratio of the variance of the value of production to the variance of the value of sales is used as a measure of production smoothing fail to

[1] An alternative inventory model called (*S,s*), suggests that firms with fixed costs of adjusting inventory will establish a maximum level of inventory (*S*), and a minimum level (*s*), and adjust only when inventory falls below the minimum [See Allen (1995) for a brief explanation of production smoothing and (*S,s*)]. The (*S,s*) model is less likely to have production varying less than sales. The purpose of this article is to test the production smoothing model only.

confirm smoothing in the majority of the SIC codes, both at the firm level and the aggregate level.

An alternative reason for the failure of the production-smoothing test is that firms also consider other factors in managing inventory. If there are severe economic penalties for running out of stock, then firms may plan to maintain some average level of inventory relative to sales over a planning horizon (see West, 1986). If increasing demand or large shocks to sales reduce inventory below this level, then a portion of production will be used to increase inventory. If this "planned" addition to inventory is large enough, the variance ratio test for smoothing will fail. A test of a model in which firms smooth around a target inventory-to-sales (I/S) ratio appears to support the buffer-stock nature of inventories.

The paper is organized as follows: The first section gives a description of the data. The next section discusses the results of tests of the production-smoothing hypothesis. The third section proposes a simple model of partial adjustment to a target inventory level. It shows the results of tests of the buffer-stock hypothesis using the correlation of changes in inventory to changes in sales at the firm level and SIC code level. Next, some specific firm data are provided for illustrative purposes, and a summary and conclusions follow.

DESCRIPTION OF DATA

The COMPUSTAT data are individual firm data on inventory and sales for publicly traded firms for the period from the first quarter of 1981 to the fourth quarter of 1991, as reported in balance sheets and income information. The original dataset contains financial information from 6,984 firms across several SIC codes. Data for all 44 quarters were not available for all firms. An average of about 31 quarters of sales data per company was available. There were 42 companies with duplicate information due to accounting changes. Some firms reported data only annually or semi-annually, while others had missing quarters. Duplicate companies, companies with nonconsecutive quarters, and SIC codes for which the notion of inventory did not correspond to the product offered for sale—for example, services—were eliminated. The last three quarters of 1991 were dropped because of insufficient data. The final dataset comprises information from 2452 companies with an average of 29 quarters of data per company over the sample period.

Table A in the appendix summarizes descriptive statistics by 2-digit SIC codes. Mining industries are grouped in SIC codes 10 through 14; construction establishments are in SIC codes 15, 16, and 17; SIC codes 20 through 39 are manufacturing industries; SIC codes 50 and 51 are wholesale establishments; and SIC codes 52 through 59 are retail establishments.

Average quarterly sales in each SIC code range from $588 million in SIC code 10 (metal mining) to $106.1 billion in SIC code 29 (petroleum and coal products). The ratios of mean quarterly inventory to mean quarterly sales range from 0.17 to 1.38. This range compares to a peak monthly inventory-to-sales ratio for total business of 1.7 during the 1981-82 recession and 1.36 in April 1997. A 1.36 ratio of inventory to monthly sales is approximately equivalent to 0.46 as a ratio of quarterly sales.

Aggregation of firms within SIC codes is performed separately for changes and levels. That is, sales and inventory are summed over firms within the same 2-digit SIC code, but changes in sales and/or inventory for the SIC code are computed by adding the changes in sales and/or inventory for each company in the sample during the quarter instead of taking the difference of the aggregate sales and/or inventory. Firms are included in the sample after the second period for which data are available, so that both changes and levels are included. This procedure was adopted because firms are added and dropped throughout the sample period. The value of production is estimated to be the sum of the value of sales and the value of the change in inventory for each quarter.

RESULTS

Variance Ratio

The typical measure of smoothing uses the ratio of the variance of production to the variance of sales. Variance ratios greater than 1.0 suggest that production varies more than sales, contradicting the expected results of smoothing. Similarly, ratios less than 1.0 confirm smoothing. Lovell (1993) questions the use of this ratio as a measure of smoothing for reasons related to aggregation and sectoral interaction between companies—that is, manufacturing firms, wholesale firms, and retailers all hold inventory and can be suppliers or customers of each other. Inventory movements of each sector can be offsetting or synchronized. Summing inventory over all firms, both downstream and within the same sector, can distort the variance ratios. The objective of this article is to test whether aggregating up to the 2-digit SIC code level can induce changes in the variance ratio measure. It does not necessarily endorse the validity of the measure.

The results in Table 1 show that virtually all ratios computed were greater than 1.0 for both the aggregate and individual firms in each SIC code. Only three SIC codes (14, 29, and 59) had *aggregate variance* ratios less than 1.0, and only three SIC codes (31, 53, and 59) had *average firm variance* ratios less than 1.0. Aggregating over firms in the same 2-digit SIC codes and comparing to the average firm-level variance ratios with the variance ratio of the aggregate suggests that aggregation does have a negative effect on the variance ratio when smoothing is confirmed for the average firms. For SIC code 53, the average variance of all firms is 0.85, but the variance ratio of the aggregate SIC code 53 is 1.01. In general, however, the variance ratio of the aggregate is less than the average variance ratio of the individual firms.

The value of production is estimated as the sum of sales and the change in inventory for that period, as shown in Equation 1 below:

$$(1) \qquad P_t = X_t + N_t - N_{t-1}$$

or

$$P_t = X_t + \Delta N_t,$$

where P is production, X is sales, and N is inventory. The variance of the value of production is then equal to the sum of the variance of sales, the variance of the change in inventory, and twice the covariance of sales and the change in inventory. Therefore, for the variance of production to be less than the variance of sales, the covariance term must be negative and more than half the value of the variance of the change in inventory.

The last column in Table 1 shows the sign of the covariance of sales and changes in inventory for the aggregate of the 2-digit SIC codes. There are 10 industries in which the covariance of sales and the change in inventory are negative, but in seven of these the negative covariance is less than half the variance of the change in inventories, leading to a variance ratio greater than 1.0.

Estimating production by adding sales revenue to changes in inventory each quarter instead of counting actual physical stock generally has had less success in confirming production smoothing. One reason could be the existence of mark-ups over production costs. Since firms have several dimensions along which to adjust, they can adjust on the price or quantity margin; production of physical units may be only loosely connected to sales revenue. In other words, a change in sales revenue can reflect a change in price or a change in quantity sold, or both.[2]

Another explanation of the variance ratio test's failure to confirm smoothing is that firms may attempt to maintain average inventory at a fixed proportion of average sales, so that if sales are trending up, then inventory will also trend up.[3] West (1986) and others recognized that when firms maintain inventory for stockout avoidance, production smoothing will not be

[2] The relative success of some researchers who use physical-product data in confirming production smoothing (Ghali, 1987; Fair, 1989; and Krane and Braun, 1991) suggests that seasonal adjustments and price flexibility (e.g., liquidation sales) may distort the relationships between value-based variables and quantity. This distortion may account for the failure to confirm smoothing by using value-based data. Unfortunately, this hypothesis is not tested here, but work by Miron and Zeldes (1988) found that seasonal adjustment did not appear to affect the empirical rejection of production smoothing.

[3] Detrending aggregate data is one method used to remove this trend effect Typical methods of detrending can introduce further distortion into the data.

Table 1

Variance Ratio

SIC Code	Industry	# of Cos.	Ratio of Variance of Production to Variance of Sales: Average	Ratio of Variance of Production to Variance of Sales: Weighted Average	Ratio of Variance of Production to Variance of Sales: Aggregate	Sign of Covariance of Sales and Change in Inventory: Aggregate
10	Metal mining	32	1.34	1.14	1.04	+
12	Coal mining	4	1.02	1.05	1.01	–
13	Oil and gas extraction	99	1.42	1.12	1.01	+
14	Nonmetallic minerals, except fuels	8	1.06	0.99	0.99	–
15	General building contractors	36	360.02	2.16	1.07	–
16	Heavy construction, except bldg.	12	1.03	1.08	1.00	+
17	Special trade contractors	17	1.08	1.07	1.06	+
20	Food and kindred products	100	1.37	1.13	1.03	+
21	Tobacco products	7	1.17	1.21	1.02	–
22	Textile mill products	40	1.10	1.24	1.02	–
23	Apparel and other textile products	45	1.14	1.02	1.03	+
24	Lumber and wood products	27	1.04	1.08	1.01	+
25	Furniture and fixtures	30	1.07	1.17	1.03	+
26	Paper and allied products	47	48.65	1.07	1.02	+
27	Printing and publishing	66	1.08	0.99	1.00	+
28	Chemicals and allied products	185	1.46	1.06	1.02	+
29	Petroleum and coal products	37	1.07	1.05	1.00	–
30	Rubber and misc. plastics products	65	1.13	1.04	1.00	+
31	Leather and leather products	18	0.89	1.04	1.02	+
32	Stone, clay, and glass products	25	1.78	1.03	1.01	+
33	Primary metal industries	80	1.30	1.21	1.02	+
34	Fabricated metal products	83	1.23	1.11	1.03	+
35	Industrial mach. and equip.	289	5.72	1.04	1.02	+
36	Electronic and other elect. equip.	263	1.51	1.05	1.02	+
37	Transportation equipment	100	1.08	1.03	1.01	+
38	Instruments and related prods.	226	1.30	1.06	1.01	+
39	Misc. manuf. industries	51	1.07	1.00	1.01	–
50	Wholesale durable goods	126	1.49	1.17	1.03	+
51	Wholesale nondurable goods	67	1.23	1.01	1.01	+
52	Retail building materials and garden supplies	14	1.14	1.06	1.06	+
53	Retail genl. merchandise stores	46	0.85	0.87	1.01	–
54	Retail food stores	40	1.04	1.05	1.01	+
55	Auto dlrs. and service stations	5	3.31	1.16	1.08	+
56	Retail apparel and acces. stores	31	1.00	0.96	1.02	–
57	Retail furniture and home furnishings stores	24	1.08	1.02	1.06	+
58	Retail eating and drinking places	54	1.03	1.01	1.00	+
59	Misc. retail establishments	53	0.93	0.91	0.97	–

confirmed in the data. In this case a portion of inventory change ("planned inventory changes") will move together with sales, while a portion of inventory change ("unplanned inventory changes") will move in the opposite direction to sales as a buffer stock. Since production is computed as the sum of sales and the contribution to (change in) inventory each period, if the planned inventory changes overwhelm the unplanned changes in inventory, then production will have a higher variance than sales. A simple model of this behavior implies that the change in inventory should nonetheless be negatively correlated with the *change* in sales. For almost all SIC codes, changes in inventory and changes in sales are indeed negatively correlated. This result suggests that inventories do act as buffer stock for unexpected changes in sales. The next section proposes the model and tests the implications of this hypothesis.

A SMOOTHING MODEL WITH A TARGET I/S RATIO

It is possible that firms smooth production over some horizon but also adjust production to maintain a mean desired inventory level at a fixed proportion of sales. A stockout avoidance motivation would favor an optimal inventory-to-sales ratio. Although, theoretically, the ratio of inventory to sales which minimizes the risk of running out of stock should fall as average sales increase, the aggregate data appear to show that firms keep the ratio relatively constant. If we assume that sales are serially correlated and that industries adjust partially to the desired inventory-to-sales ratio, then a portion of production will go toward inventory investment. We can consider this to be planned inventory investment. The length of the production planning horizon will determine how often production will be adjusted. Ideally, firms will smooth over a horizon where average sales can be predicted with reasonable accuracy. For simplicity, we assume that firms base their production plans for the next period on last period's sale and the difference between actual and planned inventory. The following equations would describe this process:

(2) $$X_t = C + \rho X_{t-1} + \varepsilon_t, \text{ where } \rho > 0;$$

(3) $$N_t^* = \theta X_t;$$

(4) $$P_t = X_{t-1} + \gamma\left(N_t^* - N_{t-1}\right), \text{ where } 0 \le \gamma \le 1; \text{ and}$$

(5) $$\Delta N_t = P_t - X_t = \gamma\left(N_t^* - N_{t-1}\right) - \Delta X_t,$$

where X_t is sales in period t, C is a constant, N_t^* is the desired inventory level and N_t is the actual inventory level in period t, P_t is production in period t, and ε_t is a random shock to sales in period t. The coefficient θ can be assumed to be constant and estimated to be the average inventory to sales ratio. The term $\gamma(N_t^* - N_{t-1})$ in Equation 5 can be thought of as the "planned" component of inventory investment, where γ represents the speed of partial adjustment to desired inventory level, and the term ΔX_t can be thought of as the buffer stock movement or "unplanned" inventory investment. The "planned" inventory investment component will be positively correlated with *sales* if the firm's target inventory is represented by Equation 3, while the unplanned term will be negatively correlated with *changes in sales* as the buffer stock notion implies.[4]

The next section shows the results of testing whether changes in sales and changes in inventory are negatively correlated.

CORRELATION COEFFICIENTS

For each SIC code and individual firm, I computed the correlation coefficients between the change in sales and the

[4] Generally, the correlation between the left-hand variable and the right-hand variables is indeterminate without prior knowledge of the coefficients However, because γ and θ are both less than 1.0 and planned inventory change will be in the same direction as the change in sales, the change in sales should dominate the planned inventory change. In this case, the correlation between the change in sales and change in inventory should be negative.

change in inventory for each period. To get a measure of the relative co-movement of changes in inventory and changes in sales for firms within the SIC code, I computed a simple average of the correlation coefficients. If there is no weighting of individual firms by size, then even if a particular firm comprises most of the aggregate data, the co-movement of that firm's change in inventory and change in sales will not proportionately influence the average correlation coefficient of individual firms. For this reason, I also computed a weighted average of the individual firm correlation coefficients, based on relative contribution to the aggregate.

Table 2 shows the results. About two-thirds of the SIC codes show a negative correlation of the change in aggregate sales to change in aggregate inventory. Likewise, the weighted and unweighted average correlation coefficients of the individual firms are negative for most SIC codes. Of the 13 SIC codes with positive correlations between changes in sales and changes in inventory, five SIC codes show negative average (unweighted) correltion coefficients at the firm level. A few SIC codes show negative correlation coefficients at the aggregate level but positive average correlation coefficients at the firm level. This could be because smaller firms with positive correlations are influencing the data.

The results are consistent with the simple model of partial adjustment. Correlation coefficients remain positive for wholesale and are negative for aggregate manufacturing and retail. This result implies that both firm-level data and aggregated data support the buffer-stock hypothesis.

ESTIMATES OF MODEL COEFFICIENTS

The anticipated negative correlation coefficients were verified in the previous section. This section estimates the model from the data. Equation 5 of the partial adjustment model can be rearranged algebraically in the following equations:

$$(6)\quad \Delta N_t = C(\gamma\theta - 1) + \left[1 + \rho(\gamma\theta - 1)\right]X_{t-1} - \gamma N_{t-1} + (\gamma\theta - 1)\varepsilon_t, \text{ and}$$

$$(7)\quad X_t = C + \rho X_{t-1} + \varepsilon_t.$$

The coefficients of Equations 6 and 2 (repeated above as Equation 7) were estimated by using ordinary least squares. The fraction of sales (θ) that represents the desired inventory level N_t^*, is estimated as the average inventory-to-sales ratio for each SIC code. Table 3 shows the results for each industry, including the constant term. Estimates of the coefficients were the same sign predicted by the equations and statistically significant at either the 95 or 99 percent confidence interval for 25 out of 37 industries for last-period inventory levels and for 21 out of the 37 industries for last-period sales. The coefficient γ was negative for two industries, petroleum and coal products and wholesale durable goods, suggesting that these firms may have been reducing inventories during the sample period.

Estimates of γ for the 25 industries with significant coefficients ranged from 0.1876 for primary metals to 1.0537 for wholesale nondurable goods and averaged 0.4062. This means the speed of adjustment toward the desired inventory level ranged from less than one quarter for wholesale nondurables to more than five quarters for primary metals and averaged about two and a half quarters. The inventory-to-sales ratio, or θ, averaged 0.6597 for the 21 industries with significant coefficients on both lagged inventory and lagged sales. Equivalent to about 1.92 months of sales in stock, this figure compares to an average seasonally adjusted figure of 1.54 months of sales for manufacturing and trade.

The results of the correlation coefficient estimates and the regressions are consistent with the notion that some firms are motivated by stockout avoidance,

Table 2

Correlation Coefficients

SIC Code	Industry	# of Cos.	Aggregate Correlation Coefficient	Average Correlation Coefficient Weighted	Average Correlation Coefficient Unweighted
10	Metal mining	32	–0.049	–0.217	–0.120
12	Coal mining	4	–0.479	–0.065	–0.086
13	Oil and gas extraction	99	0.141	0.187	0.035
14	Nonmetallic minerals, except fuels	8	–0.097	–0.119	–0.009
15	General building contractors	36	–0.500	–0.002	0.028
16	Heavy construction, except bldg.	12	0.124	0.209	0.008
17	Special trade contractors	17	0.487	0.255	0.188
20	Food and kindred products	100	–0.376	–0.078	0.020
21	Tobacco products	7	–0.287	–0.059	–0.171
22	Textile mill products	40	–0.070	0.095	–0.088
23	Apparel and other textile products	45	–0.341	–0.181	–0.152
24	Lumber and wood products	27	–0.042	–0.041	–0.034
25	Furniture and fixtures	30	–0.157	–0.047	–0.090
26	Paper and allied products	47	0.115	0.084	0.090
27	Printing and publishing	66	–0.505	–0.251	–0.107
28	Chemicals and allied products	185	0.098	0.042	–0.071
29	Petroleum and coal products	37	0.465	0.101	–0.007
30	Rubber and misc. plastics products	65	0.054	–0.200	–0.047
31	Leather and leather products	18	–0.262	–0.193	–0.401
32	Stone, clay, and glass products	25	–0.430	–0.129	–0.200
33	Primary metal industries	80	0.280	0.008	–0.028
34	Fabricated metal products	83	–0.334	0.012	0.008
35	Industrial mach. and equip.	289	–0.649	–0.219	–0.051
36	Electronic and other elect. equip.	263	–0.383	–0.121	–0.005
37	Transportation equipment	100	–0.523	–0.226	–0.120
38	Instruments and related prods.	226	–0.579	–0.233	–0.096
39	Misc. manuf. industries	51	–0.152	–0.105	–0.134
50	Wholesale durable goods	126	0.344	0.154	0.118
51	Wholesale nondurable goods	67	0.389	0.107	0.077
52	Retail building materials and garden supplies	14	0.162	0.190	–0.174
53	Retail genl. merchandise stores	46	–0.719	–0.441	–0.441
54	Retail food stores	40	0.102	0.187	0.198
55	Auto dlrs. and service stations	5	0.078	–0.012	0.186
56	Retail apparel and acces. stores	31	–0.639	–0.455	–0.287
57	Retail furniture and home furnishings stores	24	–0.693	–0.149	–0.039
58	Retail eating and drinking places	54	–0.059	0.063	0.193
59	Misc. retail establishments	53	–0.752	–0.308	–0.082

Table 3

OLS estimates of equation coefficients

SIC Code	Industry	γ	$1+\gamma\theta\rho-\rho$	ρ	θ
10	Metal mining	0.3053*	0.1481**	0.9928**	0.8763
12	Coal mining	0.3585**	0.1130*	0.6136**	0.3150
13	Oil and gas extraction	0.5258**	0.0562	0.8406**	0.2768
14	Nonmetallic minerals, except fuels	0.5320**	–0.0072	0.3839*	0.4190
15	General building contractors	0.2330**	0.3174**	0.9034**	1.3834
16	Heavy construction, except bldg.	0.3036**	0.0409	0.8748**	0.3257
17	Special trade contractors	0.0943	0.0427	0.9785**	0.2154
20	Food and kindred products	0.5914**	0.1871**	0.9651**	0.4556
21	Tobacco products	0.4102**	0.2370**	0.8864**	0.9974
22	Textile mill products	0.3213*	0.2221	0.9393**	0.7172
23	Apparel and other textile products	0.1509	0.1403	0.9457**	0.8645
24	Lumber and wood products	0.4310**	0.1995**	0.9470**	0.4759
25	Furniture and fixtures	0.4709**	0.2219**	0.9273**	0.7401
26	Paper and allied products	0.1078	0.0579	1.0033**	0.4836
27	Printing and publishing	0.2980*	0.0690**	0.9649**	0.2841
28	Chemicals and allied products	0.1260	0.0789	1.0154**	0.5739
29	Petroleum and coal products	–0.0440	–0.0205	0.8312**	0.2818
30	Rubber and misc. plastics products	0.3918**	0.2187**	0.9828**	0.5914
31	Leather and leather products	0.0902	0.0610	0.7021**	0.8648
32	Stone, clay, and glass products	0.0988	0.0422	0.7023**	0.4764
33	Primary metal industries	0.1876**	0.1206**	0.9746**	0.6843
34	Fabricated metal products	0.3413**	0.2392**	0.9810**	0.7500
35	Industrial mach. and equip.	0.2300**	0.1266**	0.8324**	0.7099
36	Electronic and other elect. equip.	0.1416	0.0910	0.9452**	0.6959
37	Transportation equipment	0.2492**	0.1059**	0.9215**	0.5497
38	Instruments and related prods.	0.2593*	0.1337*	0.9460**	0.6859
39	Misc. manuf. industries	0.0550	0.0059	0.8418**	0.6887
50	Wholesale durable goods	–0.0493	–0.0331	0.9615**	0.7530
51	Wholesale nondurable goods	1.0537**	0.3746**	0.9583**	0.3613
52	Retail building materials and garden supplies	0.3295	0.2190	1.0040**	0.6516
53	Retail genl. merchandise stores	0.5041**	0.2890**	0.7025**	0.7281
54	Retail food stores	0.1275	0.0344	0.9647**	0.2902
55	Auto dlrs. and service stations	0.4072*	0.3262**	1.0081**	0.6893
56	Retail apparel and acces. stores	0.4832**	0.2673**	0.7686**	0.7689
57	Retail furniture and home furnishings stores	0.6035**	0.5153**	0.9664**	0.8233
58	Retail eating and drinking places	0.3680**	0.0453**	0.9861**	0.1700
59	Misc. retail establishments	0.2941**	0.2459**	0.8740**	0.8142

*Significant at 95 percent confidence level; **Significant at the 99 percent confidence level.

which leads to a target inventory level. As West (1986 and 1990) observes, inventory models that include a target level of inventory tend to perform better empirically than pure production-smoothing models.[5]

EVIDENCE THAT SOME COMPANIES SMOOTH SEASONALLY

Although wholesale SIC codes 50 and 51 fail both the production-smoothing and the buffer-stock tests, there are some companies in the sample that appear to smooth on a seasonal basis. That is, when sales exhibit strong seasonal patterns, inventories are increased during slower quarters and drawn down during peak sales periods. Figure 1 shows sales, inventory, and inventory-to-sales ratio for one such company. The seasonality is obvious in the data. What's more, the negative correlation between inventory movements and sales over the seasonal cycle is also obvious. The accentuated seasonal movement in the inventory-to-sales ratio confirms the buffer stock role that inventory plays, rising during periods of low sales and increasing inventories, and falling during periods of high sales and falling inventories.

The company in Figure 1 is from the SIC code 5070, which is the wholesale hardware, plumbing, and heating equipment industry. The seasonality of this industry is probably linked to the seasonality of construction. Inventory movement suggests that the firm smooths purchases seasonally, and indeed the computed ratio of the variance of purchases/production to the variance of sales for the period is 0.94 for this firm.

Figure 2 shows another wholesale company, this time in the miscellaneous wholesale trade durable goods industry, which also appears to be smoothing seasonally. The ratio of the variance of purchases/production to sales over the sample period is 1.097, however, a result that contradicts the hypothesis of smoothing. But as the chart shows, mean sales increased significantly after the first four years of the sample period. Splitting the sample into four-year pieces yields variance ratios of 0.641 for the period from the second quarter of 1981 to the second quarter of 1985 and 0.774 for the period from the third quarter of 1985 to the third quarter of 1989, confirming smoothing in both subsample periods.

Two more examples in SIC code 51, wholesale nondurables, also show evidence of seasonal smoothing. Both firms are in SIC Code 5140, groceries and related products. Figure 3 shows one company with

Figure 1

Company A in SIC Code 5070

Wholesale Hardware, Plumbing and Heating Equipment

$ Millions (Quarterly)

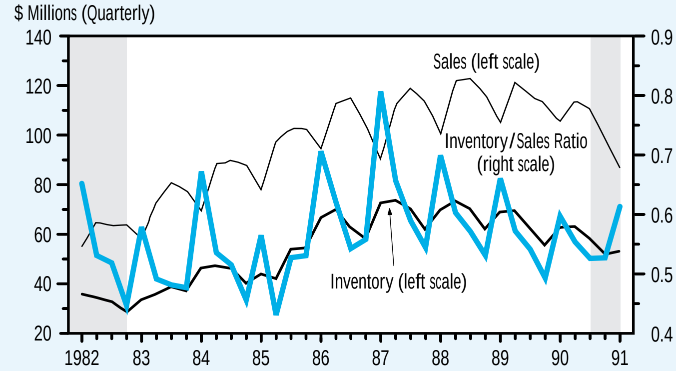
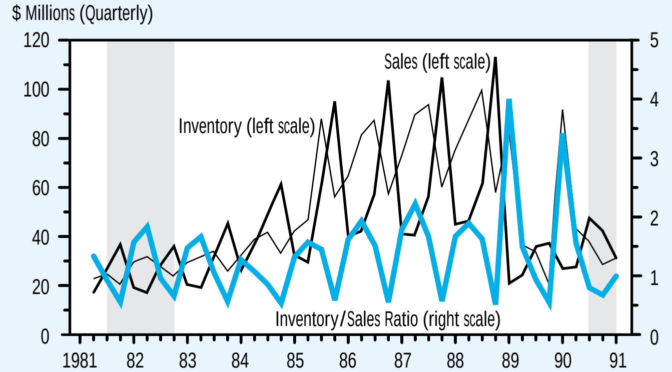


Figure 2

Company B in SIC Code 5090

Miscellaneous Wholesale Trade Durable Goods

$ Millions (Quarterly)



[5] Michael C. Lovell mentioned to me in a conversation once that despite the existence of sophisticated inventory methods, an informal survey of firms revealed a preference for target levels of inventory as a function of sales. This would also help to explain the empirical findings.

Figure 3

Company C in SIC Code 5140

Wholesale Nondurable Goods-Groceries and Related Products

$ Millions (Quarterly)

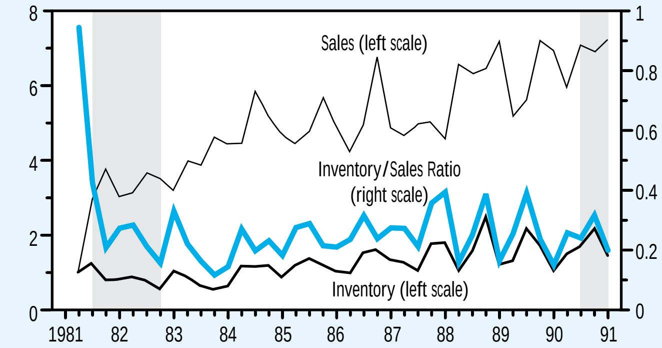
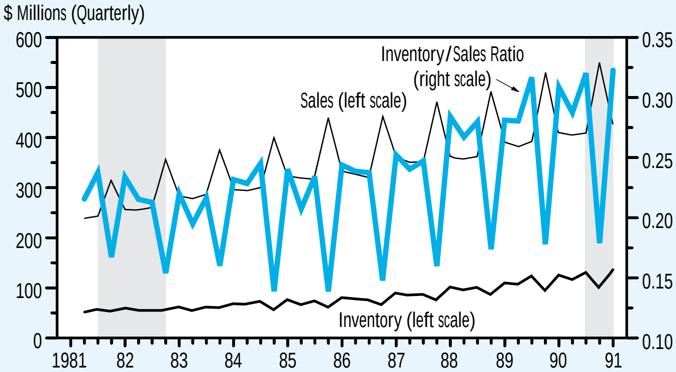


Figure 4

Company D in SIC Code 5140

Wholesale Nondurable Goods-Groceries and Related Products

$ Millions (Quarterly)



mean sales of approximately $5 million per quarter and inventory-to-sales ratio of 0.27. The variance ratio of this company is 0.95, confirming what appears to be seasonal smoothing. Figure 4 shows another company with mean sales of $356 million and with a lower inventory-to-sales ratio of 0.23. This company has a variance ratio of 0.91, which confirms the assumption that there was smoothing over the sample period. The important characteristic that allows us to confirm smoothing appears to be the relatively flat sales over the sample period. The seasonal rise and fall of the inventory-to-sales ratio also gives some indication of the degree of smoothing.

CONCLUSIONS/SUMMARY

The common assumption is that firms use inventories to smooth production. Like previous research based on aggregate data, however, my research at the level of individual companies fails to confirm this hypothesis, although select firms showed evidence of seasonal smoothing. But the results do confirm the stylized empirical regularity that production varies more than sales, both at the firm level and in the aggregate. Using the variance ratio test for production smoothing, I found that both the individual firm average and the SIC code aggregate exceeded 1.0 in most cases. Aggregation over the 2-digit SIC codes did not appear to be a major factor.

One possible explanation of the failure to confirm smoothing is that increased demand prompts firms to raise their inventory targets levels; thus "planned" inventory increases are positively correlated with sales. Unplanned inventory changes, which would reflect the buffer stock motivation, are negatively correlated with sales but insufficient to make the variance of production less than that of sales. In the buffer stock test of the correlation between changes in sales and changes in inventory, most firms and 2-digit industrial classifications showed negative correlations. This finding is consistent with the idea that inventories act as a buffer stock to unexpected changes in sales. The negative correlation between changes in sales and changes in inventory may be a better test of whether buffer stock movement is prompted by random demand in the presence of partial adjustment and serially correlated demand.

Ordinary least squares estimates of the coefficients of the simple partial adjustment model yielded statistically significant and appropriately signed coefficients in 21 of the 37 industries. This result also seems to suggest that many industries may be making partial adjustments in their inventories.

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Appendix–Table A

Descriptive Statistics of Data

SIC Code	Industry	# of Cos.	Sales $ Millions		Inventory $ Millions	
			Mean	S.D.	Mean	S.D.
10	Metal mining	36	587.6	1591.3	451.9	1350.5
12	Coal mining	4	2144.2	2421.7	660.9	592.0
13	Oil and gas extraction	102	2867.0	18274.4	787.2	4316.6
14	Nonmetallic minerals, except fuels	9	2458.0	3456.1	1022.0	1434.5
15	General building contractors	36	3125.4	4966.6	4271.5	5167.2
16	Heavy construction, except bldg.	13	10466.8	19364.0	3333.2	5994.9
17	Special trade contractors	17	1146.4	2237.8	264.5	564.4
20	Food and kindred products	101	14264.7	25629.9	6360.4	11617.4
21	Tobacco products	7	33943.4	44849.6	32265.3	40746.4
22	Textile mill products	40	3910.1	6364.7	2812.0	4871.5
23	Apparel and other textile products	45	1975.8	3425.5	1717.8	2871.4
24	Lumber and wood products	27	1330.5	2770.6	631.2	1301.8
25	Furniture and fixtures	30	2934.4	5206.3	2108.8	5037.7
26	Paper and allied products	47	13904.5	21318.2	6560.1	12072.0
27	Printing and publishing	66	4499.2	6861.4	1249.4	2295.8
28	Chemicals and allied products	188	10942.3	31451.3	6211.5	17002.1
29	Petroleum and coal products	37	106119.8	185077.1	29652.0	52072.2
30	Rubber and misc. plastics products	66	3509.1	12557.8	2051.9	7416.1
31	Leather and leather products	18	1801.8	3589.9	1553.7	2906.8
32	Stone, clay, and glass products	25	5792.5	9817.0	2731.7	4249.2
33	Primary metal industries	81	8416.4	15782.5	5639.5	11050.9
34	Fabricated metal products	83	2924.2	5062.6	2177.9	3795.6
35	Industrial mach. and equip.	297	5912.9	31654.8	4119.4	18972.6
36	Electronic and other elect. equip.	267	4213.9	25335.1	2894.9	15170.4
37	Transportation equipment	102	23862.0	74175.8	12722.4	33568.2
38	Instruments and related prods.	232	2521.1	12757.5	1698.0	8011.8
39	Misc. manuf. industries	51	1068.6	2167.5	692.0	1252.1
50	Wholesale durable goods	130	1532.2	2830.2	1151.7	2350.5
51	Wholesale nondurable goods	70	7946.8	16810.5	2863.2	5395.2
52	Retail building materials and garden supplies	14	4618.1	5878.4	3018.0	3665.9
53	Retail genl. merchandise stores	47	34161.6	75829.0	24360.9	49820.7
54	Retail food stores	40	26240.1	44964.2	7653.5	13774.9
55	Auto dlrs. and service stations	5	1868.0	2532.0	1321.9	1776.3
56	Retail apparel and acces. stores	31	6739.4	12129.2	4979.1	9492.1
57	Retail furniture and home furnishings stores	24	1692.1	2508.6	1386.0	1943.7
58	Retail eating and drinking places	56	2537.2	7290.2	400.9	1567.2
59	Misc. retail establishments	53	3362.9	7027.0	2737.2	5918.0