NBER WORKING PAPER SERIES

MORE ON THE SPEED OF ADJUSTMENT IN INVENTORY MODELS

Alan S. Blinder

Working Paper No. 1913

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
May 1986

The research reported here is part of the NBER's research program in Economic Fluctuations. Any opinions expressed are those of the author and not those of the National Bureau of Economic Research.

Working Paper # 1913
May 1986

More on the Speed of Adjustment in Inventory Models

ABSTRACT

When empirical stock-adjustment models of manufacturers' inventories of finished goods are estimated, there appear to be two local minima in the sum of squared residuals functions. At one local minimum, the estimated adjustment speed is typically quite high; at the other, it is typically quite low. Furthermore, finding two sets of estimates that fit the data almost equally well does not appear to be a quirk of this particular application. Rather, it stems from a fundamental identification problem that afflicts partial adjustment models of all kinds.

In the specific context of manufacturers' inventories of finished goods, the estimation procedure employed by Maccini and Rossana seems to pick out the solution with rapid adjustment (and high serial correlation in the disturbances) whereas the solution with slow adjustment (and little serial correlation) is more often the global minimum.

Alan S. Blinder
Gordon S. Rentschler Memorial
Professor of Economics
Department of Economics
Princeton University
Princeton, NJ 08544

I. INTRODUCTION

Applied econometricians estimating stock adjustment models of inventory investment have long bemoaned the fact that estimated adjustment speeds turn out to be "implausibly slow."[1] Other applications of stock adjustment models, such as the demands for money and for consumer durables, also turn up slow adjustment speeds.[2] In a thought-provoking recent paper in this Journal, however, Louis Maccini and Robert Rossana (1984) claim that the slow adjustment is an artifact of inappropriate estimation procedures which fail to correct for autocorrelation. Using a two-step procedure due to Hatanaka (1974), they obtain econometric inventory equations for finished goods with very fast adjustment speeds.

While Maccini and Rossana are correct that failure to correct for autocorrelation can bias estimated adjustment speeds downward, their application to manufacturers' investment in finished goods inventories produces estimates that are inappropriate in a very subtle sense. In particular, I show below that the types of models estimated by Maccini and Rossana -- and perhaps most stock adjustment models -- have two local minima in the sum of squared residuals (henceforth SSR) function, and that the Hatanaka technique that they use typically picks out the "wrong" local minimum.

This short paper has two purposes. The first is methodological. Since partial adjustment models are commonly estimated for all kinds of economic variables, it seems important to reemphasize the potential identification problem first pointed out by Griliches (1967): that it may be quite difficult to distinguish between partial adjustment and serial correlation. This is done in Section 2, where I explain why the existence of two local minima should be expected to be the norm, not the exception.

The second purpose is substantive. The empirical work reported in Section 3 strongly suggests that the estimates obtained by Maccini and Rossana -- which feature high serial correlation and rapid adjustment -- are not, in fact, the global minima of the SSR functions. Instead the global minima for most manufacturing industries are characterized by little autocorrelation but slow adjustment. Thus, if the partial adjustment model is accepted as the maintained hypothesis, the best estimates of the speed of adjustment in inventory models remain "implausibly slow."[3]

2. THE DIFFICULTY OF IDENTIFYING THE SPEED OF ADJUSTMENT

To make the point as starkly as possible, I start with a stripped-down model far simpler than those estimated either by Maccini and Rossana or by myself. The model is a special case of the one dealt with by Betancourt and Kelejian (1981). Let N_t

denote the inventory stock (or any other stock) at the <u>beginning</u> of the period, and suppose that desired inventories, N^*, are constant. Then the stock adjustment model is simply:

$$N_{t+1} - N_t = \beta(N^* - N_t) + u_t, \tag{1}$$

If the error term follows an AR(1) process:

$$u_t = \rho u_{t-1} + e_t, \tag{2}$$

the natural procedure is to quasi-difference (1) before estimating to get:

$$N_{t+1} = \beta(1-\rho)N^* + (\rho - \beta + 1)N_t - \rho(1-\beta)N_{t-1} + e_t. \tag{3}$$

This is an AR(2) model for the stock of inventories.[4] But notice the fundamental identification problem. Suppose the econometric estimate of (3) is:

$$N_{t+1} = \mu_0 + \mu_1 N_t + \mu_2 N_{t-1} \tag{4}$$

where the μ's are the estimated coefficients. We find the implied estimates for ρ and β by solving:

$$\mu_1 = \rho + 1 - \beta \tag{5}$$

$$\mu_2 = -\rho(1-\beta) \tag{6}$$

which yields:

$$\rho^2 - \rho\mu_1 - \mu_2 = 0 \tag{7}$$

Clearly, equation (7) offers two solutions for ρ:

$$\rho = \frac{\mu_1}{2} \pm \sqrt{\frac{\mu_1^2}{4} + \mu_2} \tag{8}$$

and two corresponding solutions for β .

An example that is germane to the inventory problem is where ρ and β are approximately equal. Then the two coefficients in (3) are approximately 1 and $\beta(\beta-1)$. Hence, we cannot tell β from $1-\beta$. For example, if either $\rho = \beta = .9$ or $\rho = \beta = .1$, then the coefficients in (3) are respectively 1.0 and -.09. Exact equality between ρ and β is not necessary, of course. If (4) is:

$$N_{t+1} = 1.1N_t - .1425\ N_{t-1} + \text{constant},$$

which is pretty typical in the inventory application, the two solutions of (8) are:

(a) $\rho = .95$, $\beta = .85$

(b) $\rho = .15$, $\beta = .05$.

Hereafter, I will refer to solutions like (a) as the "high ρ" solution and solutions like (b) as the "low ρ" solution. The general point is that, as Griliches pointed out years ago, any estimation technique will have trouble distinguishing between a model with strong serial correlation and fast adjustment and one with little serial correlation but slow adjustment.[5]

In the simple example of (1) and (2), both parameters are literally unidentified. Actual empirical models such as those of Maccini and Rossana, or the regressions presented in the next section, include a variety of other regressors and hence are identified in the formal sense. But identification hinges precariously on regressors which are often of minor empirical importance. Hence, while it is not <u>impossible</u> to distinguish between a "high ρ, high β" model and a "low ρ, low β" model, it is <u>difficult.</u>

All the equations reported in the next section were fit by nonlinear least squares under the assumption that the error term was AR(1).[6] If the disturbances are normal, this is a maximum likelihood procedure. In many cases, two local minima of the sum of squared residuals function were found. In such cases, one of the minima always had high ρ and rapid adjustment while the other had low ρ and slow adjustment, precisely as suggested by this simple argument. This point is important because the extremely high adjustment speeds found by Maccini and Rossana (1984) result from an estimation technique that settles on the local minimum with high ρ. (They report estimated values of ρ from the two-step Hatanaka procedure ranging from 0.67 to 0.97.) The nonlinear estimation method used here shows, however, that the low ρ solution is typically the global minimum.

3. ECONOMETRIC INVENTORY EQUATIONS

This section presents econometric estimates of stock-adjustment models for inventory investment in finished goods. I concentrate on finished goods because that is the only type of inventory for which we have a coherent and operational theory.[7]

The data are monthly, real, and seasonally adjusted, and (after allowing for lags) span the period December 1960 - March 1981.[8] Each two-digit industry is treated separately. However, for direct comparison with Maccini and Rossana, I also present results for all manufacturing and for the durable and nondurable sectors. The theoretical stock adjustment model was made operational as follows.

Demand disturbances were proxied by two variables: expected sales, X_t^e, is the one-period-ahead forecast from a 12-th order autoregression fit to each industry's actual data on shipments; and unexpected sales, X_t^u, is the residual from this autoregression. Thus expectations are assumed to be "rational," albeit in a limited sense. Experimentation with other expectational proxies led to substantially identical results. In 13 of the 20 industries, data on new orders are available. For these industries, the collinearity between the two sales measures is almost always too great to include both, so two versions of the regressions were run. Normally, a better fit was obtained using shipments.

Cost disturbances were treated by including both the real product wage, w, and the real cost of raw materials, c, in each regression. The nominal wage series is the average hourly earnings series specific to that industry or sector. The nominal materials cost series is the PPI for Crude Materials for Further Processing (and is the same for every industry). Each nominal factor price is deflated by an industry- specific price index.

In addition, the interest rate is included as a potentially important determinant of the desired steady-state level of inventories. For reasons described in Blinder (1981), the nominal interest rate, R (bank prime rate), and the expected rate of inflation, π (generated by an autoregression), are entered as separate variables rather than combined into a real interest rate.

The theoretical model in Blinder (forthcoming) recognizes the existence of only one type of inventory. But, in fact, there are three types and Maccini and Rossana have convincingly demonstrated the importance of stock interactions. Many industries also have backlogs of unfilled orders. Preliminary regressions showed clearly that investment in finished goods inventories reacts differently to the initial stock of each kind of inventory, so Table 1 presents estimates of the following flexible accelerator model of finished goods inventories:

$$\Delta F_t = \beta_1 F_t + \beta_2 W_t + \beta_3 M_t + \beta_4 U_t + \alpha_1 X_t^e + \alpha_2 X_t^u + \gamma_1 R_t + \gamma_2 \pi_t + + \delta_1 w_t + \delta_2 c_t + u_t \quad , \tag{9}$$

where

F_t = stock of finished goods (beginning of period)

W_t = stock of work in process

M_t = stock of materials and supplies

U_t = stock of unfilled orders

and the error term, u_t, is assumed to be generated by (2). The model is similar to that of Maccini and Rossana. (In the table, t-ratios are in parentheses.)

First, note that the opening stock of finished goods always enters with a significant negative coefficient, indicative of partial adjustment. However, in accord with much previous work, but in contradiction to Maccini and Rossana, most of the estimated speeds of adjustment are rather slow. Among the 17 industries for which the "low ρ" solution was the global minimum, the speeds of adjustment range from 5% to 38% per month. These speeds are slightly faster than, but not out of line with, those typically found in work at a more aggregative level.[9] But they are much slower than those reported by Maccini and Rossana (1984) using very similar data and a similar specification. The difference between my results and theirs is entirely attributable to the estimation method. In the three industries in which the "high ρ" solution is the global minimum (instruments, food, and textiles), I get extremely rapid adjustment (104 percent, 79 percent, and 100 percent per month, respectively).[10]

It is worth noting that aggregation seems to bias the estimated speed of adjustment downward. The adjustment speeds for durables and nondurables as a whole are lower than those of most of the constituent industries. This helps explain why more highly aggregated studies find slower adjustment.

The cross-adjustment coefficients, β_2 and β_3, are more novel and display a rather consistent pattern across industries. High opening stocks of either works in progress (W_t) or raw materials (M_t) usually are associated with higher investment in finished goods inventories, that is, with higher production. Whether or not this empirical regularity implies causation, of course, is another matter entirely. For example, higher planned production could induce stockpiling of works in progress and materials.

Studies that merge all three types of inventory into a single stock necessarily produce an estimated "adjustment speed" that is an amalgam of the three adjustment coefficients, β_i. Since one of these is negative and the other two are positive, we would exoect this procedure to understate the speed of adjustment if the three types of inventories covary positively. To test this idea, a version of (9) was run in which all three types of inventory were lumped together into a single aggregate. The results were as expected: estimated adjustment speeds generally declined, sometimes dramatically.

Turning to specifics, the coefficient of works in progress is positive in 17 of 20 industries, though significantly positive in only four of these. The petroleum refining industry is the only important exception; here, high stocks of work in progress apparently lead to lower levels of output.

The coefficient of the opening stock of materials and supplies inventory is positive in 18 of 20 industries, and significantly positive in ten of these. The only exceptions are the primary metals and transportation equipment industries, where high levels of raw materials apparently lead to cutbacks in production. Maccini and Rossana also found significant effects of raw materials inventories, though not in nondurables.

In contrast to these rather good results, the stock of unfilled orders performs poorly. Among the 13 industries reporting data on unfilled orders, the estimated coefficient is positive seven times (the "correct" sign, it seems to me) and negative six times. Only three coefficients are significant; and they are all negative.

As noted already, sales are measured alternatively by shipments and, in those industries offering such data, unfilled orders. Fortunately, the estimated equations proved quite insensitive to the choice of a sales measure. Since shipments perform slightly better than new orders, and are available for all industries, Table 1 reports only the results with shipments.

In general, results for the sales variables are disappointing and not always in line with a priori expectations. For example, many of the coefficients are insignificantly different from zero, suggesting either that production reacts virtually one-for-one to sales (whether expected or unexpected) or that the difference between production and sales shows up mostly in works in progress rather than in finished goods.[11]

Specifically, the coefficient of expected sales X_t^e, is normally quite small (values of .05 or less are typical) and insignificantly different from zero. Its sign is positive in 14 cases and negative in six, and only eight of the 20 industries (all in durables) display significant coefficients.

The unexpected sales variable is significant in only 7 industries. A positive coefficient for this variable is impossible to interpret in the context of the model; taken *literally, it implies that inventories of finished goods rise when there is an unexpected surge in sales. Presumably, a positive coefficient means that the sales fluctuations which we label "unexpected" are really expected by firms, in accord with the discussion in Blinder (forthcoming). Yet the point estimate is positive in 11 of 20 industries. There is evidence of a strong negative effect of* X_t^u *on* ΔF_t *in only six industries.*

Interest rates, represented here by the (monthly) nominal interest rate (R_t*) and the (monthly) industry-specific expected rate of inflation (*π_t*) do not perform as the theory suggests. The expected signs are negative for* R_t *and positive for* π_t*; but only four of 20 industries display this pattern. Taking the two variables individually, we see that* R_t *gets the expected negative coefficent in only 10 of 20 cases and* π_t *gets the expected positive coefficient in only nine of 20 cases. Only five of the 19 correctly-signed coefficients are significant; as are five of the 21 incorrectly-signed coefficients. This is not much better than what you would expect if the coefficients were randomly distributed around zero, so the overall conclusion seems to be that interest rates do not matter. This finding is consistent with older empirical work on inventory investment, and with Maccini and Rossana, but contradictory to some other work in which significant inventory effects have been found.*[12]

The wage rate is probably the least successful variable of all. Of the 20 industries, only 4 estimates get the expected negative sign. Of the 16 positive coefficients, 9 are significantly different from zero. The results here strongly suggest reverse causation running from higher production to higher wages, perhaps due to overtime premia. Thus, I conclude that wage rates are not good representations of cost shocks.

Raw materials costs are far more successful in this role. The estimated coefficient of c_t is negative in 15 of 20 cases, and is significant in about half the industries. And many of the coefficients are of an economically meaningful size. For example, the coefficient for all manufacturing indicates that a 10% rise in raw materials prices (the variable c_t is an index number with January 1972=100) will lower the desired stock of finished goods inventories by $2 billion (in 1972 dollars), or about 5% of the mean inventory stock. The strong estimated effect of raw materials prices echoes the finding of Maccini and Rossana (1984).

Finally, I note in passing that the fits of the regressions -- as measured by R^2 -- are modest at best. Time series analysis of noisy, virtually trendless series like ΔF_t encourages humility.

One objection to the standard stock adjustment model is that it assumes that all the righthand variables enter only contemporaneously. But if there are lags in adjustment, lagged values of variables like interest rates and raw materials costs may also matter. In fact, Irvine (1981c) argued that omission of such variables may bias estimated adjustment speeds downward, and Maccini and Rossana's equations include distributed lags.

There are so many possible combinations of distributed lags that might be added to (9) that I adopted a sequential search procedure to economize on computing costs. The reader is spared the laborious details of the many regressions that were run.[13] Suffice it to say that, while distributed lags of at least one variable were found to be significant in most industries, the basic findings on adjustment speeds were not changed. However, it is worth reemphasizing that, because of the two local minima in the sum of squared residuals, our ability to pin down the speed of adjustment is not nearly so good as the t-statistic suggests.[14]

4. CONCLUSION

When empirical stock-adjustment models of manufacturers' inventories of finished goods are estimated, there appear to be two local minima in the sum of squared residuals functions. At one local minimum, the estimated adjustment speed is typically quite high; at the other, it is typically quite low. That, in itself, means that we have precious little ability to pin down the speed of adjustment empirically -- certainly far less than indicated by the standard errors of the estimated coefficients.

Furthermore, finding two sets of estimates that fit the data almost equally well does not appear to be a quirk of this particular application. Rather, it stems from a fundamental identification problem that afflicts partial adjustment models of all kinds. For example, it has become common to use the *partial-adjustment specification in studies of the demand for money, and the estimated equations typically have surprisingly slow adjustment speeds.[15] It may be that money demand equations also have two local maxima.[16]*

Hence this paper stands as a generic warning to users of stock adjustment models to use estimation methods that do not mechanically select a particular local maximum. There appears to be no better procedure than to search thoroughly over alternative values of ρ and to select the maximum maximorum. If there is more than one local maximum, standard errors estimated in the usual way will certainly overstate the precision of the point estimates, but by an amount that will remain unknown until some basic econometric theory relevant to such problems is developed.

In the specific context of explaining changes in manufacturers' inventories of finished goods, the two-step procedure employed by Maccini and Rossana (1984) seems to pick out the solution with rapid adjustment (and high serial correlation in the disturbances) whereas the solution with slow adjustment (and little serial correlation) is more often the global minimum. Thus I am afraid that Maccini and Rossana (1984), despite admirable efforts and a number of interesting innovations, have not succeeded in explaining why estimated adjustment speeds in stock-adjustment models of inventory behavior are "implausibly slow."

Table 1

Simple Stock Adjustment Regressions, 1960:12 - 1981:3

Coefficient (absolute t ratio) of:

Sector	Initial Stock of: Finished Goods	Initial Stock of: Work in Progress	Initial Stock of: Materials & Supplies	Unfilled Orders	Sales: Expected	Sales: Unexpected	Interest Rate	Expected Capital Gains	Wages	Materials Costs	$\hat{\rho}$	R^2
All Manufacturing	-.080	.006	.029	.002	.003	-.052	-128*	-9.9	15.9*	-9.4*	.13	.19
	(3.3)	(0.4)	(2.8)	(0.7)	(0.4)	(3.2)	(0.7)	(0.1)	(4.5)	(3.4)	(1.8)	
Durable goods	-.061	-.002	.018	.001	.005*	-.039	8.8*	-20	10.3	-3.7	.12	.12
	(2.6)	(0.2)	(2.3)	(0.4)	(0.6)	(2.7)	(0.1)	(0.3)	(1.3)	(2.2)	(1.7)	
Primary metals	-.271	.151	-.051	.008	-.057*	-.133	-82*	-31	6.0	-4.0	.42	.37
	(4.7)	(3.5)	(2.6)	(1.3)	(2.8)	(7.6)	(2.4)	(3.4)	(2.6)	(4.4)	(5.0)	
Fabricated metals	-.257	.056	.034	.001	-.001	.025	-10	-9.2	1.7	-.69*	-.10	.21
	(5.7)	(2.9)	(4.5)	(0.4)	(0.1)	(0.9)	(0.4)	(1.0)	(1.5)	(2.1)	(1.3)	
Electrical mach.	-.112	.013	.000	-.010	.037	.004	-28*	83	5.0	-.52	.03	.12
	(2.8)	(1.2)	(0.0)	(1.8)	(2.3)	(0.1)	(0.8)	(4.1)	(2.8)	(1.3)	(0.4)	
Nonelectrical[a] machinery	-.106	.026	.029	-.005	.010	-.033	1.2*	7.7	4.9	-2.0	.01	.17
	(3.9)	(1.2)	(1.8)	(1.0)	(0.9)	(2.3)	(0.0)	(0.4)	(1.8)	(3.4)	(0.1)	
Transportation equipment	-.049	.001	-.027	.002	.027	.017	-56	104	-1.5	.17	-.14	.12
	(1.7)	(0.2)	(2.0)	(1.3)	(3.4)	(1.4)	(1.5)	(3.1)	(0.9)	(0.3)	(2.0)	
Lumber & Wood Products	-.106	.036	.040	--	-.044*	.061	14	1.3	-.05	-.55	-.03	.08
	(3.0)	(0.9)	(1.8)		(2.2)	(1.5)	(1.0)	(0.5)	(0.1)	(2.0)	(0.4)	
Furniture and fixtures	-.115	.040	.024	.009	-.020*	.070	-1.6	11.3	-.18	-.16	-.23	.18
	(3.9)	(1.2)	(2.4)	(1.3)	(0.7)	(1.8)	(0.3)	(2.6)	(0.3)	(1.6)	(3.4)	

Table 1 (continued)

	N_t	W_t	M_t	U_t	X^a_t	X^u_t	R_t	π_t	w_t	c_t	$\hat{\rho}$	$\bar{R}^2$
Stone, Clay, & Glass Products	-.179 (4.0)	.107 (1.1)	.005 (0.3)	-.008 (0.9)	.071* (2.9)	-.103 (2.8)	25 (1.7)	8.8 (0.8)	0.22* (0.4)	-.48 (2.1)	.09 (1.2)	.16
Instruments and related prods.	-1.04 (16.4)	.167 (4.5)	.068 (2.4)	.074 (1.7)	.030 (0.3)	-.002 (0.0)	29 (0.7)	-13.2 (1.7)	-4.6 (1.4)	1.32 (2.3)	.98 (80.5)	.15
Miscellaneous Manufacturing Indust.	-.221 (4.9)	.103 (2.0)	.045 (2.5)	.021 (0.9)	.137* (3.2)	-.016 (0.3)	-13 (0.9)	-1.4 (0.3)	.44 (1.3)	.23* (1.0)	.29 (3.7)	.19
Nondurable Goods	-.142 (3.8)	.184 (1.9)	.054 (2.3)	.017 (0.3)	-.026 (1.1)	-.067 (2.0)	98* (1.1)	14.5 (0.3)	12.3* (2.2)	-10.5 (4.0)	.15 (2.0)	.15
Food and Kindred Products	-.785 (10.1)	.293 (1.3)	.115 (1.8)	--	.285* (3.7)	.237 (0.6)	-99* (0.7)	-21.8 (1.9)	10.8 (2.1)	-1.85 (0.4)	.91 (25.0)	.12
Tobacco Manufacturing	-.382 (4.5)	.076 (0.8)	.026 (2.8)	--	.209 (1.6)	-.047 (0.6)	1.7 (0.2)	1.6 (0.4)	.58 (2.4)	-.24 (1.1)	.13 (1.2)	.18
Textile Mill Prods.	-.999 (15.2)	.319 (3.4)	.109 (2.3)	-.057 (2.6)	.064 (0.9)	.013 (0.4)	6.9 (0.2)	-20.6 (2.7)	3.1 (2.7)	-.68 (1.2)	.98 (68.0)	.17
Apparel Products	-.248 (4.3)	.027 (0.5)	.134 (3.9)	--	.033 (0.7)	.111 (2.4)	-12 (0.4)	-53 (1.6)	1.8 (1.0)	-.51* (1.4)	.26 (2.8)	.17
Leather & Leather Products	-.177 (4.4)	.092 (1.2)	.052 (1.9)	-.048 (2.8)	-.042* (1.1)	.032 (0.6)	8.4* (1.3)	-52 (2.1)	.31 (1.1)	.05* (0.6)	-.14 (1.8)	.17

Table 1 (continued)

	N_t	W_t	H_t	U_t	X^d_t	X^u_t	R_t	π_t	w_t	c_t	$\hat{\rho}$	$\bar{R}^2$
Paper & Allied Products	-.237	.160	.056	.001	-.001	-.074	27*	-3.4	2.4	-.54	-.11	.21
	(5.0)	(2.1)	(3.8)	(0.1)	(0.1)	(2.2)	(2.8)	(0.8)	(3.3)	(2.9)	(1.3)	
Printing and Publishing	-.151	-.014	.031	-.081	.068	.041	-28	-1.0	.08	.03	-.02	.11
	(4.6)	(0.4)	(3.3)	(3.4)	(3.0)	(1.1)	(1.9)	(0.3)	(0.1)	(0.1)	(0.2)	
Chemicals & Allied Products	-.081	.093	.009	--	.021	-.251	43	3.0	2.2	-2.6	.10	.27
	(2.9)	(1.3)	(0.4)		(1.1)	(6.5)	(1.5)	(0.0)	(2.0)	(4.0)	(1.5)	
Petroleum & Coal Products	-.123	-.248	.133	--	.008*	-.159	26*	-9.2	.84	-1.3	.02	.16
	(3.3)	(2.7)	(1.5)		(0.4)	(3.2)	(1.5)	(3.4)	(1.8)	(2.5)	(0.3)	
Rubber & Plastic Products	-.076	-.041	.048	--	.015	-.006	-34	.32	1.66*	-.76	.09	.14
	(3.3)	(0.5)	(2.9)		(0.5)	(0.2)	(2.4)	(0.1)	(3.4)	(3.2)	(1.3)	

Note: Estimation was by nonlinear least squares, with allowance for first-order autocorrelation. All regressions also included a constant, not shown here.

[a] For this industry only, new orders are used to measure sales.

FOOTNOTES

*I am indebted to Douglas Holtz-Eakin for extensive and superb research assistance, to the National Science Foundation and Alfred P. Sloan for financial support, and to John Carlson, Michael Lovell, Louis Maccini, Angelo Melino, and Kenneth West for useful comments on an earlier draft.

1. This problem has been emphasized by, e.g, Carlson and Wehrs (1974) and Feldstein and Auerbach (1976).

2. Regarding demand for money c.f. Goldfeld (1976). Regarding consumer durables, c.f. Bernanke (1985). There are numerous other examples.

3. Of course, it is possible to question the validity of the stock adjustment model for inventories. See, for example, Blinder (forthcoming).

4. Lovell (1976) shows that an AR(2) model can be derived in other ways, e.g., from adaptive expectations.

5. Betancourt and Kelejian (1981) pointed out the possibility of

multiple roots in a more general setting and argue that it can lead the standard Cochran-Orcutt procedure astray.

6. Experiments with more complicated error structures bore little fruit.

7. For a derivation and discussion, see Blinder (forthcoming).

8. Had they been available, I would have preferred to use data that were not seasonally adjusted, since the production smoothing model presumably applies to seasonal fluctuations in sales. However, such data are not available.

9. Feldstein and Auerbach (1976), for example, reported adjustment speeds between 5% and 7% per quarter for finished goods inventories in durable manufacturing. Lovell's (1961) original adjustment speed for finished goods was 18%. Auerbach and Green (1980) got much faster adjustment speeds (from 12% to 85% per quarter) using data on four two-digit industries and a model that treated finished goods and work in progress separately. Blanchard's (1983) study of the divisions of U.S. auto firms found adjustment speeds ranging from 0% to 35% per month.

10. Maccini and Rossana (1984, note 20) observe that ordinary least squares regressions (which constrain $\rho = 0$) produce

slow estimated adjustment speeds.

11\. *Because* $Y_t - X_t = \Delta F_t + \Delta W_t$, *if* F_{t+1} *does not change when* X_t *rises, then either* Y_t *must rise or* W_{t+1} *must fall.*

12\. *The earlier literature, summarized, e.g., by Irvine (1981a) found little evidence for a significant effect of interest costs on inventory holdings. However recent work by Irvine (1981a, 1981b) has detected such effects for retailers and merchant wholesalers, while Rubin (1980) and Akhtar (1983)have found aggregate inventories to be interest sensitive. Only Lieberman (1980), using micro data on a small sample of firms and a specially-constructed cost of capital variable, has found any evidence for interest sensitivity in manufacturing.*

13\. *Full details are available on request.*

14\. *For example, if we constrain* $\rho = 1$ *(by estimating the equation in first-difference form), estimated adjustment speeds are extremely high; indeed, many are above 100%.*

15\. *Goldfeld's (1973) exhaustive empirical survey began with a "conventional equation" whose adjustment speed is 28% per* quarter. He observed that "while this is not dramatically rapid, it is certainly more plausible than the 0-10 percent estimates that some writers have reported" (p. 583).

16. Hafer and Hein (1984) reported quarterly adjustment speeds even slower than Goldfeld's. But, mindful of Betancourt and Kelejian's (1981) warning, they establish these to be the global maxima.

REFERENCES

Akhtar, M. A. "Effects of Interest Rates and Inflation on Aggregate Inventory Investment in the United States," American Economic Review, LXXIII (June 1983), 319-28.

Auerbach, Alan J. and Jerry R. Green, "Components of Manufacturing Inventories," NBER Working Paper No. 491 (June 1980).

Bernanke, Ben, "Adjustment Costs, Durables, and Aggregate Consumption," Journal of Monetary Economics 15 (January 1985), 41-68.

Betancourt, Roger and Harry Kelejian, "Lagged Endogenous Variables and the Cochrane-Orcutt Procedure," Econometrica, vol. 49 (July 1981), 1073-1078.

Blanchard, Olivier J. "The Production and Inventory Behavior of the American Automobile Industry," Journal of Political Economy (June 1983), 365-400.

Blinder, Alan S., "Can the Production Smoothing Model of Inventory Behavior be Saved?," Quarterly Journal of Economics (forthcoming).

Blinder, Alan S. "Retail Inventory Behavior and Business Fluctuations," Brookings Papers on Economic Activity, 2 (1981), 443-505.

Carlson, John and William Wehrs, "Aggregate Inventory Behavior," in Trade, Stability and Macroeconomics: Essays in Honor of

L. A. Metzler edited by George Horwich and Paul A. Samuelson, pp. 31-32. New York: Academic Press, 1974.

Feldstein, Martin S. and Alan Auerbach, "Inventory Behavior in Durable Goods Manufacturing: The Target Adjustment Model." *Brookings Papers on Economic Activity*, 2 (1976), 351-396.

Goldfeld, Stephen M., "The Demand for Money Revisited," *Brookings Papers on Economic Activity*, 3 (1973), 683-730.

Goldfeld, Stephen M., "The Case of the Missing Money," *Brookings Papers on Economic Activity* (1976).

Griliches, Zvi, "Distributed Lags: A Survey," *Econometrica*, 35 (January 1967), 16-49.

Hafer, R. W. and Scott E. Hein, "Financial Innovations and the Interest Elasticity of Money Demand: Some Historical Evidence," *Journal of Money, Credit, and Banking*, vol. 16 (May 1984), 247-252.

Hatanaka, Michio, "An Efficient Two-Step Estimator for the Dynamic Adjustment Model with Autoregressive Errors," *Journal of Econometrics* 2 (September 1974), 199-200.

Irvne, F. Owen, "Retail Inventory Investment and the Cost of Capital," *American Economic Review*, 71 (September 1981), 633-648. (a)

Irvine, F. Owen, "Merchant Wholesaler Inventory Investment and the Cost of Capital," *American Economic Review* (May 1981), 23-29. (b)

Irvine, F. Owen, "Specification Errors and the Stock-Adjustment

Model: Why Estimated Speeds-of-Adjustment Are Too Slow in Inventory Equations," Federal Reserve Working Paper (January 1981). (c)

Lieberman, Charles, "Inventory Demand and Cost of Capital Effects." Review of Economics and Statistics, 62 (November, 1980), 348-356.

Lovell, Michael, "Comments and Discussion," Brookings Papers on Economic Activity, 2 (1976), 399-405.

Lovell, Michael, "Manufacturer's Inventories, Sales Expectations, and the Acceleration Principle," Econometrica, vol. 28 (July 1961), 293-314.

Maccini, Louis J. and Robert J. Rossana, "Joint Production, Quasi-Fixed Factors of Production and Investment in Finished Goods Inventories," Journal of Money, Credit, and Banking, 16 (May 1984), 218-236.

Rubin, Laura S., "Aggregate Inventory Behavior: Its Response to Uncertainty and Interest Rates," Journal of Post-Keynesian Economics (Winter 1979-80), 201-211.