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5

EXPERIMENTATIONS IN SPECIFICATION

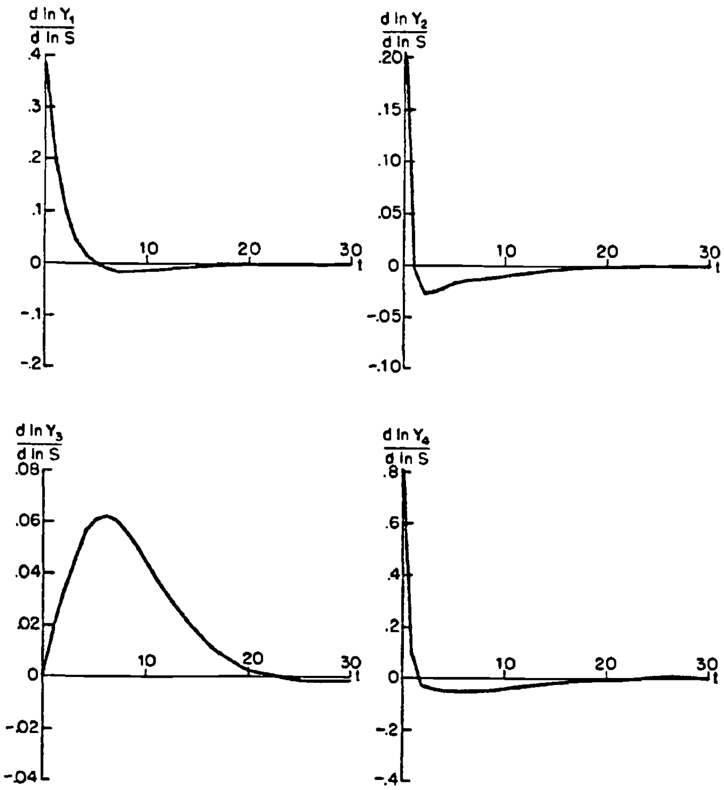
THE estimates of Table 4.1 and the computations based on them critically depend on how the model is specified. One issue is to clearly separate lags of adjustment from expectational considerations. The two phenomena (as shown by Nerlove [67] and others) are intertwined and sensitivity of distributed lag estimates may depend on the process of expectation formation. In terms of our model, estimated adjustment coefficients may capture not only genuine adjustment costs but also errors in forecasting exogenous variables. To test the sensitivity of the lag estimates to changes in the specification of exogenous variables, a variety of experiments was performed. The most important are reported in section A below. Only the main conclusions are stated in the text. Specific estimates of the various experiments performed, using total manufacturing data, are to be found in Appendix C, Tables C.2 to C.5. Another issue is that estimated structural coefficients may be affected by strong cross-serial correlation among residuals in various equations. This question is discussed in section B. A third issue, discussed in section C, concerns direct estimation of reduced form equations to check the consistency of model (4.1).

A. SENSITIVITY OF STRUCTURAL ESTIMATES TO SPECIFICATION

i. First, contrast the results of Chapter 4 with those reported earlier by Nadiri and Rosen [1969]. In that work inventories and nonproduction workers were ignored, current real output was used instead of sales, the sample period was shorter (1948I–1962IV), and the statistical methods took no account of serial correlation in the residuals. Nevertheless, distributed lag patterns generated by that model for production workers, hours per man, capital stock, and general utilization are remarkably

FIGURE 5.1

IMPLIED DISTRIBUTED LAG RESPONSES TO A UNIT OUTPUT IMPULSE, BASED ON 1969 MODEL



SOURCE: Original model (see Nadiri and Rosen [1969]), omitting total inventory (Y_5) and nonproduction workers (Y_6).

similar to those implied by Table 4.1. These similarities are readily observed in Figure 5.1, which reproduces distributed lag patterns reported in the original work by Nadiri and Rosen [1969]. The overshooting of utilization rates and the approach to equilibrium of stock variables are the same as in model (4.1) of Figure 4.1, in spite of all the differences noted above.

ii. Second, a variety of expectational sales and price variables were generated and used in place of actual variables. We assumed that future values of exogenous variables were generated by a specific stochastic structure. Such a structure was estimated and predicted values from regression estimates were used in the structural equations. In this procedure it is assumed that firms are aware of the stochastic structure generating expected values of sales and relative prices and that the structure remains stable over time. From a statistical point of view, this procedure is equivalent to the use of instrumental variables.

There are numerous ways to forecast exogenous variables, depending on the choice of the stochastic structure and approximations to explanatory variables. For sales, three alternatives have been examined. These are:

$$S_t = a_0 + a_1S_{t-1} + a_2S_{t-2} + a_3S_{t-3} + e_{1t}; \tag{5.1}$$

$$S_t = b_0 + b_1S_{t-1} + b_2S_{t-2} + b_3T + e_{2t}; \tag{5.2}$$

$$S_t = c_0 + c_1N_t + c_2N_{t-1} + c_3\left(\frac{ou}{S}\right)_t N_{t-1} + c_t\Delta P_{t-1} + c_5T + c_6S_{t-1} + e_{3t}; \tag{5.3}$$

where

S_t = deflated sales in period t (in logarithms);

T = time;

N_t = new orders (in logarithms);

ΔP = changes in the logarithms of wholesale prices;

$\left(\frac{ou}{S}\right)$ = unfilled orders divided by sales (logarithms of the ratios).

The first two equations are autoregressive and are often good predictors of quarterly time-series data; equation (5.3) is similar to that developed by Popkin [1965] and Zarnowitz [1962]. Table 5.1 indicates the regression coefficients for these equations and their statistical characteristics. S_t^e and Z_t in the definition of Y_{it}^* in model (2.7) were replaced by predicted values from these equations. Hence, the model to be estimated is similar to (4.1) except that predicted values replace actual values of exogenous variables. A similar procedure was adopted to generate the forecasted values of relative input prices on the basis of an autoregressive formulation such as (5.1) and (5.2). Various combinations of instrumental and actual values of these two variables were tried. Moreover, several values of actual lagged sales and relative prices were incorporated in Y_{it}^* as separate

TABLE 5.1

REGRESSION RESULTS OF AUXILIARY EQUATIONS (5.1), (5.2), AND (5.3) FOR PREDICTING THE LEVEL OF SALES (S) OF TOTAL MANUFACTURING

(sample period: 1948I–1967IV; all variables except trend are in natural logarithms)

Independent Variables[a]	Dependent Variable: S_t Equation (5.1)	Equation (5.2)	Equation (5.3)
Constant	.0365 (.5136)	.7668 (3.281)	.7481 (2.676)
S_{t-1}	1.248 (11.20)	1.145 (10.84)	.6088 (5.911)
S_{t-2}	−.2585 (2.261)	−.3322 (3.141)	—
S_{t-3}	.0038 (.5068)	—	—
N_{t-1}	—	—	.3160 (3.809)
N_{t-2}	—	—	−.411 (1.880)
$\left(\frac{ou}{S}\right) N_{t-1}$	—	—	.0273 (1.445)
ΔP_{t-1}	—	—	−.3603 (1.078)
Trend	—	.0017 (3.286)	.0018 (2.597)
R^2	.9818	.9840	.9860
SEE	.0295	.0277	.0269
$D.W.$	2.00	2.08	1.96

a. Figures in parentheses are t statistics. N denotes new orders; P, product prices; R^2, coefficient of determination; SEE, standard error of estimate; $D.W.$, Durbin-Watson statistic.

experiments. The main results of these empirical exercises can be summarized as follows:

a. Using different measures of relative prices did not change the estimates. Most of the information in relative prices is apparently incorporated in the trend and current values of w/c.

b. Results of using different expected sales variables were generally quite similar. To save space, the estimates using predicted values from equation (5.1) are presented in Appendix C, Table C.2. The estimates are quite similar to those in Table 4.1. Again, the distributed lag patterns based on these tables are similar and are shown in Figure 5.2. The similarity to Figure 4.1 requires no further comment.

c. Similar estimates were obtained when several past values of actual sales and relative prices were employed in Y_{it}^*. To save space, those results are not shown. Again, the patterns were similar to those reported immediately above.

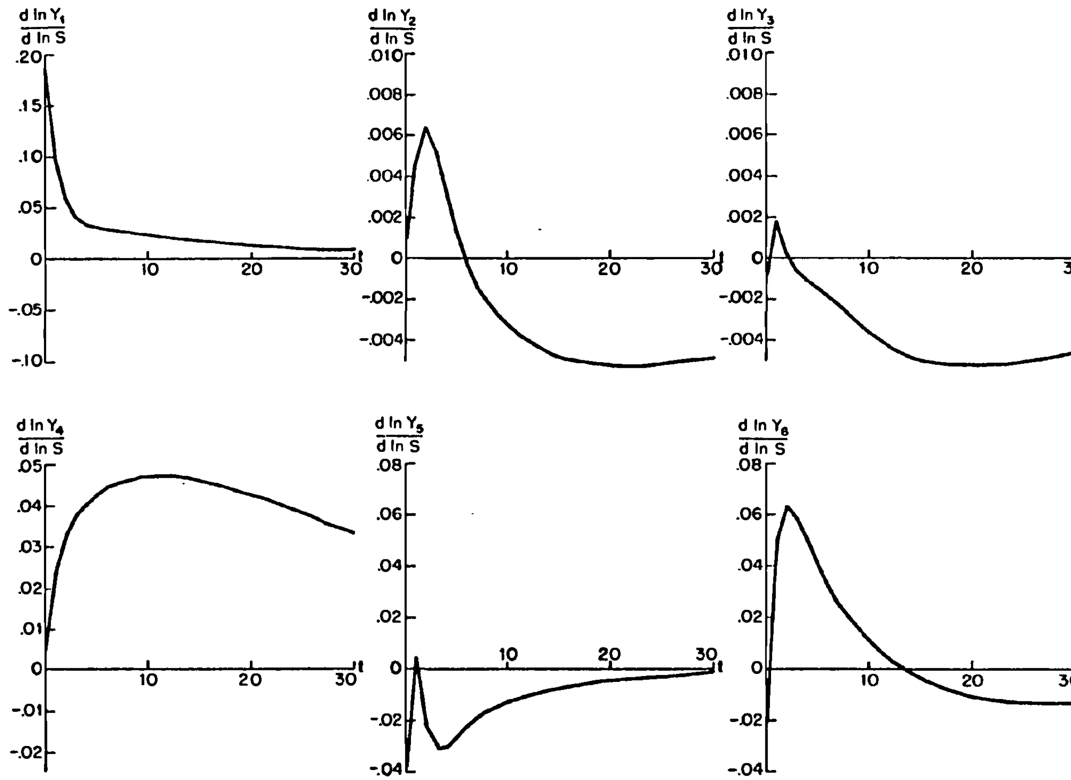
d. All the specifications of model (4.1) using unlagged exogenous variables (both instrumental and actual values) were also estimated by ordinary least squares methods, ignoring serial correlation in the residuals. Though the estimates of structural coefficients are obviously biased, these biases did not fundamentally alter the distributed lag patterns shown in the figures. An example is the result in Figure 5.3, which is the model (4.1) specification estimated by ordinary least squares, with no adjustment for serial correlation.

iii. Deficiencies in measurement of the generalized utilization rate were discussed in Chapter 4. The results of Chapter 5 show that this variable plays an important role in short-run adjustments, consistently overshooting its final equilibrium so that output and sales are maintained during the adjustment process. As will be seen below (Chapter 7), this behavior is repeated in disaggregated estimates. To check the sensitivity of responses to possible measurement errors in this variable, the model was re-estimated, and Y_4 was omitted from the system. An alternative rationale for this specification is the assumption that all utilization components in production processes represented by Y_4 are completely variable factors not subject to adjustment costs. Estimates are shown in Table C.3. Corresponding distributed lag patterns are shown in Figure 5.4. Again, the general features noted above apply.

iv. An alternative to using lagged values of exogenous shift variables

Figure 5.2

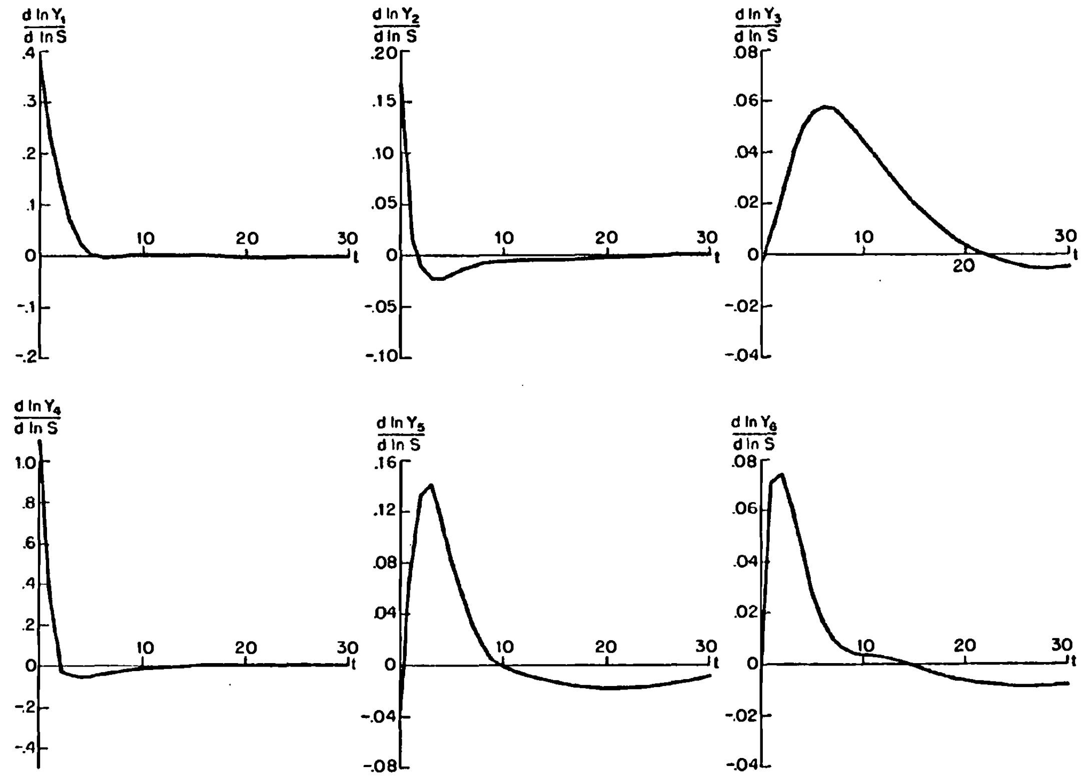
Implied Distributed Lag Responses to a Unit Sales Impulse, Based on Model (5.1)



Source: Table C.2.

FIGURE 5.3

IMPLIED DISTRIBUTED LAG RESPONSES TO A UNIT SALES IMPULSE, BASED ON ESTIMATES UNTRANSFORMED FOR SERIAL CORRELATION



SOURCE: Model (4.1) estimated by ordinary least squares, and without adjustment for serial correlation.

FIGURE 5.4

Implied Distributed Lag Responses to a Unit Sales Impulse, Based on Model (4.1), Omitting the General Utilization Rate

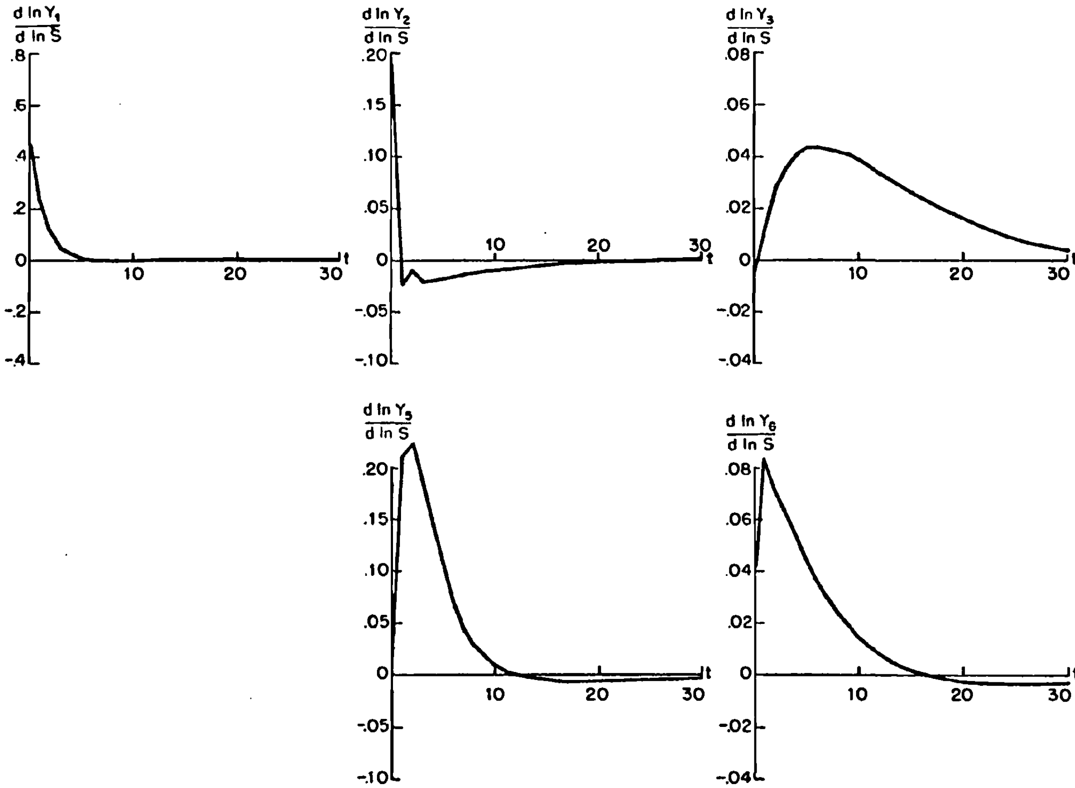
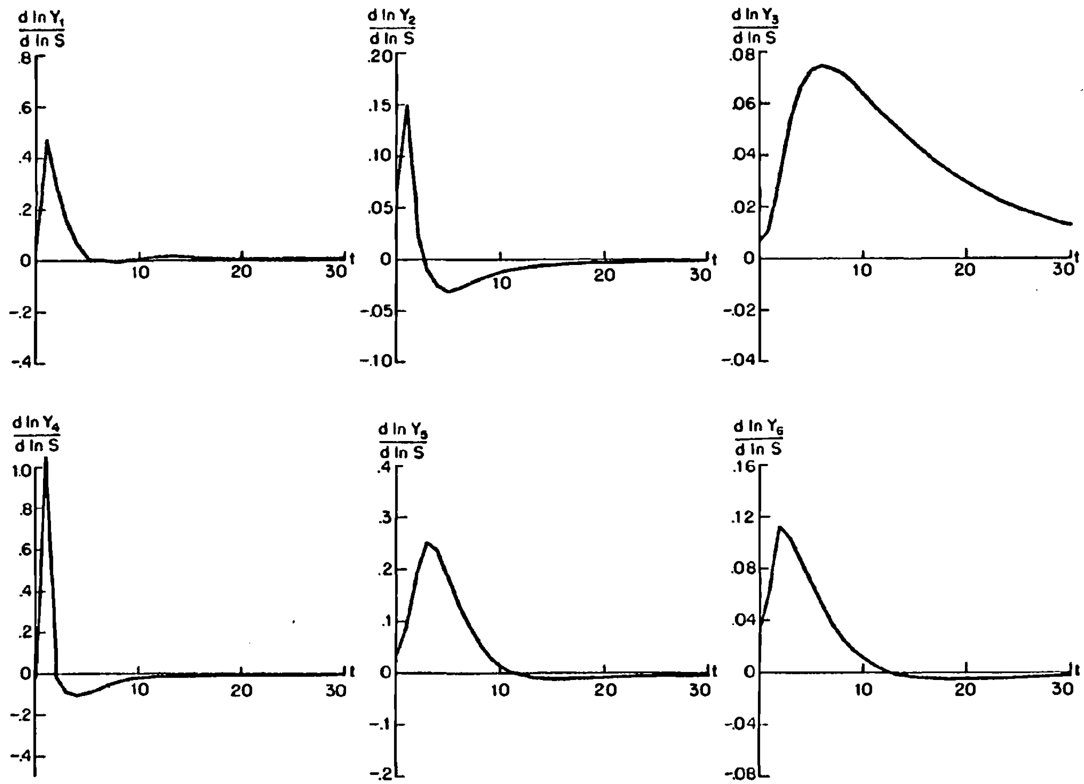


FIGURE 5.5

IMPLIED DISTRIBUTED LAG RESPONSES TO A UNIT SALES IMPULSE, BASED ON ACTUAL CURRENT AND FUTURE SALES



SOURCE: Table C.5.

is to use future values (Mills [1962]) in Y_{it}^*. The theoretical and statistical problems associated with such a procedure will be discussed in the next section. Here, we discuss only the distributed lag responses based on those estimates. In one experiment we included four future actual values of both relative prices and sales. Estimates are presented in Appendix C, Table C.4. In all cases, the future relative price coefficients are not statistically significant. Therefore, we concentrate on a second experiment in which future price terms were deleted. Those results are shown in Table C.5.

In three equations (Y_1, Y_2, and Y_6) the first future sales variable is statistically significant, possibly indicating some current anticipation of future demands. However, the coefficients are, in most cases, rather small in absolute value when compared with current sales coefficients. Most other forward coefficients are statistically insignificant and exhibit instability of signs. Therefore, in computing the distributed lag patterns, shown in Figure 5.5, only current and first future coefficients are taken into account. Again, the patterns of distributed lag responses are similar to those obtained in Chapter 4.

It is clear from all these experiments that the general forms of the distributed lag responses are very insensitive to changes in specifications of exogenous variables. This great variety of experiments provides strong and powerful evidence in favor of the general adjustment structure embedded in model (2.7). However, it should be pointed out that the long-run response elasticities of the dependent variables to changes in exogenous variables displayed substantial sensitivity to alternative specifications. Evidently, the reason for this lies in the distributed lag patterns themselves. Figures 4.1 and 5.1–5.5 often show "thick" tails long after the initial impulse. The long-run elasticity is the area under each distributed lag pattern; hence, small errors in the tail of the distribution are compounded in computing the long-run effects. Note that cumulation of errors occurs long after the initial impulses from which the lagged coefficients are derived and is not in the range of the sample experience. Further, the largest root of $(I - \beta)$ is close to unity, implying slow convergence and therefore the presence of "thick" tails. We conclude, then, that models such as (4.1) are appropriate for estimating short-run and intermediate response patterns and are not well suited for estimating long-run production parameters. We return to this point in a later chapter.

B. ANALYSIS OF RESIDUALS: CROSS CORRELATION

Parameter estimates of the model may be biased because of cross-serial correlation among residuals in various equations. Two issues arise in this connection: (i) concurrent disturbances across equations may be correlated; (ii) nonconcurrent disturbances across equations may also be correlated. The first issue presents no difficulties in the context of our model. There is nothing in principle to suggest that concurrent residuals across equations will be uncorrelated. Indeed, there may be a good reason to think they will be correlated. We have constructed an integrated model in which all input decisions are jointly determined. Hence, any stochastic component arising from the system as a whole, such as in the production function, and so on, would be transmitted to each component symmetrically. This fact provides no difficulties of estimation.

However, cross-serial correlations may exist, that is, $E(\varepsilon_{it}\varepsilon_{jt-1}) \neq 0$ for $i \neq j$, where ε_i is the disturbance in equation i and ε_{jt-1} is the lagged disturbance in equation j. If this is the case, the estimates may be biased. To check this possibility we assemble, in Table 5.2, the simple correlation coefficients of current and lagged estimated residuals from Table 4.1 across equations; $\varepsilon_1, \ldots, \varepsilon_6$ respectively refer to the residuals of the equations $Y_1, \ldots, Y_6$. We note some correlation among the residuals of the equations for production workers and hours worked (about 0.47) and some correlation among the residuals of the capital stock equation and their lagged values. However, in all other cases there is no strong evidence of cross-serial correlations among the residuals of different equations. We also used the multiple correlation to check for cross correlations among the residuals of different equations.

Note that this procedure is biased and at best can be only suggestive. The coefficients are biased because of the presence of lagged residuals across equations. Consider the regressions in Table 5.3. If ε_{it} and ε_{jt} are correlated, then the lagged values of ε_{it-1} are not independent of the error terms in the regression of ε_{it} on ε_{jt-1}. Thus, the coefficients in Table 5.3 may not give the correct results, for the same reason that the Durbin-Watson test is biased when lagged endogenous variables are present in a regression equation. Still, if the true cross correlations are sufficiently strong, they may show up in the regression coefficients. The regressions for ε_3, ε_4, and ε_5 (residuals of the equations for capital stock, utilization rate, and inventories) display no evidence

TABLE 5.2

MATRIX OF SIMPLE CORRELATION AMONG CURRENT AND LAGGED RESIDUALS[a] OF EQUATION (2.3)

	ε_1	ε_2	ε_3	ε_4	ε_5	ε_6	ε_{1t-1}	ε_{2t-1}	ε_{3t-1}	ε_{4t-1}	ε_{5t-1}	ε_{6t-1}
ε_1	1.0	.496	.368	−.155	−.124	−.070	−.045	−.007	.064	.254	−.069	−.143
ε_2		1.0	.497	−.167	.045	.049	.153	−.061	−.022	−.003	.074	−.1020
ε_3			1.0	−.051	−.038	.004	.112	.040	−.104	.058	.187	−.0111
ε_4				1.0	−.089	−.068	.220	.110	.044	−.079	.016	−.0001
ε_5					1.0	.195	−.037	−.188	−.162	−.040	.091	−.189
ε_6						1.0	.041	.016	−.020	−.335	−.091	.096
ε_{1t-1}							1.0	.489	.374	−.150	−.142	−.111
ε_{t-21}								1.0	.489	−.167	.044	.050
ε_{3t-1}									1.0	−.047	−.057	−.037
ε_{4t-1}										1.0	−.092	−.074
ε_{5t-1}											1.0	.244
ε_{6t-1}												1.0

a. ε_{it} is the residual of the regression equation of ln Y_i in period t.

TABLE 5.3

REGRESSION RESULTS OF CROSS CORRELATION OF RESIDUALS[a] OF MODEL (4.1)

Independent Variables	ε_{1t}	ε_{2t}	ε_{3t}	ε_{4t}	ε_{5t}	ε_{6t}
Constant	−.00002 (0.069)	−.00004 (0.096)	.00000 (0.005)	.0001 (0.059)	.0004 (0.405)	.0006 (0.082)
ε_{1t-1}	—	.1753 (1.352)	−.0409 (0.944)	−.9224 (1.309)	−.2159 (0.688)	.6018 (3.592)
ε_{2t-1}	.1393 (1.352)	—	.0161 (0.414)	−.2102 (0.331)	.0175 (0.063)	.5431 (3.645)
ε_{3t-1}	−.2939 (0.944)	.1453 (0.414)	—	−1.388 (0.730)	−.3951 (0.469)	−.4201 (0.868)
ε_{4t-1}	−.0248 (1.309)	−.0071 (0.331)	−.0052 (0.730)	—	.0769 (1.511)	.0273 (0.922)
ε_{5t-1}	−.0298 (0.688)	.0030 (0.063)	.0076 (0.469)	.3942 (1.511)	—	.0316 (0.469)
ε_{6t-1}	.2495 (3.592)	.2834 (3.645)	−.0243 (0.868)	.4208 (0.922)	.0948 (0.469)	—
R^2	.2967	.2691	.0492	.0702	.0477	.3794
SEE	.0035	.0040	.0013	.0217	.0096	.0055
D.W.	2.35	2.37	2.02	1.65	1.72	2.35

NOTE: Figures in parentheses are t statistics. R^2 is the coefficient of determination; *SEE*, the standard error of estimate; *D.W.*, the Durbin-Watson statistic.

a. ε_{it} is the residual of the regression equation of variable $\ln Y_i$ in period t.

of cross-serial correlation. There is some suggestion of minor feedbacks in the stochastic structure of the labor subsector, indicating a positive feedback from the stock of nonproduction labor on both hours and employment of production labor. Similarly, hours and employment of production workers have positive and equal effects on the residuals for nonproduction labor. Also, when the own lagged values of residuals were included in the regression equations (not shown) their coefficients were always statistically insignificant.

These effects could be attributed to two causes: (i) the omission of variables such as rental price of labor and hours of nonproduction workers that are expected to affect stock and flow variables in labor decisions symmetrically; and (ii) the tendency of hours to vary in discreet jumps (Charts 3.2 and 4.2), making it likely that any contemporaneous correlations will be pushed backward and that serial cross correlation will result.

It is possible to estimate model (4.1) on our hypothesis of nonzero auto- and cross-serial correlation among residuals by employing full information methods. If the results in Table 5.3 are in fact valid, our model does not capture all feedbacks in the system, and the full information method may be desirable. However, in light of the results in section A, we do not feel that the evidence in Table 5.3 is strong enough to warrant such attempts at this time. This is certainly a proper subject for future investigation. As one step in this direction, we examine the lag structure based on direct estimation of reduced form parameters.

C. REDUCED FORM ESTIMATION

The reduced form system suggests a method for incorporating future values of the exogenous variables and allows us to test whether or not such values should be included.

The model we have discussed so far may be written as

$$Y_t = Aq_t + (I - \beta)Y_{t-1} + U_t, \tag{5.4}$$

where q_t is a vector of expected sales, trend, and relative prices at time t, A and β are matrices of regression coefficients, and U_t is a vector of residuals. A reduced form is obtained by iteration:

$$Y_t = Aq_t + (I - \beta)Aq_{t-1} + (I - \beta)^2Aq_{t-2} + \dots$$
$$+ U_t + (I - \beta)U_{t-1} + (I - \beta)^2U_{t-2} + \dots . \tag{5.5}$$

Up to this point, all our efforts have been devoted to estimating A and β in equation (5.4). We now consider estimating these parameters from (5.5).

Estimation of equations (5.5) provides direct information about distributed lag relations and long-run elasticities in the model. For example, the distributed lag of capital stock (Y_3) on sales is given by the appropriate elements in the sequence $\{A, (I - \beta)A, (I - \beta)^2A, \dots\}$. The long-run coefficients are the sums of these sequences.

Notice that the residuals in (5.5) are weighted sums of current and past disturbances, U_t in (5.4). Thus, direct estimation (5.5) by least squares would not be appropriate. A proper method of estimation would be the generalized least squares technique, requiring a consistent estimate of the (6 × 6) variance-covariance matrix of the residuals.

Though maximum likelihood techniques would be most appropriate for this problem, we have adopted a second-best procedure for computational convenience. If the covariance matrix is diagonal, generalized least squares amounts to performing separate ρ transformations on each equation of system (5.5). Adopting this method can only be considered a crude approximation of the optimal method of reduced form estimation, for our model requires that $(I - \beta)$ not be diagonal. Consequently, the following results should be interpreted with caution.

The results are reported in Table 5.4, using eight lagged values of sales, plus the time trend and current sales, but ignoring relative prices. Preliminary experimentation indicated that no lagged values of relative price variables were significant. Quite remarkably, the major features of the estimates in Table 5.4 agree very well with their implied values from the estimated structure. The regression coefficients of each variable are very similar to implied distributed lags discussed in Chapter 3. Long-run elasticities computed as the sums of the coefficients on $S_t, \ldots, S_{t-8}$ are indicated in the last line of Table 5.4. By and large they agree reasonably well with those implied by estimation of the structure; and most of the differences are undoubtedly the result of including only eight lags in the table. Once again, this result confirms the insensitivity of the estimates to specification.

In section A, we examined the rationale of including S_t in the structural equations as a forecast of future shocks. The hypothesis that S_t contains most of the relevant information concerning future sales was accepted. The reduced form system (5.5) suggests an additional test, however. Suppose $\hat{S}_{t+1}, \hat{S}_{t+2}, \ldots, \hat{S}_{t+n}$, truly belonged in the structure (5.4), where $\hat{S}_{t+j}$ is anticipated sales j periods hence. If actual sales are a good predictor of anticipated sales, the structural and reduced form equations would include terms in $S_{t+n}, S_{t+n-1}, \ldots, S_{t+1}$ as well as in $S_t, S_{t-1}, \ldots$. As noted earlier, inclusion of forward sales terms in structural equations did not change the basic conclusion that the distributed lag patterns are insensitive to specification of exogenous variables.

A comparable procedure was applied to reduced form estimates. Each dependent variable was regressed on current, four future, and eight past values of sales and relative prices, all adjusted for first-order

TABLE 5.4

LAG DISTRIBUTION FROM TIME DOMAIN REGRESSIONS OF THE DEPENDENT VARIABLES ON PAST AND CURRENT VALUES OF SALES (S)

(sample period: 1948I–1967IV; all variables except trend are in natural logarithms)

Independent Variables	Dependent Variables					
	Prod. Emp. (Y_1)	Hours (Y_2)	Capital (Y_3)	Util. (Y_4)	Inven. (Y_5)	Nonprod. Emp. (Y_6)
Constant	−.0951 (2.261)	.5767 (13.72)	.0372 (8.049)	−.6308 (1.888)	−.1163 (2.449)	−.0177 (2.457)
S_{t-1}	.2336 (6.980)	−.0052 (.2192)	.0230 (1.230)	.2801 (1.950)	.2946 (4.572)	.1167 (4.334)
S_{t-2}	.0827 (2.493)	−.0156 (.6598)	.0455 (2.447)	−.2359 (1.662)	.1751 (2.737)	.1243 (4.642)
S_{t-3}	.0615 (1.856)	−.0350 (1.485)	.0641 (3.441)	−.1404 (.9972)	.1906 (2.974)	.0908 (3.387)
S_{t-4}	.0339 (.9645)	−.0360 (1.449)	.0617 (3.098)	−.2840 (1.939)	.1996 (2.922)	.0779 (2.717)
S_{t-5}	−.0175 (.5295)	−.0303 (1.284)	.0515 (2.773)	.1239 (.8797)	.2359 (3.688)	.0534 (1.996)
S_{t-6}	.0023 (.0734)	−.0216 (.9397)	.0563 (3.127)	−.1685 (1.219)	.1082 (1.745)	.0317 (1.224)
S_{t-7}	−.0214 (.6759)	.0160 (.7083)	.0608 (3.422)	−.0171 (1.276)	.0148 (.2422)	.0253 (.9880)
S_{t-8}	−.0245 (.7492)	−.0386 (1.677)	.0685 (3.682)	−.0793 (.6208)	.0372 (.5832)	.0234 (.8762)
S_t	.5060 (14.79)	.1678 (7.024)	.0171 (.8770)	.8794 (6.693)	.1870 (2.798)	.1125 (3.997)
Trend	−.0006 (6.723)	−.0002 (.2567)	.0001 (1.769)	−.0004 (.6689)	−.0002 (1.958)	−.0001 (2.669)
R^2	.8895	.6310	.6127	.6917	.6477	.6218
SEE	.0073	.0051	.0042	.0288	.0143	.0060
SSR	.0032	.0015	.0010	.0490	.0121	.0021
$\hat{\rho}$	.9049	.8432	.9854	.6184	.9500	.9840
$\sum_{i=0}^{8} S_{t-i}$	.8576	.656	−.0004	.4486	.1062	1.443

NOTE: Figures in parentheses are t statistics. R^2 is the coefficient of determination adjusted for degrees of freedom; SEE, the standard error of estimate; SSR, the sum of squared residuals. For $\hat{\rho}$, see Chapter 4, note 1.

serial correlation. Again, relative price effects were numerically small and statistically insignificant, a pattern observed throughout the study. To conserve space, only the estimates relating to sales variables are presented in Table 5.5. The coefficients on lagged and unlagged values of S are similar to those in Table 5.4. The forward values are never significant in the capital stock (Y_3), inventory (Y_5), and utilization (Y_4) equations. S_{t+1} enters significantly in all the labor equations but in most cases with numerically small coefficients relative to S_t. Other forward terms (except for S_{t+3} in the hours equation) are insignificant.[1] The same picture emerges when *only* future terms and S_t are included, as shown in Table 5.6.[2]

It is interesting to note that future sales variables display their largest effect in the labor sector, especially in hours per man. This result was also obtained in the test for cross-equation serial correlation in section A. Again, this suggests that there may be some pattern of feedback not captured by model 4.1. However, we emphasize that the future effects are small in magnitude and that the distributed lag patterns based on inclusion of future terms in *either* the structure or the reduced form are little different from those based only on current and past sales.

Furthermore, inclusion of future sales as proxies for future expectations results in biased estimates. At the time that current input and output decisions are made, only past information is available, not future realizations. Even if perfect foresight prevails, so that anticipated sales in period $t + j$ equals the *mean* of realized sales in that period, anticipated sales will be distributed around actual realizations with error. Hence, use of future sales terms introduces measurement errors in both structural

1. Table 5.5 contains sums of squared residuals (*SSR*) for computing F statistics to test the null hypothesis that the contribution of the future terms is insignificant. The figures indicate that the null hypothesis can be accepted in every case, except, possibly, that of hours (Y_2).

2. An alternative method is to use a filter such as $1-\alpha_1 L+\alpha_2 L^2$, where L is the lag operator and α_{i1} and α_{i2} are fixed coefficients estimated from each series of the variables. Define variables

$$S_t^* = S_t - \alpha_{11} S_{t-1} + \alpha_{12} S_{t-2};$$

$$Y_{it}^* = Y_{it} - \alpha_{i1} Y_{it-1} + \alpha_{i2} Y_{it-1};\ i = 1, \ldots, 6.$$

Regressing Y_{it}^* on future and past values of S^* provides information similar to that in Tables 5.4–5.6 (Sims [1971]). The regression coefficients and F statistics calculated from these regressions were quite similar to those based on the sums of squared residuals shown in the tables mentioned, and therefore are not reported here. The evidence from these results suggests acceptance of the null hypothesis mentioned above.

TABLE 5.5

LAG DISTRIBUTION FROM TIME DOMAIN REGRESSIONS OF THE DEPENDENT VARIABLES ON PAST, CURRENT, AND FUTURE VALUES OF SALES (S)
(sample period: 1948I–1967IV; all variables except trend are in natural logarithms)

	Dependent Variables					
Independent Variables	Prod. Emp. (Y_1)	Hours (Y_2)	Capital (Y_3)	Util. (Y_4)	Inven. (Y_5)	Nonprod. Emp. (Y_6)
Constant	−.1331	1.284	.0419	−.4154	−.1112	−.0205
	(2.600)	(23.99)	(6.900)	(1.113)	(1.661)	(1.826)
S_{t+1}	.0875	.0866	−.0026	−.0395	.0653	.0555
	(2.545)	(3.815)	(.1302)	(.2435)	(.9220)	(1.994)
S_{t+2}	.0227	−.0015	−.0234	.0699	−.0021	.0132
	(.6490)	(.0674)	(1.129)	(.4282)	(.0301)	(.4702)
S_{t+3}	.0193	.0628	−.0188	−.1993	−.0798	−.0416
	(.5433)	(2.744)	(.8989)	(1.219)	(1.093)	(1.459)
S_{t+4}	−.0492	.0063	−.0124	−.2558	−.0176	−.0464
	(1.380)	(.2998)	(.5873)	(1.869)	(.2387)	(1.605)
S_{t-1}	.2350	.0088	.0114	.2422	.2622	.0962
	(6.886)	(.4047)	(.5547)	(1.550)	(3.695)	(3.433)
S_{t-2}	.1025	−.0076	.0335	−.2049	.1701	.1305
	(3.006)	(.3457)	(1.628)	(1.304)	(2.399)	(4.660)
S_{t-3}	.0971	−.0151	.0614	−.0873	.2176	.1173
	(2.874)	(.6948)	(3.015)	(.5654)	(3.105)	(4.242)
S_{t-4}	.0212	−.0429	.0591	−.2928	.2060	.0708
	(.5984)	(1.882)	(2.750)	(1.821)	(2.789)	(2.425)
S_{t-5}	−.0132	−.0251	.0491	.1404	.2162	.0447
	(.3969)	(1.136)	(2.480)	(.8874)	(3.151)	(1.661)
S_{t-6}	.0098	−.0396	.0532	−.0753	.1166	.0453
	(.2938)	(1.795)	(2.697)	(.4810)	(1.700)	(1.689)
S_{t-7}	−.0009	.0244	.0669	.0197	.0465	.0488
	(.0280)	(1.159)	(3.459)	(.1311)	(.6918)	(1.854)
S_{t-8}	−.0573	−.0648	.0710	−.0839	.0249	.0038
	(1.731)	(3.238)	(3.604)	(.6489)	(.3651)	(.1427)
S_t	.4656	.1447	.0104	.8843	.1585	.0763
	(12.84)	(6.270)	(.4718)	(5.417)	(2.094)	(2.545)
Trend	−.0008	−.0004	.0006	.0005	−.0002	−.0001
	(6.764)	(3.755)	(2.013)	(.7038)	(1.558)	(2.230)
R^2	.9069	.8380	.6277	.8217	.6708	.6868
SEE	.0070	.0041	.0042	.0268	.0145	.0057
SSR	.0027	.0009	.0009	.0396	.0116	.0018
$\hat{\rho}$	.9011	.5877	.9860	.3528	.9462	.9798
$\sum_{i=0}^{8} S_{t-i}$	.9401	.6144	.1370	.3588	−.1171	1.38

NOTE: Same as NOTE, Table 5.4.

TABLE 5.6

LAG DISTRIBUTION FROM TIME DOMAIN REGRESSIONS OF THE DEPENDENT VARIABLES ON CURRENT AND FUTURE VALUES OF SALES (S)

(sample period: 1948I–1967IV; all variables except trend are in natural logarithms)

Independent Variables	Dependent Variables: Prod. Emp. (Y_1)	Hours (Y_2)	Capital (Y_3)	Util. (Y_4)	Inven. (Y_5)	Nonprod. Emp. (Y_6)
Constant	−.0111	.4130	.0565	−1.050	.1870	.0472
	(1.915)	(15.63)	(20.18)	(3.857)	(7.918)	(5.819)
S_{t+1}	.0419	.0727	−.0250	.0209	−.0819	.0059
	(.9571)	(3.485)	(1.129)	(.1476)	(1.059)	(.1733)
S_{t+2}	−.0603	.0048	−.0260	.1505	−.1120	−.0458
	(1.379)	(.2307)	(1.176)	(1.046)	(1.450)	(1.332)
S_{t+3}	−.0759	.0437	−.0079	−.3043	−.2119	−.0733
	(1.713)	(2.075)	(.3556)	(2.127)	(2.710)	(2.104)
S_{t+4}	−.0937	.0066	−.0141	−.2747	−.0389	−.0591
	(1.972)	(.3077)	(.5870)	(2.178)	(.4665)	(1.587)
S_t	.4966	.1741	−.0347	.8869	.0298	.0595
	(10.74)	(8.269)	(1.484)	(7.129)	(.3664)	(1.639)
Trend	.00003	−.0004	.0001	−.0010	.0003	.0001
	(.5908)	(6.470)	(3.854)	(1.756)	(3.408)	(3.309)
R^2	.7498	.6676	.2203	.7063	.2607	.3194
SEE	.0107	.0048	.0054	.0288	.0188	.0084
SSR	.0076	.0015	.0019	.0547	.0233	.0046
$\hat{\rho}$	.9883	.8306	.9892	.5019	.9670	.9755
$\sum_{i=4}^{8} S_{t+i}$	.3086	.3019	.1077	.4793	.4149	.1128

NOTE: Same as NOTE, Table 5.4.

and reduced form equations. Current anticipations data are often used in economic models to approximate future events. We used some of these data to construct the expected sales variable, Z_t, in equation (2.7), but the results reported in section A were no different from those obtained by using current sales. It is unlikely that use of other anticipations data would give better results.

It is certainly reasonable to suppose that, when adjustments are costly, firms may "build ahead of demand," by holding input inventories in anticipation of future increases in sales. In the equations for hours and other labor variables, the coefficients of future sales variables may be consistent with this phenomenon. It also implies the possibility of simultaneity between sales and input decisions in the system. At an early stage of the investigation, we decided not to use GNP and similar general aggregate measures as demand shift variables that would serve to avoid the simultaneity issue, because the aggregates are too far removed in time and pattern from the experience of specific industries.

Thus, the results reported in this chapter indicate the potential desirability of using more sophisticated estimation techniques, and taking simultaneity and alternative stochastic structures into account more explicitly. The ultimate problem here lies in the economic theory: The integration of a *dynamic* theory of the firm with that of the market is one of the most important unresolved problems in economics. Nevertheless, the multitude of experiments reported here indicate that dynamic response patterns in our model are extremely robust, given the limitations of theory and data. Alternative estimation techniques that are available (Sims [1971]) are no better than the ones we have employed.