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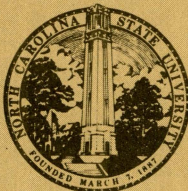
# FACULTY WORKING PAPERS

On Estimates of the Speed of Adjustment  
in Inventory Investment Equations

Alastair Hall and Robert J. Rossana

Faculty Working Paper No. 112

December 1987



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in Inventory Investment Equations\* \*

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## I. Introduction

Applied research on inventory investment has typically provided estimates of the adjustment speed arising in partial adjustment models of the form

$$F_t - F_{t-1} = \lambda(F_{t-1} - F^*)$$

where  $F$  refers to the stock of inventories (finished goods, materials, work-in-process or, possibly, the sum of the three components), an asterisk denotes a steady-state or desired level and  $t$  refers to calendar time. The parameter  $\lambda$  is the speed of adjustment, measuring the fraction of the gap between desired and actual levels which is made up each period. As noted by Carlson and Wehrs (1974) and Feldstein and Auerbach (1976), the typical estimate of this parameter is implausibly low for at least two reasons. If slow adjustment speeds are associated with severe costs of adjustment, then these parameter estimates imply very severe costs of adjustment which appears peculiar a priori. If firms are making expectational errors which are large, then it might be possible to rationalize these slow adjustment speeds. However, direct estimates of these errors find them to be on the order of one or two days production and thus easily corrected. Therefore these errors seem not to provide a resolution to this puzzle.

Maccini and Rossana (1984) (hereafter M-R) claim to provide an answer for these implausible empirical results. They argue that research on inventory investment has misspecified the nature of the optimal decision rules used by firms by assuming that inventory investment decisions are made independent of decisions on employment, hours, capital stocks and other inputs. In this context, inventory investment should depend upon the levels of all these quasi-fixed factor inputs, as well as their associated factor prices.<sup>1</sup> In addition,

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<sup>1</sup>This is the essence of the multivariate flexible accelerator first examined by Lucas (1967).

they argue that inappropriate attention to the presence of serial correlation has produced biased estimates of adjustment speeds with the bias tending to understate the true speed of adjustment. They produce empirical evidence for the manufacturing sector (Total Manufacturing, Nondurable and Durable Manufacturing) which, at monthly data frequencies, suggests that adjustment speeds are on the order of sixty percent or more per month. In addition, they find significant stock adjustment effects in all estimated finished goods equations.

Blinder (1986) has recently taken issue with these results. Using data which is more disaggregated than that used by M-R, he produces estimated adjustment speeds which are much smaller than those reported by M-R. To reconcile differences in results, Blinder argues that in the presence of serial correlation, the identification of adjustment speeds is problematic since these parameters are identifiable only if other parameters in estimated equations are significant. In practice, these other parameters are often barely significant rendering empirical estimates formally identified yet unreliable. Second, he argues that the estimation method used by M-R produces parameter estimates that correspond to a local minimum sum of squared residuals where serial correlation parameters and adjustment speeds are high. Evidence is presented that low speeds of adjustment are found at the global minimum sum of squared errors. Although these points are raised in the context of a particular empirical model of inventory investment, these issues have potentially far reaching implications for applied work since partial adjustment models are widely used in applied macroeconomic research.

In this paper, we re-examine the issues raised by Blinder and find that his rationale for the causes of the discrepancies in results appearing in these

two studies is only partly correct. There are a number of differences between each empirical study which make it difficult to determine why results differ. For example, M-R use the residual adjusted Aitken estimator devised by Hatanaka (1974) while Blinder uses nonlinear least squares. In Section 2, we examine the properties of each estimator and find that they generally may be expected to produce different parameter estimates in finite samples, despite the fact that they have identical asymptotic properties. In this same section, we also find that it is not possible to predict how parameter estimates will differ using these two methods because each study differs in model specification. For example, Blinder uses time series models to approximate expectations whereas M-R use Almon lags for the same purpose. In addition, these studies differ in their selection of other regressors. In Section 3, we attempt to control for model specification in assessing the performance of each estimation method by using the model structure employed by M-R at the same level of aggregation used by Blinder. There we report estimates of adjustment speeds under each estimation method, for the same model specification, and under the two model specifications for the same estimation method. In this way, we can observe how model specification and estimation method influence results.

Generally speaking, our empirical results confirm Blinder's results in that, for the same model specification, the Hatanaka estimator seems to systematically overstate the speed of adjustment relative to nonlinear least squares. We also find that, for a given estimation method, adjustment speeds tend to be lower when time series models are used to approximate expectation formation. We also find some evidence, by comparing our results to Blinder's, that estimated adjustment speeds can be very different as one changes model specification, suggesting that applying the same model across industries may be

a misspecification. This may also account for implausible estimated adjustment speeds.

## II. Econometric Issues

In this section we examine two econometric issues raised by Blinder (1986). First, we consider the question of identification in partial adjustment models with serial correlation. Second, we consider both the relationship between Hatanaka's estimator and nonlinear least squares, and the extent to which these estimators are affected by the existence of multiple optima.

For the purpose of our discussion of multiple optima in partial adjustment models with serially correlated errors, it is sufficient to consider the following model:

$$y_t - y_{t-1} = \beta(y^* - y_{t-1}) + \alpha x_t + u_t \quad (2.1)$$

$$u_t = \rho u_{t-1} + e_t, \quad (2.2)$$

where  $y^*$  represents the desired level of  $y_t$ , and  $x_t$  is an exogenous variable and  $e_t$  an independently and identically distributed mean zero error term.

Equations (2.1) and (2.2) imply

$$y_t = \beta(1-\rho)y^* + (1+\rho-\beta)y_{t-1} + (\beta-1)\rho y_{t-2} + \alpha x_t - \rho\alpha x_{t-1} + e_t, \quad (2.3)$$

Consider also the unrestricted form of (2.3), namely

$$y_t = \mu_0 + \mu_1 y_{t-1} + \mu_2 y_{t-2} + \mu_3 x_t + \mu_4 x_{t-1} + e_t. \quad (2.4)$$

If the model in (2.4) is estimated by nonlinear least squares, then the optimand,  $\sum e_t^2$ , will have multiple minima as a function of  $(\beta, \rho, \alpha)$  if more than one set of values for  $(\beta, \rho, \alpha)$  which yield a particular set of values for  $\mu_i$ .

In the special case where  $\alpha = 0$ , then as Blinder observes, there are multiple optima because there are pairs of values  $(\beta, \rho)$  which give a particular set of values for  $\mu_0, \mu_1, \mu_2$ . These two solutions for  $(\beta, \rho)$  are characterized by a "high  $\rho$ " or "low  $\rho$ " solution. Blinder argues that although M-R's model includes "a variety of other regressors and hence are identified in the formal sense," the "identification hinges precariously on regressors which are often of minor empirical importance" rendering distinguishing between high  $\rho$  and low  $\rho$  solutions "difficult" (Blinder, 1986, p. 357). This supposition is based on the following continuity argument. We can take the following mean value expansion of the optimand for estimation,

$$L(\beta, \rho, \alpha) = L(\beta, \rho, 0) + \left. \frac{\partial L}{\partial \alpha} \right|_{\alpha^*} \alpha \quad (2.5)$$

where  $0 \leq \alpha^* \leq \alpha$ . If  $\alpha$  is close to zero then  $\left. \frac{\partial L}{\partial \alpha} \right|_{\alpha^*} \alpha$  is close to zero. In which case the two sets of  $(\beta, \rho)$  values which minimize  $L(\beta, \rho, 0)$  are going to yield roughly equal values of  $L(\cdot)$ , both close to the global minimum. However, whether or not high  $\rho$  or low  $\rho$  solutions yield the global minimum depends on  $\left. \frac{\partial L}{\partial \alpha} \right|_{\alpha^*} \alpha$ . In other words, it depends crucially on the model estimated. Of course if  $\alpha$  is not close to zero the problem disappears.

There are several differences between the models estimated by Blinder and M-R, which we explore in further detail in Section 3. However, for the present, it is sufficient to note that these differences imply that one should be cautious in generalizing multiple optima arguments from one model to the other. Furthermore, these specification differences may cause the "high  $\rho$ " solution to be the global minimum in one model, but the "low  $\rho$ " solution to



be the global minimum in the other model. The existence of multiple optima or near multiple optima is clearly an empirical matter and we examine this question for the stock adjustment models considered by Blinder and M-R, in Section 3.

For the remainder of this section we consider the relationship between Hatanaka's estimator and nonlinear least squares. To facilitate the exposition, we consider the following simple model:

$$y_t = \alpha x_t + \beta y_{t-1} + u_t \quad (2.6)$$

$$u_t = \rho u_{t-1} + e_t \quad (2.7)$$

where  $x_t$  and  $e_t$  are as in (2.1).

Hatanaka's method consists of two steps. First, estimate (2.6) by instrumental variables (IV) to yield consistent estimators of  $\alpha$ ,  $\beta$ , which we denote  $\tilde{\alpha}$ ,  $\tilde{\beta}$ . These in turn can be used to construct a consistent estimator of  $\rho$ ,  $\tilde{\rho}$  given by

$$\tilde{\rho} = \frac{\sum_t \tilde{u}_t \tilde{u}_{t-1}}{\sum_t \tilde{u}_t^2} \quad (2.8)$$

where  $\tilde{u}_t = y_t - \tilde{\alpha}x_t - \tilde{\beta}y_{t-1}$ .

In the second step  $\tilde{\rho}$  is used to quasi-difference (2.6) and estimators of  $\alpha$ ,  $\beta$  and  $\rho - \tilde{\rho}$  are obtained by ordinary least squares applied to this quasi-differenced model. Hatanaka's estimators are therefore  $\hat{\alpha}$ ,  $\hat{\beta}$  and  $\hat{\rho} = \hat{\theta} + \tilde{\rho}$  where  $\hat{\alpha}$ ,  $\hat{\beta}$  and  $\hat{\theta}$  minimize

$$O_n = \sum_{t=2}^n [(y_t - \tilde{\rho}y_{t-1}) - \alpha(x_t - \tilde{\rho}x_{t-1}) - \beta(y_{t-1} - \tilde{\rho}y_{t-2}) - \theta u_{t-1}]^2 \quad (2.9)$$

where  $\theta = \rho - \tilde{\rho}$ . Such an estimation strategy is equivalent to minimizing

$$0_n = \sum_{t=2}^n [e_t + (\rho - \tilde{\rho})u_{t-1} - (\rho - \tilde{\rho})\tilde{u}_{t-1}]^2, \quad (2.10)$$

$$= \sum_{t=2}^n e_t^2 + (\rho - \tilde{\rho})^2 \sum_{t=2}^n (u_t - \tilde{u}_{t-1})^2 + 2(\rho - \tilde{\rho}) \sum_{t=2}^n e_t (u_t - \tilde{u}_{t-1}) \quad (2.11)$$

with respect to  $\alpha$ ,  $\beta$ ,  $\rho$ .

The nonlinear least squares (NLS) estimators of  $\alpha$ ,  $\beta$  and  $\rho$  minimize

$$L_n = \sum_{t=2}^n e_t^2. \quad (2.12)$$

Therefore in finite samples the respective minimands of Hatanaka's and NLS estimation methods are different. In general, therefore, one would expect the Hatanaka estimator to be numerically different from NLS. The size of this difference depends on the relative magnitudes of the three elements of  $0_n$  in (2.11). Although no definitive statements are possible, some observations about the possible impact of the second and third terms in  $0_n$  (2.11) can be made. Note that if  $\sum_{t=2}^n e_t (u_t - \tilde{u}_{t-1}) > 0$ , then there is an incentive for the estimator to stay close to  $\tilde{\rho}$ . However, if

$$\sum_{t=2}^n e_t (u_t - \tilde{u}_{t-1}) < -\frac{1}{2} \sum_{t=2}^n (u_t - \tilde{u}_{t-1})^2 \quad (\rho - \tilde{\rho}) < 0,$$

then there is an incentive for the Hatanaka estimator to move away from  $\tilde{\rho}$ . In moderate to large sized samples, one would expect  $\sum e_t^2$  to be the dominant term in (2.11) in the sense that the values of  $(\alpha, \beta, \rho)$  which  $\sum e_t^2$  should approximately minimize  $0_n$  due to the consistency of the IV estimator. By the same reasoning, Hatanaka's estimator is asymptotically equivalent to NLS. This allows an interpretation of the Hatanaka estimator. It can be shown, see Harvey (1981, p. 270) for instance, that Hatanaka's estimator is equivalent to the estimator obtained by minimizing (2.12) with a two step Gauss Newton

method. This implies also that Hatanaka's estimator is asymptotically efficient under normality (see Harvey, 1981, p.140-1).

It is interesting to examine the performance of the Hatanaka estimator in the model (2.3) with  $\alpha = 0$ . The natural solution to underidentification is to introduce sufficient additional information to identify the parameters. At first sight it would appear that the use of IV is such additional information and so the Hatanaka estimator circumvents the underidentification problem. However this is not so. To see this, consider the case where  $\alpha = 0$  in (2.6). The properties of Hatanaka's estimator depend on the consistency of the IV estimator of  $\beta$ . However due to the multiple optima, it is not possible to obtain a unique expression for  $y_t$  in terms of  $\beta$ , and so conventional arguments for consistency of IV break down.

A summary of our arguments is as follows: the stock adjustment models estimated by M-R and Blinder are formally identified, but if the exogenous variables do not contribute much to explanation of the change in inventories, one might observe near multiple optima. However, the nature of the problem depends not only on the structure of model but also on the exogenous variables included. If the model is identified, then the Hatanaka estimator is consistent and asymptotically efficient under normality; the relevant question is whether the sample size is large enough (relative to the number of estimated parameters) for the estimator to have converged to its limit. Both these issues are empirical by nature, and so in the next section we compare the estimation results for both M-R and Blinder's models using both NLS and Hatanaka's technique.

### III. Empirical Results

In this section, we provide estimates of inventory equations using NLS and the Hatanaka estimator under alternative model specifications whenever serial correlation is indicated in the disturbances. Our basic estimating equation is similar to, though not identical with, the one used by M-R. We incorporate hours per worker as a state variable in our estimating equations. In view of our earlier discussion concerning identification, it is wise to include an additional state variable as an aid to identification. Second, we use an implicit deflator for materials inventories and thus omit the prices of intermediate materials which are not held in inventory. These differences are minor and have little bearing upon conclusions drawn from our empirical results. The Blinder model differs by including a measure of expected demand errors, a nominal interest rate and a measure of inflation expectations.<sup>2</sup> We chose the M-R specification since it seemed desirable to test that model in a more disaggregated data set to observe the effects of disaggregation upon adjustment speeds.

Our basic estimating equation can be written in log-linear form as

$$\begin{aligned} \ln F_t = & \gamma_0 + (1 + \gamma_1)\ln F_{t-1} + \gamma_2\ln E_{t-1} + \gamma_3\ln H_{t-1} + \gamma_4\ln M_{t-1} \\ & + \gamma_5\ln W_{t-1} + \gamma_6\ln U_{t-1} + \gamma_7\ln Q_t^e + \gamma_8\ln V_t^e + \epsilon_t \end{aligned} \quad (3.1)$$

where F = Finished Goods, E = Production Workers, H = Hours per Production Worker, M = Materials, W = Work-in-Process, U = Unfilled Orders, Q = Real New orders, V = Real Materials Prices, t = Calendar Time,  $\epsilon_t$  = disturbance term. The superscript e refers to an expectation. A discussion of the economics

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<sup>2</sup>Blinder also uses shipments whereas we use new orders in our regressions. This is obviously unimportant for stock producing industries where delivery lags are negligible.



underlying (3.1) may be found in M-R, a discussion which may be used to place sign restrictions on the parameters  $\gamma_i$ .<sup>3</sup> Our data sources are the same as M-R with exceptions noted above.<sup>4</sup> The analysis uses monthly data, covering 1958 through 1984. The sample size for all estimates is well above two hundred. We provide estimates for nondurable goods producing industries at the two digit manufacturing level. Unlike Blinder, we exclude durable goods industries. It is generally believed that stock producing firms produce a homogeneous output and this seems to correspond to nondurable goods industries. On the other hand, durable goods industries produce a more heterogeneous output and thus appear to be producing to order.<sup>5</sup> So as to avoid estimating inventory equations where it may be inappropriate, we simply exclude durable goods industries.

We report estimates of adjustment speeds under alternative assumptions about expectation formation. Following Blinder, we use twelfth order autoregressions as one way of approximating expectation formation. In addition we use Almon (distributed) lags as another method of approximation as in M-R. We assume that the lag on new orders is 36 months and that the lag on real materials prices is 12 months. These lag lengths are roughly on the order of those used by M-R. We use the same lag lengths in all regressions.

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<sup>3</sup>An analysis of the relationship between finished goods and labor inputs is provided in Rossana (1984).

<sup>4</sup>Data on hours per production worker can be obtained from Employment and Earnings, published by the Bureau of Labor Statistics. Materials prices are obtained from nominal materials data provided by the Census Bureau, and deflated materials stocks, provided by the Bureau of Economic Analysis.

<sup>5</sup>This is the essence of the distinction between stock and order producing firms introduced by Belsley (1969).

The data are seasonally adjusted. As a result, we tested the disturbances for first and twelfth order serial correlation. Test statistics indicate that, in all industries but two, serial correlation was present at these orders of the autoregressive disturbance process.

For those industries where serial correlation was absent, we can examine ordinary least squares estimates of adjustment speeds. Table 1 provides these estimated adjustment speeds for each method of expectation formation.

Table 1  
Adjustment Speeds-Investment in Finished Goods  
Nondurable Goods Industries

<u>Industry</u>	<u>Time Series Models</u>	<u>Almon Lags</u>
22	-.05	-.045
Textile Mill Products	(.019)	(.021)
29	-.101	-.0803
Petroleum and Coal Products	(.026)	(.034)

Standard errors are given within parentheses beneath each estimated adjustment speed. Here we can make unambiguous statements about adjustment speeds which are independent of the method used to approximate expectations. These adjustment speeds are small and are of the magnitude felt to be implausible by many researchers. These results are little affected by alternative methods of modelling expectations and seem especially peculiar from a different perspective. Aggregation over firms is widely believed to reduce estimates of adjustment speeds. Here we find that, relative to M-R's results, adjustment speeds are slower as we disaggregate, the opposite of the conventional view.

The remaining industries all displayed evidence of serial correlation so that, for these industries, the estimation method is now an issue to be addressed. We provide estimates, in Table 2, of the remaining nondurable two digit industries using the Hatanaka estimator (H) and nonlinear least squares.

Instruments must be chosen to implement the Hatanaka method. In all cases, we used a constant, a time trend with linear and quadratic components, and one lagged value of new orders, real wages and real materials prices. These variables are sufficiently correlated with inventories so as to be satisfactory

Table 2  
Adjustment Speeds - Investment in Finished Goods  
Nondurable goods Industries

<u>Industry</u>	<u>Time Series Models</u>		<u>Almon Lags</u>	
	<u>H</u>	<u>NLS</u>	<u>H</u>	<u>NLS</u>
20	-.12	-.079	-.25	-.067
Food and Kindred Products	(.031)	(.025)	(.057)	(.027)
21	-.32	-.35	-.50	-1.13
Tobacco Manufactures	(.044)	(.061)	(.053)	(.064)
23	-.18	-.15	-.77	-.21
Apparel and Other Textile Products	(.052)	(.034)	(.060)	(.048)
26	-.082	-.082	-.38	-1.14
Paper and Allied Products	(.025)	(.021)	(.045)	(.065)
27	-.65	-.13	-.98	-.18
Printing and Publishing	(.079)	(.029)	(.088)	(.042)
28	-.077	-.031	-.76	-.032
Chemicals and Allied Products	(.034)	(.016)	(.069)	(.018)
30	-.29	-.034	-.76	-.025
Rubber and Miscellaneous Plastic Products	(.045)	(.024)	(.067)	(.023)
31	-.16	-.14	-.28	-.25
Leather and Leather Products	(.038)	(.036)	(.093)	(.051)

for our purposes.

Consider the estimated adjustment speeds in Table 2 where we compare estimation methods for a given structural specification of expectation formation. In almost every case, the Hatanaka estimator produces a parameter estimate which exceeds the nonlinear least squares estimate, sometimes by an enormous amount. For example, in industry twenty seven, the Hatanaka estimator produces an adjustment speed which indicates complete adjustment within the month, whereas NLS produces an estimate indicating that twenty percent of the gap between desired and actual levels is made up each month. It is clear that,

in these models, the Hatanaka estimator overstates the speed of adjustment as Blinder suggests.

We argued above that, purely as a theoretical matter, there was no reason to believe that the Hatanaka estimator would systematically choose a local minimum sum of squares in these models. In any particular application, it is then an empirical question as to whether or not this occurs. We observed the same results as Blinder in that all of our NLS results produced "convergence" at high and low values of the adjustment speed and first order serial correlation parameter. To guard against locating a local minimum sum of squared residual, we initialized our nonlinear estimation using various values of these two parameters and, due to the fact that the parameter space is large, we initialized all other parameters at the same values. Even with an extremely tight convergence criterion, we observed multiple minima.<sup>6</sup> Further, it was generally true that the Hatanaka estimator produces parameter estimates corresponding to a local minimum associated with high values of the adjustment speed and first order serial correlation parameter. Within this data set, Blinder's conjecture is correct that the Hatanaka method produces estimates close to, though not identical with, a local minimum use of squares. Given our arguments in Section 2 about the finite sample differences between the minimand in estimation by NLS and the Hatanaka method, these observations suggest our sample was insufficiently large for the IV estimator to have converged to their limits.

Finally, consider how the parameter estimates vary as we change our method of approximating expectation formation for a given estimation method. With few

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<sup>6</sup>The default value of our convergence criterion was 10E-08 which controls the reductions in the sum of squared errors. We reduced this to 10E-13 to guard against multiple minima.



exceptions, the Almon lag method systematically produces adjustment speeds which exceed the time series method, again by an enormous amount in some instances. To cite just one example, NLS estimates for industry twenty six produce an adjustment speed of eight percent when time series models are used and, in the Almon lag case, produce an adjustment speed indicating complete adjustment within the month. The Almon lag - Hatanaka estimates generally corroborate those provided by M-R as a researcher looking only at these results would be likely to conclude that adjustment speeds are considerably higher than those observed in previous research. They also seem to make sense from the point of view of disaggregation in the sense that they seem somewhat higher overall than those reported by M-R in more highly aggregated data.

It is interesting to compare our results with those reported in Blinder (1986). Blinder finds a high speed of adjustment in industries 20 and 29 ( $-.785$  and  $-.999$  respectively). Whereas with a different model, we find high speeds of adjustment in industries 21 and 26. One possible interpretation of this result is that empirically low adjustment speeds may be due to the imposition of a common model specification across industries which are too disaggregated for such a strategy to be appropriate. These observations on speeds of adjustment complement the results in Ghysels (1987) where it is demonstrated the time series properties of several industrial series for two digit industries are neither constant across type of series nor industry.

#### IV. Summary

Estimating the speed of adjustment in dynamic models can provide important insights into the adjustment path followed by aggregate economies. Many empirical studies have found estimates of speeds of adjustment in inventory models which are thought to be implausibly low. M-R argued that these low

speeds were due to taking insufficient account of serial correlation in the errors during model estimation. Using an estimator proposed by Hatanaka (1974), they estimated the speeds of adjustment which were both higher than those previously reported and also in a plausible range of values. In a recent article Blinder (1986) argued that when serial correlation in the errors is allowed for in estimation, stock adjustment models for inventories exhibit multiple optima: one with a high speed of adjustment and one with a low speed of adjustment. He argues that M-R's results were due to the use of the Hatanaka estimator, which typically converged to the local, but not global, optimum with the high speed of adjustment.

In this paper we have provided a more thorough examination of the issues raised by Blinder and find that his criticism of M-R is only partially correct. It is demonstrated that while the Hatanaka estimator is asymptotically equivalent to NLS, the two estimators are different in finite samples. Provided the model is identified, the relevant question is therefore whether the sample size is large enough relative to the number of parameters estimated for the estimator to have converged to its limit. The empirical evidence reported here suggests that M-R's sample is insufficiently large. By extending Blinder's analysis, we find that in general the problems caused by near multiple optima depend on the model being estimated. Our empirical results demonstrate that one observes different speeds of adjustment depending on the method used to approximate expectations. Furthermore, the Almon lag specification used by M-R seems to generate higher speeds of adjustment than the autoregressive approximation used by Blinder. There are other differences between the model here and the one in Blinder (1986). It is interesting to observe that both studies only observe "plausible" speeds of adjustment in 2

out of the 10 two digit SIC nondurable industries considered here, and that the two industries concerned are different in each study. One possible interpretation of this result is that the slow adjustment speeds estimated may be due not only to an inadequate model specification but also to the imposition of a common specification across industries which may be too disaggregated for such a strategy to be appropriate.

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