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Estimation and inference in inventory models with integrated technology shocks

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Abstract

This paper shows that the presence of integrated technology shocks will prevent input prices and sales from being cointegrated with inventories. It is further shown that the commonly used cointegration tests are not applicable to the inventory equation arising from a dynamic linear-quadratic (LQ) model, because of the long run endogeneity of the regressors and the moving-average error term. The paper examines suitable estimation methods for the LQ inventory model in the presence of endogenous regressors and moving-average errors. Using appropriate estimation methods, cointegration is found among inventories, material prices, and sales for two-digit sectoral data, thus, providing evidence against the presence of integrated technology shocks. The results also indicate that the implausible parameter estimates obtained by previous researchers are the result of inappropriate estimation methods and ignored structural changes.

1. Introduction

A considerable amount of research has emerged in recent years concerning dynamic inventory models. Many of these studies use models that can be placed within the framework of the LQ intertemporal model of the firm holding stock of finished goods. One such model is the production smoothing model, in which firms wish to smooth production relative to sales either to avoid rising marginal costs or the adjustment costs attached to its factor inputs. Firms thus use their stock of inventories to smooth production flow in the face of fluctuating demand. The production smoothing model implies a long run relationship among stock of inventories, input prices, and sales. The production smoothing model of inventories has been the dominant framework for the study of inventory behavior for the last two decades. Recently, there has been growing skepticism of this model as a suitable framework for the analysis of inventory investment decisions, as there are a number of peculiar empirical results that arise in tests of this model.

One such puzzling result concerns the speed of adjustment displayed by inventories. As noted by Carlson and Wehrs (1974), Felstein and Auerbach (1976), and Blinder (1986b), speeds of adjustment are typically found to be very small, thus suggesting that adjustment costs attached to inventories are very severe or that sales forecasting errors are large. However, direct measures of sales forecasts find these errors to be a few days of production, and intuition suggests that adjustment costs are large enough to rationalize such a slow adjustment speed for inventories. Second, Blinder (1986a) has noted that the fundamental premise of the production smoothing model is that, because of increasing marginal costs of changing production flows and/or because productive inputs are quasi-fixed, firms should wish to avoid sharp changes in production levels so that production is smooth relative to sales. Yet direct inspection of production and sales data finds production to be more variable than sales, thus casting doubt on the production smoothing model of inventories. Finally, Miron and Zeldes (1988) estimate a set of Euler equations arising from a model of production smoothing by the firm. They find very little evidence to support the model, as the large majority of their parameter estimates are not in accord with the predictions of the production smoothing model of the firm.

This paper presents a thorough examination of the LQ model in an attempt to explain the puzzling results obtained in the previous literature. There are four main objectives of the paper. The first objective is to show the link between economic theory and econometric methods by deriving the vector error-correction relationship arising from the LQ model of the firm. A difficulty with the literature to date is that it has focused almost exclusively on econometric issues. Relatively little theoretical analysis has been carried out that shows how cointegration arises as a result of the optimizing behavior of the firm. Without any guidance from theory, the interpretation of econometric tests becomes difficult because it will often be hard to determine how many cointegration vectors one should find in time series systems, and it is also not clear how to interpret the parameters of the estimated cointegration vectors. The paper provides part of the link between economic theory and econometric methods by providing an analysis of the cointegration characteristic of the LQ intertemporal model of the firm. The analysis of the LQ model will show that, in the absence of unit root (integrated) technology shocks, if the forcing variables faced by the firm are unit root processes, then the vector autoregression (VAR) arising from this model will contain one cointegration vector for each state variable held by the firm. Further, using a simple transformation of the long run relationship among the time series in the model, estimated cointegration vectors will provide estimates of the static inventory investment function obeyed by the firm, if adjustment costs disappear in the firm's equilibrium as typically assumed.

The second objective of the paper is to show that commonly used cointegration tests and estimation methods associated with them, including the Engle-Granger (Engle and Granger, 1987) and Johansen (Johansen, 1988; Johansen and Juselius, 1990) methods, cannot be used to estimate parameters of the LQ inventory model because of the long run endogeneity of regressors and/or moving-average error terms. The paper demonstrates that nuisance parameter dependency introduces second order bias effects and noncentralities in the limit distributions of estimators. We show that these bias effects are significant and if they are ignored will lead to highly biased estimates. Earlier empirical studies often estimated parameters of the LQ inventory model using estimation methods that do not correct for these second order bias effects. In this paper, we use an estimation method (Phillips and Hansen, 1990) that takes account of the second order bias effects. This method is equivalent to the full information maximum likelihood estimation and superior to previously proposed two-step estimators (Kennan, 1979; Wickens, 1982; Dolado *et al*., 1991).

The third objective is to show that cointegration tests applied to inventories, factor input prices, and sales provide evidence on whether or not firms experience any integrated or $I(1)$ technology shocks specific to any input used in the production. The real business cycle literature (for example, Long and Plosser, 1983) explains business cycles as the manifestation of real shocks in the economy, and it is often assumed in this literature that these technology shocks have a unit root. The analysis contained here indicates that the existence of $I(1)$ technology shocks affecting the firm will eliminate cointegration among inventories, factor input prices, and sales. Thus, if $I(1)$ technology shocks are a prominent feature of industrialized economies, cointegration should have little empirical relevance. Therefore, cointegration in the LQ model offers an indirect test of integrated technology shocks. But there is a growing literature which finds cointegration relationships among many economic time series, indicating that these shocks are not $I(1)$, which raises questions about how one might reconcile existing empirical work with the fact that many forms of supply-side shocks do appear to be permanent in nature. Although the paper contains only a model of the firm, it is clear that the results provided here carry over to problems involving household intertemporal choice. The empirical section of this paper finds cointegration among inventories, material prices, and sales using time series data on two-digit standard industrial classification (SIC) industries. Thus we find evidence against the presence of $I(1)$ technology shocks.

The fourth objective of the paper is to offer an explanation for the implausible parameter estimates obtained by previous researchers. Most researchers obtained poor results for the production smoothing model of the firm. The question of what explains statistically insignificant or incorrectly signed parameter estimates still remains as an empirical as well as a theoretical puzzle. We investigate whether structural breaks may be responsible for the poor results, since ignored structural breaks may seriously distort estimates. There is a growing interest in the theoretical and applied time series literature about the effects of regime changes. It has been shown that structural breaks may be a cause of the unit roots found in economic time series. For those sectors that we obtained insignificant or incorrectly signed parameter estimates, we also found by formally testing for parameter instability enough evidence to seriously shed doubt about the stability of the cointegration relationships. Thus, the evidence suggests that structural instabilities cause implausible parameter estimates.

The organization of the paper is as follows. Section 2 discusses the LQ model of the firm holding finished goods inventories. Section 2 also shows the effects of integrated technology shocks in the LQ model. Section 3 takes up estimation issues and discuses newly proposed estimation methods that are preferable when regressors are integrated and nonstrictly exogenous. Econometric implications of the integrated technology shocks are also discussed in Section 3. Section 4 presents the empirical results. Section 5 concludes the paper.

2. A dynamic model of the firm holding finished goods

In this section, we analyze the dynamic LQ model of the firm holding stock of finished goods. The LQ model is extensively used in the literature.[1] The version of the LQ model that we examine is consistent with the inventory-only model of Blanchard (1983), where the only choice variable is the stock of finished goods. The model involves two steps.[2] The first step may be a static optimization problem that yields a

[1] See Rossana (1993a, 1993b) and Eichenbaum (1989) for a model that has similar implications.

[2] For brevity we will not discuss details of the first step. See Ilmakunnas (1989), Kennan (1979), Nickell (1985), and Layard and Nickell (1986) for examples.

cointegration relationship among inventories and forcing variables or a dynamic optimization where the cointegration relationship is obtained as the steady state solution. The second step is a dynamic optimization where the inventories sequence $\{y_t\}_{t=1}^{\infty}$ is chosen to minimize the expected value of a quadratic loss function given by

$$E_t \sum_{s=0}^{\infty} \phi^s [\alpha_1 (y_{t+s} - y_{t+s}^*)^2 + \alpha_2 (\Delta y_{t+s})^2], \tag{1}$$

where E_t is the expectation operator conditional on the firm's information set $\Re_t$ at time t and $\phi \in (0,1)$ is the subjective discount rate. The first term in this expression is a disequilibrium cost reflecting the fact that the firm sets an equilibrium relationship between inventories and forcing variables to avoid stockouts etc., and if this equilibrium relationship does not hold the firm incurs costs $(\alpha_1 > 0)$. The second term captures the adjustment costs incurred $(\alpha_2 > 0)$, when the level of inventories are adjusted back to the equilibrium quantity from a disequilibrium position. In this model, observable values of y_t are chosen to chase a stochastic target y_t^*, which is linearly related to forcing variables x_t by

$$y_t^* = \beta' x_t + u_t, \quad \beta = (\beta_1, ..., \beta_m)', \quad x_t = (x_{1t}, ..., x_{mt})' \tag{2}$$

where u_t is a white noise error. Inventories with a stochastic target can serve to buffer production making it smooth in the face of shocks, such as demand fluctuations, as well as to cut backlog costs. Therefore, both production and cost smoothing can be incorporated into the model. We assume that the information set $\Re_t$ contains u_t, but the information set of an econometrician $\Im_t \in \Re_t$ does not contain u_t, where $\Im_t = \{y_{t-s}, x_{t-s+1}\}_{s=1}^{\infty}$ and $\Re_t = \{u_t, y_{t-s}, x_{t-s+1}\}_{s=1}^{\infty}$. The cointegration relationship in (2) can be derived from a static optimization problem. Forcing variables x_t include variables such as shipments, and factor input prices. Rossana (1993b) derives a similar cointegration relationship from a dynamic optimization problem.

The first order necessary condition for minimization of (1) yields the Euler equation

$$E_t \Delta y_{t+1} = \phi^{-1} \Delta y_t + \lambda \phi^{-1} [y_t - \beta' x_t - u_t], \tag{3}$$

where $\lambda = (\alpha_1 / \alpha_2)^{-1}$. The parameter λ measures the relative importance of disequilibrium and adjustment costs. The model satisfies the Simon-Theil conditions for the first period certainty equivalence, since only the first order moments enter into the Euler equation. We also impose the transversality condition

$$\lim_{T\to\infty}\phi^T E_t[y_{t+T} - y^*_{t+T} + \lambda^{-1}\Delta y_{t+T}] = 0 .$$

Using the method contained in Sargent (1987), (3) can be solved for the closed form

$$y_t = \mu y_{t-1} + (1-\mu)(1-\phi\mu)\sum_{s=0}^{\infty}(\phi\mu)^s \beta' E_t x_{t+s} + (1-\mu)(1-\phi\mu)u_t , \quad (4)$$

where μ is the stable characteristic root of the saddle-path quadratic given by

$$f(\kappa) = \kappa^2 - (1+\phi^{-1} + \lambda\phi^{-1})\kappa + \phi^{-1} = 0 .$$

We assume that $f(0) > 0,$ $f(1) < 0,$ and $f(\kappa) \to \infty$ as $\kappa \to \infty$ to guarantee the existence of a stable characteristic root, which is satisfied by assuming $\lambda, \phi > 0.$ A version of (4) is known as the partial adjustment rule, which can be derived by defining

$$g_t = (1-\phi\mu)\sum_{s=0}^{\infty}(\phi\mu)^s \beta' E_t x_{t+s} + (1-\phi\mu)u_t = (1-\phi\mu)\sum_{s=0}^{\infty}(\phi\mu)^s \beta' E_t y^*_{t+s} \quad (5)$$

as the long run target. Then, combining (4) and (5), we obtain the partial adjustment rule

$$\Delta y_t = (1-\mu)(g_t - y_{t-1}). \quad (6)$$

In this model, the static expectations, i.e., $E_t y^*_{t+s} = y^*_t$, imply that $g_t = y^*_t$, which can be verified by substituting the static expectations into (5). In this case, the partial adjustment equation is the same as the one derived from a static optimization problem. If we assume that there are no adjustment costs $(\alpha_2 = 0)$ the optimal plan for the firm is $E_t y_t = E_t y^*_t$ for all *t*. Therefore, the present decision is completely independent of all past and future expectations. In addition, inventories will be adjusted instantaneously, which makes the adjustment coefficient in (6) equal to one.

If we set the elements of x_t to be real wages plus technology shock and shipments as in Rossana (1993b), then the entire future paths of shipments, real wages, and technology shocks determine the current investment in finished goods. For instance, the firm will hold higher inventories if future sales are expected to be higher. Additionally, the firm will service out current shipments out of inventories to avoid higher marginal costs that results from raising the level of output. The firms will also hold higher inventories in response to higher expected costs. Therefore, an increase in real wages and a technology shock that raises the productivity of labor input will lead to higher inventory levels.

The model will be complete after the data generating process (DGP) for x_t is specified. We assume that the DGP for x_t is given by[3]

$$\theta(L)x_t = \varepsilon_t, \tag{7}$$

where $\theta(L) = 1 - \sum_{j=1}^{k} \theta_j L^j$ is a polynomial in the lag operator L. When x_t is integrated of order $p \geq 1$, $I(p)$, (i.e., $\theta(L)$ contains p unit roots) we can write this lag polynomial as $\theta(L) = (1-L)^p \theta^*(L)$, where $\theta^*(L) = 1 - \sum_{j=1}^{k-p} \theta_j^* L^j$ contains all roots outside the unit disc. To obtain an estimable form of (4) the expected future sequences should be eliminated using some kind of mechanism that lets the firm calculate the expected values. If we assume that the firm uses linear least squares projections to form the relevant expectations, then we can use the Wiener-Kolmogorov (Hansen and Sargent, 1982; Sargent, 1987) prediction formula to eliminate the expectations in (4). Using (7) and the Wiener-Kolmogorov prediction formula, (4) can be written as

$$y_t = \mu y_{t-1} + (1-\mu)(1-\phi\mu)\frac{\theta(\phi\mu) - \phi\mu L^{-1}\theta(L)}{\theta(\phi\mu)(1-\phi\mu L^{-1})}\beta' x_t + (1-\mu)(1-\phi\mu)u_t . \tag{8}$$

If one proceeds from (8) for estimation, the DGP for x_t should be given a specific form. Rossana (1993a) provides evidence that each component of x_t that one may consider in an estimable form of (8) contains a unit root. Based on this evidence, we will assume that x_t follows a random walk without drift. The assumption that the DGP for x_t does not contain any deterministic component is only made to simplify the presentation and will be relaxed in Sections 3 and 4. We will also assume that $\theta^*(L) = 1$ for simplicity. Then, the existence of a unit root[4] in the each component of x_t implies

$$\Delta x_t = \varepsilon_t . \tag{9}$$

Conditioning on (9), i.e., using $\theta(L) = 1 - L$, the DGP for y_t can be written as

$$y_t = \mu y_{t-1} + (1-\mu)\beta' x_t + (1-\mu)(1-\phi\mu)u_t . \tag{10}$$

This expression is equivalent to the partial adjustment rule. From (10), it is easy to see that y_t is $I(1)$ when x_t is $I(1)$. In order to obtain the error-correction form we write (10) as follows:

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[3] Following Kennan (1979) one can introduce an additional disturbance into the model to reflect the fact that the actual values of y_t may deviate from the planned values because of unforeseeable events. As in Dolado *et al*. (1991), we avoid such a specification by assuming that u_t is realized before y_t is chosen and our assumptions about the information set of the decision maker and the DGP for x_t are sufficient to guarantee this.

[4] The unit root DGP in (9) greatly complicates the estimation of the LQ inventory model. This issue will be taken up in the next section.

$$\Delta y_t = (\mu - 1)(y_{t-1} - \beta' x_{t-1}) + (1-\mu)\beta'\Delta x_t + (1-\phi\mu)(1-\mu)u_t . \tag{11}$$

The Bewley (1979) form is given by

$$y_t = -(\mu/(1-\mu))\Delta y_t + \beta' x_t + (1-\phi\mu)u_t . \tag{12}$$

From the Bewley form in (12), we can easily see that $(1-\beta')'$ is the cointegration vector, since all other variables on the right hand side of (12) are $I(0)$. To see that let $x_t = (s_t, w_t)'$, where s_t is sales and w_t is real wages, then using (9) and (11), the error-correction VAR for this model can be written as

$$\begin{bmatrix} \Delta y_t \\ \Delta s_t \\ \Delta w_t \end{bmatrix} = -\begin{bmatrix} -(1-\mu) & (1-\mu)\beta_1 & (1-\mu)\beta_2 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} y_{t-1} \\ s_{t-1} \\ w_{t-1} \end{bmatrix} + \begin{bmatrix} (1-\mu)[(\beta_1\varepsilon_{1t} + \beta_2\varepsilon_{2t}) + (1-\phi\mu)u_t] \\ \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix} \tag{13}$$

Since two of the eigenvalues of the matrix preceding the lagged levels are zero, this matrix is of rank one. Therefore, the system contains two common stochastic trends and one cointegration vector[5].

The existence of cointegration implies that a linear combination of the variables expressed in levels should be an $I(0)$ process. Otherwise, deviations from the long run equilibrium would be permanent in the face of a shock. Let $z_t = y_t - \beta' x_t$ be the deviations from the long run equilibrium. From (10), it can easily be shown that

$$z_t = (1-\mu L)^{-1}[(1-\mu)(1-\phi\mu)u_t - \mu\beta'\varepsilon_t]. \tag{14}$$

Thus, z_t is an *ARIMA*(1,0,0) process. Inventories, shipments, and real wages are cointegrated, since z_t is $I(0)$.

An issue that has not been taken up until now is the unit root technology shocks commonly associated with the real business cycle theory initiated by Long and Plosser (1983). In the context of the representative firm model with a LQ objective, unit root technology shocks prevent any long run relationship among inventories, shipments, and real wages. The reason is that once a shock is realized that raises or reduces input prices, the use of inputs, the production of output, and inventories may rise or fall permanently. This eliminates any cointegration relationship among the variables in the model and the firm may not be on its static inventory demand function even in the long run. Cointegration tests applied to the inventory model can, therefore, be

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[5] Consider the following model (Rossana, 1993b): $E_t\sum_{s=0}^{\infty}\phi^s[s_{t+s} - c_{t+s}]$ where c_t is given by $c_t = (a/2)(s_t - dy_t)^2 + (h/2)y_t^2 + w_t(s_t + \Delta y_t) + (c/2)(s_t + \Delta y_t)^2$. We obtain the cointegration vector $[1, (ad^2 + h^{-1})(c(1-\phi) - ad), (ad^2 + h^{-1})(1-\phi)]'$ from the first order conditions in the steady state.

interpreted as tests about the presence of unit root technology shocks.[6] To illustrate the implications of the unit root technology shocks, let $x_t = (s_t, w_t + \xi_t)'$, where ξ_t is the unit-root technology shock. Then, the equation relating to the cointegration relationship $z_t = y_t - \beta' x_t$ can be written as

$$z_t = (1-\mu L)^{-1}\left[(1-\mu)(1-\phi\mu) - \mu\left(\beta_1\varepsilon_{1t} + \beta_2\left(\varepsilon_{2t} + \varepsilon_{3t}\right)\right)\right] + \beta_2\xi_t, \quad (15)$$

where $\varepsilon_{2t} = \Delta w_t$ and $\varepsilon_{3t} = \Delta\xi_t$. Rearranging (15) we get

$$(1-\mu L)z_t = (1-\mu)(1-\phi\mu)u_t - \mu(\beta_1\varepsilon_{1t} + \beta_2\varepsilon_{2t}) + (1-\mu)\beta_2\xi_t. \quad (15')$$

From this last expression, we observe that z_t is an *ARIMA*(1,1,0) process, since ξ_t is *I*(1). Thus, y_t, s_t, and w_t are not cointegrated, because of the presence of unit root technology shocks. The linear combination of these series, z_t, is now difference stationary. In the terminology of Stock and Watson (1988), this three variable system contains three common stochastic trends. Then, a finding of no cointegration among these series implies the existence of unit root technology shocks.

3. Estimation issues in linear-quadratic models with integrated variables

Most researchers have obtained unsatisfactory empirical results using the production smoothing, cost smoothing, or buffer stock variants of inventory models. The estimated coefficients are usually unreasonable in magnitude and/or incorrectly signed. Particularly, the speed of adjustment is always estimated to be very low. There seems to be a tendency to attribute the unsatisfactory empirical results to inadequate econometric methods. Unfortunately, dynamic equations with serially dependent errors may well lead to biased estimates particularly in small samples. In these instances, one can never be sure about the magnitude and direction of the bias unless a comparison is made with estimates obtained from an unbiased estimator.

Another problem with the current practice is the ignorance about the time series properties of the data. Some researchers de-trend the data prior to estimation. Here, an implicit assumption of trend stationarity is made. However, if the data contain stochastic trends rather than deterministic trends, de-trending will lead to biased estimates. One should also expect the distribution of estimators to be nonstandard, if the methods that are appropriate for trend stationary (TS) time series are applied to difference stationary (DS) time series.

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[6] See Rossana (1993b) for further discussion of unit root technology shocks and cointegration.

Estimation of the dynamic LQ inventory model examined in Section 2 follows either from the Euler equation or from the closed form solution. Ignoring the DGP for the forcing variables, and hence any time series properties that they may possess, one method to estimate the Euler equation in (3) is to assume that

$$E_t \Delta y_{t+1} = \Delta y_{t+1} + \varsigma_{t+1}, \tag{16}$$

where ς_{t+1} is a mean zero error term. Substituting (16) into (3) we obtain

$$\Delta y_{t+1} = \phi^{-1} \Delta y_t + \lambda \phi^{-1} \left(y_t - \beta' x_t \right) + v_{t+1}, \qquad \varsigma_{t+1} \tag{3'}$$

where $v_{t+1} = -(\varsigma_{t+1} + \lambda \phi u_t)$. The innovations can be obtained by applying the Wiener-Kolmogorov prediction formula or directly from (11). Using the latter approach, we obtain

$$\varsigma_{t+1} = -(1-\mu)\beta' \varepsilon_{t+1} - (1-\mu)(1-\phi\mu)u_{t+1}$$

from (11). Substituting for ς_{t+1} we get

$$v_{t+1} = (1-\mu)\beta' \varepsilon_{t+1} + (1-\mu)(1-\phi\mu)u_{t+1} + \lambda \phi u_t.$$

Estimates of the parameters[7] in (3′) can be obtained by the instrumental variables (IV) methods, drawing instruments from the information set $\Im_t \in \Re_t$ as suggested by McCallum (1976). Alternatively, the generalized method of moments (GMM) estimator of Hansen and Sargent (1982) can also be used.

Other methods make use of the DGP for the forcing variables, but they assume that it is stationary. Thus, cross-equation restrictions are taken into account. The asymptotically fully-efficient method of Hansen and Sargent (1982) proceeds from the closed form solution and exploits the cross-equation restrictions. The less efficient but consistent estimation methods of Kennan (1979) and Wickens (1982) are popular in the literature and directly estimate the parameters in the Euler Equation. Kennan's method uses a two-step OLS regression, while Wickens's procedure is an errors-in-variables IV estimator. Because of the high computation costs, being not robust to *a priori* restrictions, and complications due to the instability of the solution, fully-efficient methods are not usually preferred to two-step procedures.

[7] Most researchers assume that the discount factor is known and fix it at values such as 0.95 or 0.99. The main argument behind this pre-specification is that it is difficult to obtain accurate estimates. Gregory *et al*. (1993) point out that there is a serious identification problem in certain cases when ϕ is estimated. In order to avoid the identification problem one may prefer to fix the discount factor at some pre-specified value.

Dolado *et al*. (1991) retains the assumption of strictly exogenous regressors, but relax the assumption of stationary forcing variables. Assume that the DGP for x_t is given by (9), then y_t and x_t are cointegrated, if technology shocks are not integrated. Based on this result, Dolado *et al*. (1991) point out that a static regression of y_t on x_t yields an estimate of β that converges to its true value proportionally to the sample size by the super-consistency result in Stock (1987). This static regression is the first step of the procedure proposed by Dolado *et al*. (1991). Other parameters of the Euler equation can be estimated from a second stage regression using the super-consistent estimate of β.

When error terms are correlated across equations, we cannot retain the strict exogeneity of x_t, and estimates obtained from the two-step procedure of Dolado *et al*. (1991) display serious bias in finite samples. However, the fully-modified (FM) method of Phillips and Hansen (1990) yields bias-adjusted estimates in models that are broader and more complicated than the model we use in this paper. Now, we also introduce a deterministic component, d_t, into the model. After adding the deterministic component d_t, we can rewrite (9) and (12) as

$$y_t = \beta' x_t + \delta_1' d_t + e_t = \alpha' h_t + e_t, \quad \alpha = (\beta', \delta_1')', \quad h_t = (x_t', d_t')' , \tag{17}$$

$$\Delta x_t = \delta_2' d_t + q_t , \tag{18}$$

where $e_t = -(\mu/(1-\mu))\Delta y_t + (1-\phi\mu)u_t$. In most applications, d_t contains a constant and a linear time trend. As in Phillips and Hansen (1990), one may easily generalize this model to a system of equations by taking y_t as an n-dimensional vector. It is also possible to incorporate instrumental variables estimation by adding an instruments vector and specifying an equation similar to (18) with x_t replaced by the instrument vector. Assume that the innovations $\zeta_t = (e_t, q_t')'$ are strictly stationary, ergodic, and satisfy the multivariate invariance principle. Let the covariance function of the stationary stochastic process ζ_t be given by

$$W(k) = E(\zeta_t \zeta_{t+k}') , \quad \Sigma = W(0) , \quad \Lambda = \sum_{k=1}^{\infty} W(k).$$

Then, the long run covariance matrix Ω can be decomposed as

$$\Omega = \Sigma + \Lambda + \Lambda' . \tag{19}$$

We further define $\Delta = \Sigma + \Lambda$ and partition the matrices Ω and Δ conformably with ζ_t as

$$\Omega = \begin{bmatrix} \Omega_{11} & \Omega_{12} \\ \Omega_{21} & \Omega_{22} \end{bmatrix}, \qquad \Delta = \begin{bmatrix} \Delta_{11} & \Delta_{12} \\ \Delta_{21} & \Delta_{22} \end{bmatrix}.$$

The long run covariance matrix Ω is equal to $2\pi\lambda_{\zeta\zeta}(0)$, where $\lambda_{\zeta\zeta}(0)$ is the spectral density matrix of ζ_t at frequency zero. If the ζ_t is serially uncorrelated and stationary, Ω is the usual contemporaneous covariance matrix. If serial correlation is present, which will happen in the presence of serially correlated technology shocks and/or regressors that are not strictly exogenous, the additional term Λ should be incorporated. The OLS estimator of the parameters in (17) is given by

$$\tilde{\alpha} = \left(\sum_1^T y_t h_t'\right)\left(\sum_1^T h_t h_t'\right)^{-1}. \tag{20}$$

Phillips and Durlauf (1986) showed that the OLS estimator in (20) is consistent. A particularly important result is the $O_P(T^{-1})$ convergence of $\tilde{\alpha}$. Therefore, the de-meaning and de-trending implied in (17) and (18) does not affect the consistency of the OLS estimator. Although the OLS estimator is consistent, the correlation between e_t and lagged values of q_t introduces a 'second order' bias effect. Phillips and Hansen (1990) referred to this bias effect as second order, since the consistency of the OLS estimator still holds. The second order bias effect makes Δ_{12} nonzero and introduces a noncentrality in the limit distribution. This bias may be substantial in finite samples. The simulations in Banerjee *et al*. (1986) showed the presence of significant bias effects due to the nonzero Δ_{21}.

The second order bias effect can be eliminated by semiparametric estimation of the covariance matrix as suggested by Park and Phillips (1988, 1989) and Phillips and Hansen (1990). The 'bias-corrected' estimator allows inference based on the asymptotic distribution. The bias-corrected estimator defined in Phillips and Hansen (1990) is given by

$$\tilde{\alpha}^* = \left[\sum_1^T y_t h_t' - T\left(\tilde{\Delta}_{21}, 0\right)\right]\left(\sum_1^T h_t h_t'\right)^{-1}. \tag{21}$$

Phillips and Hansen (1990) showed that the bias-corrected estimator given in (21) is consistent, asymptotically unbiased, and converges at the rate of $O_P(T^{-1})$.

Phillips and Hansen also showed that the limiting distribution depends on the nuisance parameters. This nuisance parameter dependency in turn induces biases that result from the long run endogeneity of the regressors. This bias effect can be interpreted as the simultaneous equations bias. Phillips (1991a) proposed a full information maximum likelihood method to remove the bias, which amounts to the joint estimation of (17) and (18). The semiparametric FM method of Phillips and Hansen (1990) is based on this method and asymptotically equivalent to the full information maximum likelihood estimation.

The FM method is based on the bias corrected residuals $\tilde{e}_t^{+} = \tilde{e}_t - \tilde{\Omega}_{12}\tilde{\Omega}_{22}^{-1}\tilde{q}_t$ and the long run covariance matrix

$$\begin{bmatrix} \tilde{e}_t^{+} \\ \tilde{q}_t \end{bmatrix} = \begin{bmatrix} I & -\tilde{\Omega}_{12}\tilde{\Omega}_{22}^{-1} \\ 0 & I \end{bmatrix} \begin{bmatrix} \tilde{e}_t \\ \tilde{q}_t \end{bmatrix} = \tilde{\mathrm{P}}_{aa}\tilde{\zeta}_{at},$$

where 'a' means that indices 1 and 2 are taken together. It is easy to show that $\tilde{\Omega}_{aa}^{+} = \tilde{\mathrm{P}}_{aa}\tilde{\Omega}_{aa}\tilde{\mathrm{P}}_{aa}' = \mathrm{diag}\{\tilde{\Omega}_{11\cdot 2}, \tilde{\Omega}_{22}\}$, where $\tilde{\Omega}_{11\cdot 2} = \tilde{\Omega}_{11} - \tilde{\Omega}_{12}\tilde{\Omega}_{22}^{-1}\tilde{\Omega}_{21}$. Then, the FM estimator[8] is given by

$$\tilde{\alpha}^{+} = \left[\sum_1^T \tilde{y}_t^{+} h_t' - T\left(\tilde{\mathrm{P}}_{1a}\tilde{\Delta}_{1a}', 0\right)\right]\left(\sum_1^T h_t h_t'\right)^{-1}, \tag{22}$$

where $\tilde{y}_t^{+} = y_t - \tilde{\Omega}_{12}\tilde{\Omega}_{22}^{-1}\tilde{q}_t$.

Up to now, we have assumed that the relationship in (17) is the cointegration relationship. The vector $(1,-\beta')'$ becomes the unique normalized cointegration vector once the stationarity of e_t is established. The assumption of cointegration should of course be verified by the data. Hansen (1992a) and Park (1990) proposed cointegration tests based on the FM estimator. Hansen's tests are an adaptation of Phillips's (1987) residual-based unit root test. Park's test is a 'variable addition' test, which allows testing for the null hypothesis of cointegration as well as the null hypothesis of no cointegration. Park's test for the null hypothesis of cointegration is based on the following least squares regression:

$$y_t^{*} = \tilde{\alpha}^{*'} h_t^{*} + \tilde{\gamma}^{*'} s_t + \tilde{e}_t^{*}, \tag{23}$$

where

$$\begin{aligned} h_t^{*} &= (x_t^{*'}, d_t')', & x_t^{*} &= x_t - \tilde{\Delta}_{2a}\tilde{\Sigma}_{aa}^{-1}\tilde{\zeta}_t, \\ y_t^{*} &= y_t - (\tilde{\beta}\tilde{\Delta}_{2a}\tilde{\Sigma}_{aa}^{-1} + \tilde{c}_a)\tilde{\zeta}_t, & \tilde{c}_a &= (0, \tilde{\Omega}_{12}\tilde{\Omega}_{22}^{-1})', \end{aligned} \tag{24}$$

$$s_t = (s_{1t}', s_{2t}')', \quad s_{1t} = b_t, \quad s_{2t} = s_{2t-1} + v_t, \quad v_t \sim i.i.d.(0, \sigma_v^2). \tag{25}$$

In these equations, b_t is a k-dimensional vector that contains the deterministic trends distinct from d_t, and s_{2t} is an n-dimensional vector of $I(1)$ variables. It is assumed that s_{2t} and x_t are not cointegrated. If y_t and x_t are cointegrated s_t becomes a superfluous regressor. A careful inspection of (23)-(25) reveals that Park's (1992) least squares estimator of the cointegration relationship in (23), which is called 'canonical cointegrating regression' (CCR) , is equivalent to the FM estimator, if we set $s_t = 0$. A test for cointegration is developed by Park (1990) based on the Wald statistics for the hypothesis H_0: $\gamma = 0$. This test is denoted by J_1 and defined as

[8] The FM estimator is a semiparametric estimator, since the covariance matrix used for the bias correction is estimated nonparametrically.

$$J_1 = \frac{\tilde{\sigma}_{11}^*}{\tilde{\Omega}_{11\cdot 2}} G_B(\tilde{\alpha}^*, \tilde{\Omega}_{11\cdot 2}) = \frac{\sum_{t=1}^{T} \tilde{e}_t^{+2} - \sum_{t=1}^{T} \tilde{e}_t^{*2}}{\tilde{\Omega}_{11\cdot 2}} . \tag{26}$$

When the linear combination of y_t and x_t is stationary the distribution of J_1 is χ^2_{n+k}. But if y_t and x_t cease to be cointegrated, then $T^{-1+\psi} J_1 \xrightarrow{p} \infty$.

In the simulations (Phillips and Hansen, 1990; Hansen and Phillips, 1990) the FM estimator performed well with lower variance than other estimators. The simulations also showed that the OLS estimator has the best performance for high signal-to-noise ratios, but it is still dominated by the FM estimator. Gregory *et al*. (1993) proposed two modifications to the FM estimator, which performed better in their simulation-based comparison. Both modifications replace the dependent variable in (17) with a variable that contains more information. These variables are obtained from the Euler equation (EE) and the error-correction (EC) forms. The first modification applies the FM estimation to

$$y_t + \tilde{\lambda}^{-1}(\Delta y_t - \phi \Delta y_{t+1}) = \alpha' h_t + v_t , \tag{17′}$$

$$\Delta x_t = \delta_2' d_t + q_t , \tag{18′}$$

which is obtained by replacing λ with a consistent initial estimate in the EE. The second modification applies the FM estimation to

$$y_t + \tilde{\mu}(1-\tilde{\mu})^{-1} \Delta y_t = \alpha' h_t + \upsilon_t , \tag{17″}$$

$$\Delta x_t = \delta_2' d_t + q_t , \tag{18″}$$

which is obtained by replacing μ in the Bewley form (12) with a consistent initial estimate. Other parameters in the EE can be obtained by applying the IV estimation to the EE or EC forms after replacing β with the FM estimate $\tilde{\beta}$. The instruments can be chosen according to the principles of the GMM.

The estimation methods we examined so far are single equation methods. There might be some gains from jointly estimating the system. Johansen (1988) and Phillips (1991a) describe full information maximum likelihood estimation methods under the assumption that a finite order VAR representation for the system containing y_t and x_t exists. Phillips (1991b) also develops a spectral estimation method. Unfortunately, it is difficult to apply the first two methods to the EEs since no finite order VAR exists due to the *MA*(1) error term in (3′). The spectral and FM methods are appropriate in this case.

4. Empirical results

In the last two decades, a considerable amount of literature on inventory models has accumulated. Unfortunately no consensus exists about which model fits best to the data. Some of the implausible results are attributed to the inappropriateness of the econometric methods employed. A number of studies have ignored the nonstationarity in the data while some others either de-trended or differenced the data in order to remove the nonstationarity. De-trending leads to information loss and biased estimates, if the true process is $I(1)$. Differencing is inappropriate, because it makes the long run relationship unrecoverable. Differencing also removes the valuable information contained in the data, which can be used to improve the estimates. In this section, we explicitly consider the DGP for the forcing variables in order to avoid the issues arising from arbitrary transformations of the data and use the FM and CCR methods, described in Section 3, to make corrections for the integrated data structure.

There are three objectives of this section. The first objective is to show that unit root technology shocks do not exist. This is evidenced by showing that a cointegration relationship exists among inventories, shipments, and material prices. The second objective is to show that reasonable parameter estimates can be obtained by appropriate estimation methods. For this purpose, we use the FM and CCR methods and obtain reasonable estimates for most cases. We also show that low adjustment speed estimates obtained previously in the literature are also due to inappropriate estimation methods. The paper obtains quite high adjustment speed estimates by using the FM method. The third objective is to show that implausible parameter estimates are caused by ignored structural changes. We use three structural instability tests based on the FM method and show that the hypothesis of structural stability is rejected for cases where implausible parameter estimates are obtained.

4.1. The variables and data

Before proceeding to estimation we need to specify the variables of the model. We will use inventories of finished goods as the inventory variable. Inventories are often assumed to be quasi-fixed in most empirical studies. This would be true, if inventories are subject to adjustment costs as we assumed in the model presented in Section 2, or if the firm has a technology that displays diminishing returns to each of its productive inputs. The production smoothing model uses these features to explain why the firm would wish to smooth production. Rossana (1990) provides evidence that factor input demands contain significant cross-price effects. Therefore, we will not restrict the firm’s technology to be separable and include both real wages and real material prices as forcing variables. Shipments will also be included as a forcing variable, since firms may be imperfectly competitive in their output markets, which creates a motivation to hold finished goods inventories as a buffer against demand fluctuations.

We use data on six two-digit manufacturing industries (SIC 20, 21, 23, 28, 29, and 30) from the nondurable goods sector. Industries at this level of aggregation have been repeatedly used in previous research. The sample period covers 1960:1-1993:3 at monthly frequency and all data are measured in logarithms. The data are seasonally adjusted to make a suitable comparison with the previous research, most of which has used seasonally adjusted data. The wage rate is given by average hourly earnings which is available from *Employment and Earnings* published by the Bureau of Labor Statistics. The data on seasonally adjusted constant dollar sales and inventories in finished goods are provided by the Bureau of Economic Analysis. The constant dollar finished goods inventory data are adjusted with the data in West (1983), so that inventories of finished goods and shipments are comparably measured. Materials input prices are measured by the Producer Price Index of Crude Materials for Further Processing. This data are available in Citibase. Real wages and real material prices are obtained by deflating with the implicit shipments deflator that is obtained from the constant and current dollar shipments data available from the Census Bureau.

We should first establish the degree of integration for each series. This can be carried out by testing the null hypothesis of a unit root using the augmented Dickey-Fuller tests. We will, however, not test for unit roots, because Rossana (1993a) used the same data and established that each series contains a unit root. He further showed that the data do not contain more than one unit root and there was no unit root at the seasonal lag. Thus, there is no need for higher order differencing and/or seasonal differencing.

We should also determine whether the forcing variables (shipments, real wages, and real material prices) are cointegrated or not. If they are cointegrated, a prior transformation of these variables is necessary before proceeding to the cointegration tests. We used the maximal eigenvalue and trace tests of Johansen (1988) and Johansen and Juselius (1990) to determine whether shipments, real wages, and real material prices are cointegrated.[9] For each sector, we were not able to reject the hypothesis of no cointegration among shipments, real wages, and material prices at the 5% level.

4.2. Cointegration tests

[9] We do not report the results of these tests for brevity, but they are available upon request.

In order to show the validity of the LQ inventory model we need to test whether inventories, shipments, real wages, and real material prices are cointegrated. As pointed out earlier, this test is also a test for the absence of the unit root technology shocks. For this purpose, we calculated Park's J_1 statistics for each industry. This can be verified by observing that the error term in (3′) is a MA(1) process, and thus the order of the VAR is infinite. We did not use Johansen tests, since a finite order VAR in the levels of series does not exist. The J_1 statistics is calculated as follows: First, we obtain the transformed variables x_t^* and y_t^* in (24) and (25) using the consistent estimates of the covariance matrices[10]. Then, we estimate the regression in (23) by OLS. For the spurious deterministic regressors in (23), we tried following polynomial and sinusoidal trends:

$$\left\{t^{P_1}, t^{P_2}, ..., t^{P_N}, \sin(2\pi\lambda_1 t/T), \cos(2\pi\lambda_1 t/T), ..., \sin(2\pi\lambda_N t/T), \cos(2\pi\lambda_N t/T)\right\}$$

In all cases, results were not sensitive to the spurious deterministic trends used. Here, we report results where only a sinusoidal trend is used. We used computer generated random walks without drift for stochastic spurious regressors. The results were not sensitive to the addition of three or more stochastic spurious regressors. The results reported here all use three random walks without drift.

In order to construct the cointegration tests the long run covariance matrices should also be estimated. To estimate these matrices we need two sets of residuals. The first set of residuals are obtained by regressing inventory series on a constant, a linear time trend, shipments, real wages, and real material prices. We regress each of the first differences of shipments, real wages, and real material prices on a constant to obtain the second set of residuals. Then, the long run covariance matrices are calculated from the estimation equations

$$\tilde{\Delta} = T^{-1}\sum_{j=0}^{k}\sum_{t=j+1}^{T}\tilde{\zeta}_{t-j}\tilde{\zeta}_t', \qquad \tilde{\zeta}_t = \left(\tilde{e}_t, \tilde{q}_{1t}, \tilde{q}_{2t}, \tilde{q}_{3t}\right)',$$

$$\tilde{\Omega} = T^{-1}\sum_{t=1}^{T}\tilde{\zeta}_t\tilde{\zeta}_t' + T^{-1}\sum_{j=0}^{k}w(j,k)\sum_{t=j+1}^{T}\left(\tilde{\zeta}_{t-j}\tilde{\zeta}_t' + \tilde{\zeta}_t\tilde{\zeta}_{t-j}'\right), \qquad w(j,k) = 1 - j/(k+1).$$

These estimators are proposed by Newey and West (1987) and the triangular weights $w(j,k)$ are used to constrain $\tilde{\Omega}$ to be positive definite. The matrix $\tilde{\Delta}$ does not need to be constrained. The lag truncating parameter k is arbitrarily chosen to be 12.[11] Although the Newey-West

[10] These covariance matrices are also needed for estimating cointegration vectors.

[11] We also estimated these covariance matrices with lower and higher lag truncation orders. The difference in the estimated test statistics and parameters were not significant under these

(NW) method is commonly used to estimate long run covariance matrices, it will be highly biased in cases where the cointegration residuals $\tilde{\zeta}_t$ are serially correlated. The bias in the NW kernel estimate can be reduced by using a large bandwidth parameter, but this in turn increases the variance of estimates. For this reason, we also calculated the covariance matrices using the VAR pre-whitened kernel estimator (Andrews, 1991; Andrews and Monahan, 1992).

The pre-whitened kernel estimator also requires a kernel and a bandwidth choice (M). Andrews (1991) provides some useful guidelines for the choice of kernel and bandwidth parameter. The Parzen, Barlett, and quadratic spectral kernels all yield positive semidefinite estimates, but the quadratic spectral (QS) kernel yields the minimum asymptotic mean square error. Andrews recommends a plug-in bandwidth estimator for M. Besides removing the arbitrariness associated with the choice of bandwidth, a plug-in bandwidth parameter has several advantages. In what follows, we report estimates based on the QS kernel and plug-in bandwidth parameter in addition to estimates based on the NW method.

Cointegration test results are given in Table 1 for each industry. To calculate the test statistics given in this table we first estimate the regression in (23). Then, we restrict the coefficients attached to the spurious regressors to be zero and calculate the Wald statistics under this restriction. Using this Wald statistics, the J_1 statistics can be calculated from (26). As seen from the marginal significance levels given in Table 1, the null hypothesis of cointegration cannot be rejected for any of the industries at the 5% level. This result is complimentary to those in Rossana (1993b) who also found cointegration in a model with multiple factor inputs. The results in Table 1 rule out the existence of unit root technology shocks, since the presence of unit root technology shocks would eliminate cointegration among inventories, shipments, real wages, and real material prices.[12]

Table 1

Cointegration Tests

	J_1 Statistics	Significance Level

different lag truncation orders and none of the conclusions in this paper is affected. Results with different lag orders are available upon request.

12 It is by now well known that cointegration and unit root tests lack power when roots are close to but not equal to one. Particularly, when inference is based on asymptotic distributions one may expect the acceptance of the null more often than it should be. Although the test statistics we use have a standard chi-square distribution, one may suspect lack of power in finite samples. However, this is very unlikely for the results in Table 1 due to very high marginal significance levels.

Industry	NW	A-QS	NW	A-QS
SIC 20	7.65	3.08	0.11	0.55
SIC 21	8.22	7.55	0.08	0.11
SIC 23	1.84	2.60	0.77	0.63
SIC 28	2.31	3.51	0.69	0.48
SIC 29	2.72	1.62	0.61	0.81
SIC 30	2.61	0.66	0.63	0.96

4.3. Estimates of cointegration relationships

After establishing the existence of cointegration, we now estimate the parameters of the cointegration relationships. At first we tried to estimate the discount factor along with the other parameters, but we obtained unreasonable estimates. These unreasonable estimates may be due to a singular covariance matrix between instruments and regressors. This is shown to be the case by Gregory *et al*. (1993) when regressors follow an *ARIMA*(0,1,0) process. Thus, there might be serious identification problems, if one tries to estimate all the parameters in the model. Therefore, we restrict the discount factor to be 0.995. This corresponds to an annual interest rate of 6%. The results are not sensitive to values between 4 and 8%.

In Table 2, we report the OLS and ECM estimates of the parameters in (17). All these regressions and subsequent ones include a constant and a linear time trend in addition to other regressors, but we do not report the parameter estimates for constant and trend for brevity. These OLS and ECM estimates are reported for comparison. The difference between the OLS and ECM estimates is negligible. Most estimates are significant even at the 1% level even though we may well expect the OLS estimates and corresponding variances to be biased particularly in finite samples. The shipments coefficient should be positive to reflect the desire of the firm to produce more output and hold a larger stock of inventories in the face of increasing equilibrium sales. This is found to be true for all industries. From the standard model of the firm holding finished goods, we would expect the wage rate and material prices coefficients to be negative. Real wage coefficients are negative only for two industries. The real material prices have the expected sign except for the estimate for SIC 30. These results indicate that there may be some serious estimation issues with the real wage rate. The most prominent feature of the real wage series is the trend break in these series around the first oil price shock. Although we will examine the issue of structural breaks later and present statistical tests, we point out that some of the wrong signs may be attributed to the biases in the OLS estimates.

Table 2
The OLS and Error-Correction Model (ECM) Estimates

	Shipments		Wages		Material Prices	
Industry	OLS	ECM	OLS	ECM	OLS	ECM
SIC 20	1.38[a]	2.00[a]	-0.10[c]	-0.21[a]	-0.19[a]	-0.31[a]
SIC 21	0.09	0.82[d]	-0.12	-0.60[b]	-0.08	0.03
SIC 23	0.56[a]	0.87[a]	1.33[a]	1.34[a]	-0.23[a]	-0.28[a]
SIC 28	0.59[a]	0.73[a]	0.21[a]	0.26[a]	-0.16[a]	-0.06[b]
SIC 29	0.16[a]	0.19[a]	0.23[a]	0.16[a]	-0.25[a]	-0.14[a]
SIC 30	0.52[a]	0.83[a]	0.00	0.03	0.28[a]	0.45[a]

Notes: Superscripts a, b, c, d and e show significance at 1%, 5%, 10%, 15% and 20%, respectively.

Cointegration estimation results from six different methods are given in Table 3 and Table 4. For comparison we report estimates obtained from both the NW and QS methods. In Table 3, FM refers to the Phillips-Hansen FM method defined in (17) and (18), and FM-E and FM-C refer to the same method applied to the EE variant (17′)-(18′) and the EC variant (17″)-(18″), respectively. In Table 4, CCR, CCR-E, and CCR-C refer to Park's canonical cointegrating regression applied to (17)-(18), the EE variant (17′)-(18′), and the EC variant (17″)-(18″), respectively. Results in Table 3 and 4 show that the OLS and ECM estimates may, to some extent, be highly biased due to the second order bias effects. All six methods yield considerably different estimates than the OLS and ECM. Another feature of these results is that most of the positive real wage coefficients become negative particularly with the FM-E when NW is used. The same is true with the FM-C when QS is used. Note particularly that the FM-C and QS combination yields correct signs for all six industries, although two exceptions remain for material prices. It should also be noted that almost half of the estimates relating to the real wage rate and material prices are insignificant. Most of the sales coefficients are estimated to be positive. There are three instances where sales enter with a negative coefficient, but all of these negative coefficients are insignificant even at the 10% level. In accordance with the prediction of the inventory model, real material prices mostly have negative coefficients irrespective of the method used. Exceptions are associated mostly with SIC 21, 29, and 30. The FM method usually yields significant estimates with correct signs. The NW method yields significant estimates more frequently than the QS method. Although some minor differences remain in terms of the magnitude of estimates, the CCR performs analogous to the FM almost in all cases. This should not come as a surprise, since the FM and CCR are equivalent estimators.

Table 3

The Fully-Modified Method (FM) Estimates

	Shipments		Wages		Material Prices	
Industry	NW	QS	NW	QS	NW	QS
	Method: FM					
SIC 20	1.84[a]	2.74[a]	-0.23d	-0.31d	-0.34[a]	-0.42[a]
SIC 21	0.01	0.63[c]	-0.50d	-0.42d	0.15	-0.02
SIC 23	0.81[a]	1.11[a]	1.39[a]	1.42[a]	-0.28[a]	-0.27[a]
SIC 28	0.79[a]	0.79[a]	0.22[a]	0.17[b]	-0.14[b]	-0.06
SIC 29	0.22[a]	0.23[c]	0.18[b]	-0.06	-0.16[d]	0.16
SIC 30	0.86[a]	1.11[a]	-0.32	-0.54	0.30[b]	0.40c
	Method : FM-E					
SIC 20	1.71[a]	1.36[a]	-0.20	-0.18	-0.33[a]	-0.21[c]
SIC 21	-0.58[e]	0.16	-0.60[c]	-0.31	0.33[e]	0.01
SIC 23	0.83[a]	0.69[a]	1.40[a]	1.37[a]	-0.28[a]	-0.24[a]
SIC 28	1.10[a]	0.58	-0.19	0.12	-0.29	0.05
SIC 29	-0.01	0.15	-0.12	0.08	0.20	-0.10
SIC 30	0.92[a]	0.59[a]	-0.39	-0.10	0.28[b]	0.36[b]
	Method : FM-C					
SIC 20	1.70[a]	1.68[a]	-0.54[b]	-1.00[b]	-0.54[b]	-0.36[e]
SIC 21	-0.69d	0.02	-0.70[c]	-0.35	0.40[c]	0.07
SIC 23	0.52c	1.34[a]	1.19c	-0.34	-0.36[b]	-0.31[b]
SIC 28	0.77[a]	1.35[a]	0.17[a]	-0.18	-0.40[b]	-0.74[a]
SIC 29	0.20c	0.15	0.16	-0.01	-0.10	0.04
SIC 30	0.98[b]	1.35[a]	0.15	-0.25	-0.19d	-0.47

Notes: See notes to Table 2.

There seems to be no merit in choosing one method over the other. Since the EE and EC variants use more information than the plain FM, we would expect them to yield more significant and correctly signed estimates than the FM. However, there seems to be no significant difference among the FM, FM-E, and FM-C. This result may be due to the initial estimates used to create dependent variables in the EE and EC variants. We used consistent estimates from Kennan's procedure as initial estimates. However, these estimates may contain some second order bias effects. How much of the poor performance in terms of failing to yield significant and correctly signed estimates can be attributed to the bias in the initial estimate is not clear. Moreover, most of these insignificant estimates are associated with real material prices and real wages, and it may well be the case that these variables are indeed insignificant or there

Table 4

The Canonical Cointegration Regression (CCR) Estimates

	Shipments		Wages		Material Prices	
Industry	NW	QS	NW	QS	NW	QS
	Method: CCR					
SIC 20	1.85[a]	1.17[a]	-0.21e	0.42[b]	-0.33[a]	-0.13
SIC 21	-0.08	1.04[a]	-0.51[d]	-0.39	0.17	-0.13
SIC 23	0.82[a]	0.97[a]	1.33[a]	1.49[a]	-0.28[a]	-0.27[a]
SIC 28	0.77[a]	0.53[a]	0.23[a]	0.39[a]	-0.15[b]	0.04
SIC 29	0.23[a]	0.25[b]	0.18[b]	-0.03	-0.16d	0.14
SIC 30	0.83[a]	0.59[c]	-0.28	0.15	0.29[b]	0.48[b]
	Method : CCR-E					
SIC 20	1.76[a]	1.37[a]	-0.22	-0.18	-0.33[a]	-0.21[c]
SIC 21	-0.82[b]	0.52d	-0.61c	-0.29	0.39d	-0.08
SIC 23	0.85[a]	0.70[a]	1.35[a]	1.36[a]	-0.28[a]	-0.24[a]
SIC 28	1.09[a]	0.57	-0.17	0.13	-0.23	0.05
SIC 29	-0.01	0.14	-0.11	0.10	0.18	-0.10
SIC 30	0.94[a]	0.57[a]	-0.42	-0.09	0.28[b]	0.36[a]
	Method : CCR-C					
SIC 20	1.77[a]	1.71[b]	-0.57[d]	-1.02[b]	-0.55[b]	-0.36[e]
SIC 21	-0.94[b]	0.34	-0.72[b]	-0.33	0.46c	-0.01
SIC 23	0.47[d]	1.36[a]	1.26[c]	-0.40	-0.36[b]	-0.32
SIC 28	0.78[a]	1.33[a]	0.15	-0.18	-0.41[b]	-0.74[a]
SIC 29	0.20[d]	0.14	0.15	-0.02	-0.08	0.05
SIC 30	0.98[b]	1.35[a]	0.15	-0.25	-0.19	-0.47[d]

Notes: See notes to Table 2.

may be some misspecification in the model. In simulations conducted by Gregory *et al*. (1993), the FM method performed better when applied to the EE and EC variants. The same performance does not hold here. Another possibility causing the poor results might be the regime shifts. It is very likely that regime shifts cause insignificant and incorrectly signed parameter estimates.

An issue in the previous empirical work was the low estimates of adjustment speeds. We estimated adjustment speed coefficients for each industry using the procedure suggested by Kennan (1979) by regressing inventories on a constant, a linear time variable, current value, and one to three lags of each forcing variable. The estimated adjustment speeds are given in Table 5. Estimates are 0.04, 0.48, 0.07, 0.04, 0.12, and 0.03 for

SIC 20, 21, 23, 28, 29, and 30, respectively. Only the adjustment speed for SIC 21 seems to be reasonable. Four of the adjustment speeds are even below 0.10. Table 5 also reports corrected adjustment speeds that are based on the cointegration residuals obtained from the FM estimates. In contrast to the estimates from Kennan's method, these estimates are reasonably high for five industries. This result points to the possibility of incorrect inferences that may result from inappropriate estimation techniques.

Table 5

Adjustment Speed Estimates

Industry	Adjustment Speeds*	
	Kennan's Method	FM Method
SIC 20	0.04	0.70
SIC 21	0.48	0.57
SIC 23	0.07	0.18
SIC 28	0.04	0.95
SIC 29	0.12	0.76
SIC 30	0.03	0.30

*All estimates are significant at the 1% level.

4.4. Structural instability tests

What explains the insignificant and incorrectly signed parameter estimates still remains an empirical puzzle. The data used in this study contains at least two regime changes. The OPEC cartel increased the relative price of crude oil in October 1973. The Federal Reserve System changed the operating procedure from pegging the interest rate on federal funds to reserve targeting in October 1979. Rossana (1993b) found significant effects of these regime changes on the number of cointegration vectors. Regime changes lead to parameter nonconstancy, a form of model misspecification. Insignificant or incorrectly signed estimates that we obtained may be due to regime changes. For this reason it is worth investigating whether the model we estimated captures a fairly stable relationship.

Traditional ways of dealing with parameter instability, such as the Chow test, have some well-known disadvantages and inference does not easily carry to cointegration regressions where the regressors are nonstationary. Hansen (1992b) suggested some parameter instability tests in cointegrating regressions and derived their asymptotic distributions.

These tests use cointegration residuals from the FM estimation method. The tests use a particular feature of the FM method:

$$T^{-1}\sum_{t=1}^{T} h_t \tilde{e}_t^{+\prime} = \begin{bmatrix} 0 \\ \tilde{\Delta}_{21}^{+} \end{bmatrix}, \tag{27}$$

where $\tilde{\Delta}_{21}^{+} = \tilde{\Delta}_{21} - \tilde{\Delta}_{22}\tilde{\Omega}_{22}^{-1}\tilde{\Omega}_{21}$. In an OLS regression, the expression in (27) would be identically zero. Therefore, the scores of the problem are defined as

$$\tilde{s}_t = \left(\sum_{t=1}^{T} h_t \tilde{e}_t^{+\prime} - \begin{bmatrix} 0 \\ \tilde{\Delta}_{21}^{+} \end{bmatrix} \right). \tag{28}$$

This last expression satisfies $\sum_{t=1}^{T} \tilde{s}_t = 0$. In order to allow time-varying parameters Hansen modified (17) as follows:

$$y_t = \alpha_t' h_t + e_t . \tag{29}$$

Thus, possible parameter instabilities are incorporated into the model. Hansen suggested four different parameter instability tests. Two of these tests treat α_t as obeying a single structural break at time t.

The first test corresponds to the classical Chow test and allows a structural break or regime shift at time t, $1< t <T$, by assuming $\alpha_i = \{\alpha_1 |(i \le t), \alpha_2 |(i > t)\}$. For the null hypothesis of $H_0: \alpha_1 = \alpha_2$ against the alternative $H_1 : \alpha_1 \ne \alpha_2$, the test statistic is given by

$$F_{nt} = \mathrm{vec}(S_{nt})' \left(\tilde{\Omega}_{1\cdot 2} \otimes V_{nt}\right)^{-1} \mathrm{vec}(S_{nt}) , \tag{30}$$

where $S_{nt} = \sum_{i=1}^{t} \tilde{s}_i$, $V_{nt} = M_{nt} - M_{nt} M_{nn}^{-1} M_{nt}$, and $M_{nt} = \sum_{i=1}^{t} x_i x_i'$. The time of the structural break is assumed to be known under the alternative.

The second test treats the time of the structural break as unknown. For this test, the alternative hypothesis is $H_2: \alpha_1 \ne \alpha_2$, $[t/T] \in \Im$, where $\Im$ is some compact subset of (0, 1) and $[\cdot]$ means the integer part. This test statistic is defined as

$$\mathrm{SupF} = \sup_{t/T \in \Im} F_{nt} . \tag{31}$$

The remaining two tests model α_t as a martingale process, i.e., $\alpha_t = \alpha_{t-1} + z_t$, $E(z_t \mid \Im_{t-1}) = 0$, $E(z_t z_t') = \sigma^2 G_t$. For these tests the null hypothesis constrains the variance of the martingale differences to be 0, i.e., $H_0: \sigma^2 = 0$. For the alternative hypothesis $H_3: \sigma^2 > 0$, $G_t = (\tilde{\Omega}_{1\cdot 2} \otimes V_{nt})^{-1}$, $t/T \in \Im$, the test statistic is

$$\text{Mean F} = \frac{1}{T^*} \sum_{t/T \in \Im} F_{nt}, \quad T^* = \sum_{t/T \in \Im} 1. \tag{32}$$

If the alternative hypothesis is constructed as $H_4: \sigma^2 > 0$, $G_t = (\widetilde{\Omega}_{1\cdot 2} \otimes M_{nn})^{-1}$, then the test statistic is given by

$$L_c = \text{tr}\left\{ M_{nn}^{-1} \sum_{t=1}^{T} S_t \widetilde{\Omega}_{1\cdot 2}^{-1} S_t' \right\}. \tag{58}$$

The asymptotic distributions of the SupF, MeanF, and L_c tests are nonstandard and can be found in Hansen (1992b). Hansen (1992b) also tabulated critical values of these test statistics for some particular cases. The distribution of F_{nt} statistics does not pose any problem. This test statistic is distributed as the standard χ^2 distribution. A particular difficulty with the SupF and MeanF tests is that one has to determine the region $\Im$. Andrews (1990) points out that this region should not include end points zero and one. If one includes end points zero and one test statistics diverge to infinity almost surely. Andrews suggested a practical, if not arbitrary, solution. He recommends $\Im$ = [0.15, 0.85]. We follow Andrews (1990) and Hansen (1992b) and set $\Im$ = [0.15, 0.85].

We calculated the above tests using both the NW and QS kernels. We report estimates of SupF, MeanF, and L_c statistics in Table 6. The F_{nt} tests calculated[13] with the NW and QS are in the same direction, except for SIC 21. Three are only some minor differences and results from these two kernels disagree rarely. One particular application of the F_{nt} test is to test for structural breaks in a known time. We cannot reject the hypothesis of structural break in a known time for any of the industries at the 5% level, when the QS kernel is used. There are two exceptions when the NW kernel is used. The structural break in 1974 cannot be rejected for all industries.

If one is interested in testing whether there was a swift regime shift, the SupF statistic is the appropriate statistic. The null for the SupF statistic can be rejected for three industries when the NW kernel is used and for two industries when the QS kernel is used. There is evidence of swift regime changes, but this can only be supported for half of the industries. On the other hand, if one interested in testing whether the model is a good one that captures a stable relationship over time, then the notion of martingale parameters is appropriate. For that purpose, we may use the MeanF statistic. The hypothesis of unstable parameters can be supported for four industries at the 5% level when the NW kernel is used. If the QS kernel is used, then the same hypothesis can be supported for

[13] The estimates of the F_{nt} test are very lengthy, since the test is evaluated at 288 points for each series and each kernel. We do not report these results for brevity, but they are available upon request.

three industries at the 5% level. These test results imply that most of these industries do not have a stable cointegration relationship over time, thus insignificant and incorrectly signed parameter estimates may result.

Table 6
Parameter Instability Tests

	SupF Statistics		MeanF Statistics		L_c Statistics	
Industry	NW	QS	NW	QS	NW	QS
SIC 20	21.72	17.97	14.81	9.56	1.45	0.59
	(0.08)	(0.18)	(<0.015)	(0.09)	(<0.015)	(>0.20)
SIC 21	10.4	35.57	3.57	22.98	0.37	2.6
	(>0.20)	(<0.015)	(>0.20)	(<0.015)	(>0.20)	(<0.015)
SIC 23	11.79	14.62	5.42	6.71	0.65	0.44
	(>0.20)	(>0.20)	(>0.20)	(>0.20)	(0.19)	(>0.20)
SIC 28	46.46	34.42	12.56	10.9	0.49	0.59
	(<0.015)	(<0.015)	(0.03)	-0.05	(>0.20)	(>0.20)
SIC 29	19.26	14	12.23	8.66	0.65	0.37
	(0.13)	(>0.20)	(0.03)	(0.13)	(0.18)	(>0.20)
SIC 30	21.13	20.04	11.75	5.43	0.91	0.29
	(0.03)	(0.11)	(0.03)	(>0.20)	(0.06)	(>0.20)

Notes: Significance levels of estimates are given in parentheses below the estimates. ">" means greater than and "<" means less than the following number.

The L_c test is of particular interest, since it can be interpreted as a test of cointegration. Under the null of L_c, the constant of the regression behaves as a random walk and the relationship ceases to be cointegrated. The results of the L_c test confirm our earlier tests for cointegration. The null hypothesis of cointegration cannot be rejected at the 5% level for five industries with both QS and NW kernels. These results provide further evidence for the absence of unit root technology shocks.

5. Summary and discussion

The paper contains an analysis of the LQ inventory model of the firm. The LQ model of inventories was the traditional framework for the analysis of inventory decisions for a long time. In recent years, there has been growing skepticism toward this approach because of a number of peculiar empirical results arising from tests of this model. This paper examines the LQ inventory model in order to shed some light on the issues that arise when estimating this model and to elucidate the role of technology shocks on the cointegration relationship which may exist between inventories, shipments, and input prices.

The analysis reveals that the existence of any unit root technology shocks specific to an input in production will prevent cointegration among inventories, shipments, and input prices. Thus, if $I(1)$ technology shocks are a prominent feature of industrialized economies, cointegration should have little empirical relevance. Therefore, the cointegration in the LQ inventory model offers an indirect test of the presence of integrated technology shocks. The empirical section of this paper finds cointegration among inventories, material prices, and shipments using disaggregate time series data on two-digit classification level. Thus we find evidence against the presence of $I(1)$ technology shocks.

The paper shows that commonly used cointegration tests and estimation methods cannot be used to estimate the parameters of the LQ inventory model due to long run endogeneity of the regressors and/or moving-average error term. The paper demonstrates that the nuisance parameter dependency introduces second order bias effects and noncentralities in the limit distribution of estimators. We show that these bias effects are significant and if they are ignored will lead to highly biased estimates. Earlier empirical studies often estimated parameters of the LQ inventory model using estimation methods that do not correct for the second order bias effects. The paper obtains reasonable parameter estimates using appropriate estimation methods. The paper also shows that low adjustment speed estimates obtained previously in the literature are also due to inappropriate estimation methods. The paper obtains quite high adjustment speed estimates by using the FM method.

The paper also offers an explanation for the implausible parameter estimates obtained by previous researchers. We investigate whether structural breaks may be responsible for the poor results. Ignored structural breaks may seriously distort estimates. For the sectors that we obtained insignificant or incorrectly signed parameter estimates we also found enough evidence by formally testing for parameter instability to shed serious doubts about the stability of the cointegration relationships. We use three structural instability tests based on the FM method and show that the hypothesis of structural stability is rejected for cases where implausible parameter estimates are obtained. Thus, the evidence suggests that structural instability causes implausible parameter estimates.

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Özet

Bütünleşmiş teknoloji şokları içeren stok modellerinde tahmin ve çıkarsama

Bu çalışma bütünleşmiş teknoloji şoklarının girdi fiyatları ve satışların, stoklar ile bir eş-bütünleşmeye sahip olmasını engelleyeceğini göstermektedir. Çalışma ayrıca yaygın olarak kullanılan eş-bütünleşme tahmin yöntemlerinin dinamik doğrusal-karesel bir modelden ortaya çıkan stok denklemine içsel regresyon değişkenleri ve hareketli-ortalama hata teriminin varlığı nedeniyle uygulanamayacağını göstermiştir. Çalışma içsel regresyon değişkenlerinin ve hareketli ortalama hata teriminin varlığı durumunda kullanılabilecek uygun tahmin yöntemlerini incelemektedir. Uygun tahmin yöntemlerini kullanarak, iki basamaklı sınıflama seviyesindeki sektörel veriler için stoklar, ham madde fiyatları ve satışlar arasında eş-bütünleşme olduğu bulunmuştur. Böylece, bütünleşmiş teknoloji şoklarının varlığını desteklemeyen kanıtlar elde edilmiştir. Çalışma daha önceki araştırmacılar tarafından elde edilen ve teori ile uyuşmayan katsayı tahminlerinin uygun olmayan tahmin yöntemlerinden ve dikkate alınmayan yapısal değişikliklerden kaynaklandığını da göstermiştir.