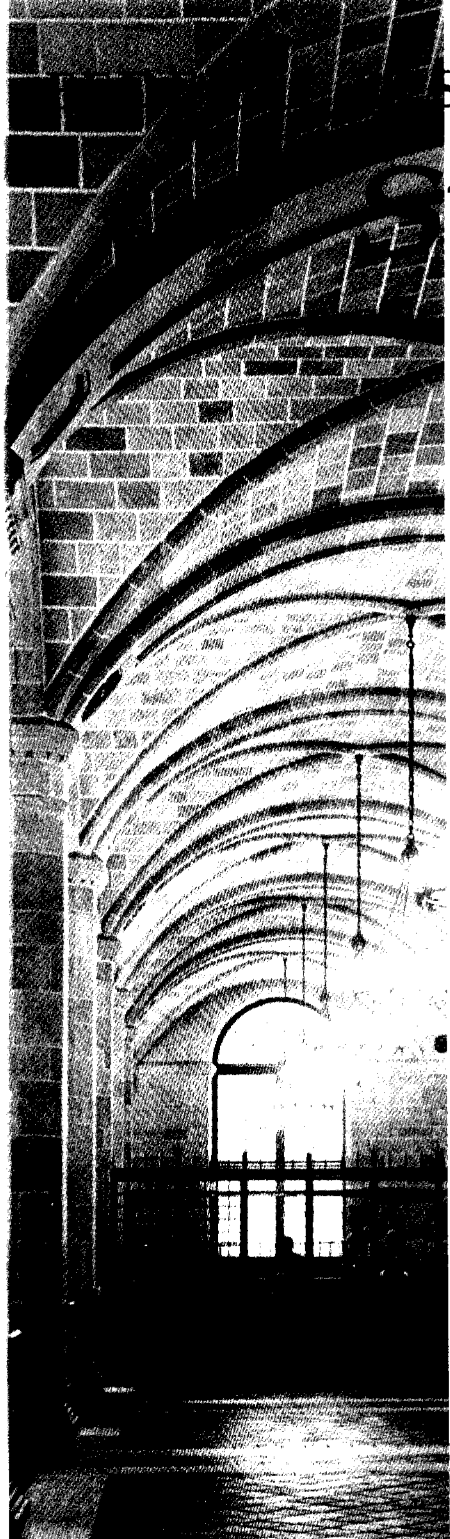

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Trade Inventories

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Trade Inventories*

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Abstract

We examine the behavior of trade inventories using both industry-level and high frequency firm-level data. The cost structure underlying the firm's optimization problem—convex delivery costs vs. fixed costs of ordering—provides the two competing hypothesis. In the presence of fixed costs (S, s) inventory policies are optimal, and steady-state reduced-form predictions regarding the dynamics of inventories and sales can be used to test the model. The alternative of convex delivery costs is provided by structural estimation of a linear-quadratic (L-Q) model. At the industry-level, the results are consistent with the reduced-form predictions of the (S, s) model, and structural parameter estimates obtained from Euler equation estimation indicate that the L-Q model does not fit the data. At the firm-level, however, estimates of the structural cost parameters are economically plausible, statistically significant, and generate observationally equivalent dynamics of inventories and deliveries as those predicted by the steady-state reduced-form probability relationships derived from the (S, s) model.

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1 Introduction

Following a period of dormancy during the 1960s and 1970s, empirical research on inventories has undergone a veritable renaissance during the last two decades. The impetus for this renewed effort came from a well-known, but periodically forgotten, empirical observation that inventory fluctuations seem to contain valuable information about the business cycle.[1] This observation have led macroeconomists to examine inventories as a possibly effective way to identify both business cycle shocks and the propagation mechanism of such shocks.

The vast majority of the recent empirical research effort on inventories has focussed on the behavior of manufacturing inventories—see Ramey and West (1997) for a recent comprehensive review of the literature. In one respect, this focus is very surprising. As can be seen in Figure I, trade (retail plus wholesale) inventories have accounted for more than one-half of total business inventory stocks in the US over the last decade—consistent with the secular shift from manufacturing to services, the share of trade inventories has also been trending upward.

Furthermore, the trade sector contains some of the most volatile components of aggregate inventory investment. Figure II plots the growth rates of inventories for the three components (manufacturing, retail, and wholesale trade) of the U.S. business sector.[2] As can be seen in the figure, movements in trade inventories, in particular retail inventories, contribute significantly to aggregate inventory fluctuations.[3] Despite the significance of trade inventories, empirical research has produced little evidence on the behavior of trade inventories and their role in aggregate fluctuations; the exceptions include Trivedi (1973), Irvine (1981b, 1981a), and Zakrajšek (1997).

In another respect, however, the focus on manufacturing inventories is not surprising. The traditional workhorse model of applied inventory research, the linear-quadratic (L-Q) model (Holt et al. (1960)), appears to describe more naturally the behavior of manufacturers than the behavior of retailers and wholesalers. The prototypical L-Q model assumes that firms face convex adjustment costs of production/deliveries, which implies that firms will smooth production/deliveries in the face of randomly fluctuating sales. Although some argue that the larger aggregate will behave as if firms are solving such an optimization problem—even if individual trans-

[1] Nearly half a century ago, Abramowitz (1950) provided the first statistical evidence, showing that a typical U.S. recession prior to World War II was characterized by intense inventory disinvestment. More recently, Blinder and Maccini (1991) have shown that this regularity continues to hold in the postwar data.

[2] The data are quarterly, end-of-period, and in billions of 1992 chain-weighted dollars. Inventory growth rates have been demeaned and smoothed by a nonparametric Splus filter; the filter smoothes the data by means of running medians and is designed to pick up broad trends in the data.

[3] Using the variance of inventory investment as a measure of volatility, Blinder and Maccini (1991) find that nearly 25 percent of the aggregate variance comes from movements in retail inventories alone.

actions are not precisely the same as those in the model (see, for example, Blanchard (1983) and Section 3.4 of Ramey and West (1997))—the primary advantage of the L-Q model for macroeconomists is that it is relatively easy to aggregate.

In contrast to the convex costs structure of the L-Q model, operations research literature and business manuals suggest that firms in the trade sector are likely to face fixed costs of ordering. Blinder (1981), Caplin (1983, 1985), Mosser (1988, 1991), Blinder and Maccini (1991), and Fisher and Hornstein (1995) provide compelling arguments that these fixed costs are crucial for understanding the dynamics of trade inventory investment. Such costs lead to (S, s) inventory policies, which induce delivery "bunching" rather than delivery smoothing. The inherent nonlinearities in these models, however, make aggregation and estimation harder and thus less appealing to empirical macroeconomists.[4]

Despite these problems, the (S, s) model has the potential to explain many interesting features of the macroeconomic inventory data. The bunching of deliveries implied by the (S, s) model, for example, suggests that small shocks could be magnified into larger fluctuations of inventories and deliveries, with implications for production in the rest of the economy. In addition, as discussed in reference to consumer durable goods expenditures by Caballero (1993), (S, s)-type policies are consistent with sluggish aggregate adjustment. Such policies, therefore, could provide an explanation for the slow adjustment speeds that are typically estimated in stock-adjustment models, or equivalently, the persistence of the "inventory-sales relationship" observed in the data (see Ramey and West (1997)).[5]

In light of the relative significance of trade inventories and the implications of (S, s) inventory policies, we believe that it is important to conduct more research into the behavior of trade inventories. This paper is one small step in this process as we examine the behavior of trade inventories using both aggregate industry- and high-frequency firm-level data. Given the microeconomic foundations of the (S, s) model and the difficulties in aggregating the model, an examination of the micro data is an important first step before expending more effort in determining macroeconomic implications of trade inventories. Our firm-level data are especially useful in this context because our panel has a fairly long time dimension.

In the first part of the paper, we investigate whether the data are consistent with the steady-state distribution predictions of Caplin's (1983, 1985) (S, s) model. Like Mosser (1988, 1991), we find that the industry-level wholesale and retail data are

[4] Although there has been some progress in recent years to examine the macroeconomics of models similar to (S, s). For example, see Bertola and Caballero (1990), Grossman and Laroque (1990), Caballero and Engel (1991, 1993), Caballero (1993), and Eberly (1994).

[5] The "inventory-sales" relationship in Ramey-West (1997) terminology is a (linear) generalization of the inventory-sales ratio. Letting H_t denote inventories in period t and X_t sales in period t, the inventory-sales relationship is defined as a stationary linear combination $H_t - \lambda X_t$, where the parameter λ (i.e., cointegration parameter) determines the "long-run" equilibrium relationship between inventories and sales.

largely consistent with Caplin's model. We then extend her results by examining the firm-level data and find that these data are also consistent with the Caplin model.

We further extend the analysis of Mosser in another direction. While her work discussed the "delivery smoothing" model as an alternative to the (S, s) model, no true alternative model is presented. In this paper, we estimate and test an inventory model with convex adjustment costs—the L-Q model—as an alternative to the (S, s) model. Our results indicate that the L-Q model cannot adequately describe inventory investment at the industry level. At the firm-level, however, the structural estimates of the L-Q model are economically sensible and imply observationally equivalent patterns of inventories, sales, and deliveries as those predicted by the (S, s) model in the steady state.

The rest of this paper proceeds as follows. The next section provides a brief summary of the steady-state distribution predictions of the Caplin (1983, 1985) (S, s) model that were used by Mosser (1988, 1991). In this section, we also present the alternative L-Q model and derive a testable specification of the associated Euler equation. Section 3 discusses econometric issues. Section 4 describes the industry- and firm-level data used in the analysis. Section 5 presents some preliminary evidence in the form of variance ratios and simple correlations. Section 6 presents the results from regressions similar to those in Mosser (1988, 1991). Section 7 presents the results from estimating the L-Q model. Section 8 concludes and discusses the implications for future research.

2 Theoretical Framework

In this section, we derive the empirical specifications that will be used to test various inventory models. Section 2.1 uses theoretical results due to Caplin (1985) on the reduced-form probability rules governing the dynamics of both individual and aggregate inventories when fixed costs of ordering are present and firms use (S, s) policies to manage their inventory stocks. Section 2.2 presents a version of the L-Q model and derives an estimable specification of the associated Euler equation characterizing the optimal sequence of inventory decisions.

2.1 The (S, s) Model

Consider a firm facing an exogenous demand process that is independently distributed over time and must purchase its goods from a downstream supplier. The cost function of the firm consists of two parts: a fixed cost per order and a constant marginal cost per unit. Formally,

$$\begin{aligned} C(Y_t) &= c_0 + c_1 Y_t, \text{ if } Y_t > 0 \\ &= 0, \text{ if } Y_t = 0 \end{aligned} \tag{1}$$

where Y_t are real orders in period t, c_1 is the constant marginal cost of placing an order, and c_0 is the fixed cost of placing an order. Scarf (1960) proves that under these assumptions an (S, s) inventory policy is optimal—that is, (S, s) inventory policy minimizes the expected, discounted present value of costs.

If the (S, s) targets are constant over time, an observer who examines data from the firm at regular intervals will see it behaving according to the following rules:

$$D_t = m_t Q, \;\; m_t \geq 0 \text{ an integer} \tag{2a}$$

and

$$s < H_t = H_{t-1} + D_t - X_t \leq S. \tag{2b}$$

In equations (2a) and (2b), H_t denotes real end-of-period inventories, X_t real final sales, $Q = S - s$ the order size, D_t real deliveries, and m_t the number of orders during period t.

As demonstrated by Caplin (1985), this model implies that a firm's inventory level is a stationary Markov process with a uniform ergodic distribution between s and S. In addition, these distributions are independent across firms, which greatly simplifies aggregation. The aggregate distribution is unimodal and symmetric about the aggregate $(s, S]$ interval. Consequently, inventories in any period have the same unconditional distribution:

$$E(H_t) = E(H_{t-1}) = \ldots = E(H_{t-k}) = E(H), \quad \forall k. \tag{3}$$

Using similar reasoning, Caplin (1985) shows that the expected value of inventories conditional on sales, X_t, is the same as the unconditional expectation:

$$E(H_t \mid X_t) = E(H_{t-1}) = E(H_t). \tag{4}$$

Taking conditional expectations of the inventory accounting identity, $H_t - H_{t-1} = D_t - X_t$, and using equation (4), the expectation of deliveries conditional on sales is given by

$$E(D_t \mid X_t) = X_t, \tag{5}$$

implying that

$$D_t = X_t + \epsilon_t, \text{ where } E(\epsilon_t \mid X_t) = 0. \tag{6}$$

From equation (6), it follows immediately that

$$\text{Var}(D_t) > \text{Var}(X_t). \tag{7}$$

This is the first prediction of the (S, s) model that we will test. Because the (S, s) rule is assumed to be monitored continuously, but observed at discrete intervals only, equation (7) is true for any frequency of data. This prediction is the opposite of that expected from simple delivery-smoothing models.

Equation (6) also implies that inventory investment is uncorrelated with sales,

$$\mathrm{Cov}(X_t, \Delta H_t) = 0, \tag{8}$$

where $\Delta H_t = H_t - H_{t-1}$ denotes inventory investment. This is in direct contrast with a delivery-smoothing model which would predict that $\mathrm{Cov}(X_t, \Delta H_t) < 0$. Equation (8) is a stronger condition than the variance condition (7), because the variance condition may hold when the correlation is positive or negative. Some L-Q models, for example, would predict the variance condition, but they predict zero correlation between sales and inventory investment only under special conditions.[6] In contrast, equation (8) is a general prediction of the (S, s) model and holds both for individual firms and for aggregate inventories.

Using equation (6) and the inventory accounting identity, we can derive the following regression that is the basis for most of our tests of the (S, s) model:

$$\Delta H_t = \alpha + \beta X_t + \epsilon_t. \tag{9}$$

If firms are using constant (S, s) inventory policies to manage their inventory stocks, we would expect that $\alpha = 0$ and $\beta = 0$. If, on the other hand, the delivery costs are convex and relatively large so as to induce delivery smoothing, then we would expect $\beta < 0$ and $\alpha > 0$.

2.1.1 Delivery Lags and Serial Correlation in Sales

The predictions of the (S, s) model so far are based on several unrealistic assumptions: i.i.d. sales and no delivery lags. In this section, we consider some complications of the basic (S, s) model. First, we relax the assumption of no delivery lags. Suppose we extend our basic regression (9) to include lags of sales. If there are no delivery lags, then the regression

$$\Delta H_t = \alpha + \beta_0 X_t + \beta_1 X_{t-1} + \ldots + \beta_k X_{t-k} + \epsilon_t \tag{10}$$

will have $\alpha = \beta_0 = \beta_1 = \ldots = \beta_k = 0$. However, if there is a one-month lag between orders and deliveries, then regression (10) would predict $\beta_0 = -1, \beta_1 = 1$, and $\beta_2 = \ldots = \beta_k = 0$. Under more complicated delivery lag structures, the model would predict a nonpositive coefficient on current sales and nonnegative coefficients on lagged sales with the sum totalling zero. Depending on their structure, L-Q

[6]The L-Q model with quadratic delivery costs and an accelerator term that is sufficiently strong to offset the delivery-smoothing motive can generate the variance condition. Under those conditions, the L-Q model will also generate procyclical inventory movement, implying positive correlation between sales and inventory investment (see Blinder (1986) and Kahn (1987)).

models can also predict nonzero values for the coefficients on lagged sales, but these coefficients may be either positive or negative.

Another potential complication is serially correlated sales. With serially correlated demand, the current realization of sales provides a signal about future sales. Suppose firms periodically change their (S, s) targets based on the recent behavior of sales.[7] Under such policies, Blinder (1981) shows that deliveries should be positively related to the change in the state of demand, provided that state changes occur relatively infrequently. Caplin (1985) provides similar results for aggregate inventories across steady states, proving that

$$\begin{aligned} E(D_t \mid X_t, \text{good state}) &> X_t; \\ E(D_t \mid X_t, \text{bad state}) &< X_t. \end{aligned}$$

This implies that firms that adjust their (S, s) targets down in a recession will under-replace sales and those that adjust their targets up in an expansion will overreplace sales. This exaggerates the variance condition (7), and so in regression (9), we would expect $\beta > 0$.

Finally, as discussed section 4.1, time-series evidence indicates that industry level and aggregate sales have unit roots. If sales are $I(1)$ and firms do not continuously update their (S, s) targets, the steady state distribution of inventories conditional on sales may not be uniform, which is crucial for Caplin's aggregation results. Caballero and Engel (1991), however, prove that even if inventories are not at their steady state (uniform) distribution, changes in aggregate demand will on average be uncorrelated with aggregate inventory investment. This suggests that in the following regression,

$$\Delta H_t = \alpha + \beta \Delta X_t + \epsilon_t, \tag{11}$$

we would expect that $\beta = 0$ if firms are using (S, s) inventory policies.

2.2 The L-Q Model

The empirical predictions of the (S, s) model developed in the previous section are not true structural economic relationships. Rather they are a set of reduced-form steady-state relationships, with parameters that, unfortunately, cannot be mapped back to an underlying optimization problem. In addition, alternative models with

[7] This type of behavior appears to be used in practice (see Ehrhardt (1979)). Periodic updating of the (S, s) targets is not the optimal policy when sales are serially correlated, because ideally, firms would adjust their targets after each realization of the demand process. This type of continually optimizing behavior, however, is not readily observed—the complexity of continually calculating new targets probably entails greater costs than maintaining constant targets over slightly longer periods. Because the steady-state predictions of the (S, s) model do not depend on the optimality of (S, s) policies, but only on the use of such policies, the steady-state predictions remain valid if firms continue to use constant (S, s) targets.

convex adjustment costs—the L-Q model in particular—can rationalize and generate most of the reduced-form predictions implied by the (S, s) model in the steady state. Thus it is important to examine whether inventory dynamics in the trade sector are consistent with alternative cost structures.

In this section, we examine the most obvious alternative hypothesis, the L-Q model with convex delivery costs. A simple variant of the L-Q model can be described as follows. A representative retailer chooses an inventory policy that maximizes the expected present discounted value of future cash flows, subject to the inventory accounting identity and a cost function that includes linear and quadratic costs of purchasing goods from manufacturers (i.e., delivery costs) and of holding inventories. The problem is stated formally as follows:

$$\max \quad \Pi_t \equiv \lim_{T\to\infty} E_t\left[\sum_{j=0}^{T} \rho^j [p_{t+j}X_{t+j} - C(D_{t+j}, X_{t+j}, H_{t+j-1})]\right]$$

subject to

$$H_{t+j} = H_{t+j-1} + D_{t+j} - X_{t+j};$$

$$C(D_{t+j}, X_{t+j}, H_{t+j-1}) = \frac{a_1}{2}D_{t+j}^2 + \frac{a_2}{2}(H_{t+j-1} - a_3X_{t+j})^2 + u_{t+j}D_{t+j};$$

$\{p_{t+j}, X_{t+j}, u_{t+j}\}_{j=0}^{\infty}$ exogenous stochastic processes;

$H_{t-1} \geq 0$ given;

where p_t is the market price in period t at which the retailer can sell the goods to his customers, $0 < \rho < 1$ is the one-period discount factor, and E_t is the mathematical expectations operator conditional on information known at time t, which is assumed to be equivalent to linear projections.

The scalar u_t is an unobservable cost shock with zero mean (possibly serially correlated), which captures any stochastic variation in the cost structure of the firm. For simplicity, we assume that revenues are exogenous, implying that profit maximization is equivalent to cost minimization.

The model with convex delivery costs imposes the following restrictions on the parameters: $a_1, a_2 > 0$ and $a_3 \geq 0$. The parameter a_1 captures the increasing marginal costs of purchases and is interpreted as the second-order term in a quadratic approximation to an arbitrary convex cost function.[8] The parameters a_2 and a_3 are related to inventory holding and stockout or backlog costs. The accelerator term, $\frac{a_2}{2}(H_{t+j-1} - a_3X_{t+j})^2$, captures a trade-off between inventory holding costs on the

[8] A generic version of the L-Q model would also include quadratic delivery adjustment costs of the form $\frac{a_0}{2}(\Delta D_t)^2$, where the parameter a_0 captures increasing costs of changing deliveries. This form of cost structure seems far more relevant for the manufacturing sector, where increasing costs of changing production have economic meaning. In the trade sector, however, convex costs associated with the change in deliveries do not seem economically plausible.

one hand and stockout costs on the other. Maintaining a high inventory level implies large holding costs but lower probability of stocking out. The firm's optimal inventory policy balances the two competing costs, with the optimal inventory level increasing in the level of expected sales, hence, the accelerator effect.

The problem is solved in the usual manner. The Euler equation characterizing the optimal sequence of inventory decisions is given by

$$E_t[a_1(D_t - \rho D_{t+1}) + \rho a_2(H_t - a_3 X_{t+1}) + u_t - \rho u_{t+1}] = 0. \tag{12}$$

Following West (1995), the Euler equation (12) is transformed into an estimable specification by the Legendre-Clebsch normalization (i.e., choice of the left-hand-side variable). Substituting the inventory accounting identity into equation (11), we can define,

$$cH_t \equiv -(\partial^2 \Pi_t / \partial H_t^2) H_t = [a_1(1+\rho) + \rho a_2] H_t. \tag{13}$$

Because the optimization problem is well-behaved, $c > 0$, hence we can put cH_t on the left side of equation (12), divide through by c and rearrange to obtain

$$\begin{aligned} H_t &= \left(\frac{a_1}{c}\right) W_{1,t+1} + \left(\frac{\rho a_2 a_3}{c}\right) X_{t+1} + \nu_{t+2} \\ &\equiv W_t' \gamma + \nu_{t+2}, \end{aligned} \tag{14}$$

where

$$\begin{aligned} W_{1,t+1} &\equiv -X_t + H_{t-1} + \rho(X_{t+1} + H_{t+1}); \\ \nu_{t+2} &\equiv \left(\frac{1}{c}\right)(u_t - \rho E_t u_{t+1}) + e_{t+2}; \\ e_{t+2} &\equiv -\left(\frac{a_1}{c}\right)[W_{1,t+1} - E_t W_{1,t+1}] - \left(\frac{\rho a_2 a_3}{c}\right)[X_{t+1} - E_t X_{t+1}]; \\ W_t &\equiv (W_{1,t+1}, X_{t+1})'; \\ \gamma &\equiv (\gamma_1, \gamma_2)' \equiv (a_1/c, \rho a_2 a_3/c)'. \end{aligned}$$

Given a vector of instruments that is uncorrelated with ν_{t+2}, but correlated with W_t, the parameter vector γ can be estimated by one of the family of instrumental variable (IV) estimators developed in the Generalized Method of Moments (GMM) literature initiated by Hansen (1982). From the estimate of γ, the structural parameter a_1/c can be recovered directly and of a_2/c and a_3 using

$$\frac{a_2}{c} = \frac{1 - \gamma_1(1+\rho)}{\rho}, \quad a_3 = \frac{\gamma_2}{(\rho a_2/c)}. \tag{15}$$

The estimates of the model's structural parameters $a_1/c, a_2/c$, and a_3 determine the relative variability of deliveries and sales in the model.[9] The sign of parameter a_1 determines the sign of the marginal cost of deliveries, and hence the extent to which there is delivery smoothing motive because of convex costs. If $a_3 = 0$ and $a_1, a_2 > 0$, the firm's optimal inventory policy will lead to delivery smoothing, implying that the variance of deliveries should be less than the variance of sales. If $a_3 > 0$, as advocated by Kahn (1987), the stockout avoidance motive may dominate, and the optimal inventory policy may lead to delivery bunching, implying a variance relationship in equation (7). As shown by Krane (1994), given $a_3 > 0$, the smoothing or bunching of deliveries will depend on the relative magnitudes of a_1 and a_2.

3 Econometric Methodology

In this section, we briefly discuss various econometric issues behind the estimation of both the reduced-form implications of the (S, s) model and structural parameters of the L-Q model derived from Euler equations.

3.1 Reduced-Form (S, s) Regression

3.1.1 Industry-Level Estimation

Because the (S, s) predictions can be expressed as simple reduced-form regressions, the estimation and testing of this model uses a standard OLS framework.[10] The primary complication is the treatment of upward trending sales in the industry-level data. If sales are stationary about a deterministic trend, then the (S, s) band increases deterministically. The targets in (S, s) models usually are a function of the square root of demand (i.e., sales). In this case, by including trend terms in the regression, we can estimate the (S, s) regressions in levels. In particular, we estimate the generalized model with delivery lags (equation (10)) including linear and quadratic trend terms in the regression.

Unit roots tests at the industry-level, however, indicate that industry-level sales and inventories are $I(1)$. Consequently, inference from the model estimated in levels is invalid.[11] In this case, sales must be first differenced, and as discussed in Section 2.1.1, we should estimate equation (11). Because the evidence clearly indicates unit

[9] Note that the parameters a_1 and a_2 are identified only up to a scale. Thus from the Euler equation we can only estimate ratios of these parameters.

[10] Standard errors in all OLS regressions are calculated using the Newey-West (1987) variance-covariance matrix robust to heteroskedasticity and serial correlation (of up to 12 lags) in the residuals.

[11] Given this evidence in favor of unit roots in the industry-level data, the reader may wonder why we bothered to estimate the (S, s) regressions in levels. Our response is that the levels regression can still be a useful check of the robustness of our results as well as providing a comparison with the previous literature, in particular, Mosser (1988, 1991).

roots in the industry-level data, we consider this specification as providing the most reliable results concerning the validity of the (S, s) predictions at the industry level.[12]

3.1.2 Firm-Level Estimation

The basic reduced-form prediction of the (S, s) model that we test at the firm-level involves two modifications of equation (9). The first modification follows heterogeneous panel literature, which assumes parameter heterogeneity across firms and is given by

$$\Delta H_{it} = \alpha_i + \beta_i X_{it} + d_{mt} + \epsilon_{it}, \tag{16}$$

where $i = 1, \ldots, N$ indexes firms and $t = 1, \ldots, T$ indexes time. We assume that the linear regression coefficients, β_i, $i = 1, \ldots, N$, are constant over time but differ randomly across firms in the sense that the distribution of coefficients is independent of the exogenous regressors and disturbances; α_i denotes a fixed firm effect, which controls for any (time-invariant) unobservable heterogeneity in the conditional mean among firms; d_{mt} denotes an industry-specific time effect, which controls for shocks common to all firms in a given industry in any given time period, and ϵ_{it} is i.i.d. $(0, \sigma_i^2)$ disturbance, assumed to be distributed independently of β_i and X_{it}.

We assume that the parameter β_i is random and can be characterized by

$$\beta_i = \beta + \eta_i,$$

where η_i is assumed to have zero mean and constant variance ω^2. The parameter of interest is the average of coefficients β_i across firms, which should equal zero under the null hypothesis that firms use (S, s) inventory policies. The above assumptions yield a standard heterogeneous panel formulation, and the average effect β can be estimated consistently by the Mean-Group (MG) approach outlined by Pesaran, Smith, and Im (1996).

The MG procedure first estimates equation (16) for each firm separately—after nullifying fixed firm and industry-specific time effects—and the resulting estimates of the slope coefficients β_i are then averaged. This average yields a consistent estimate of β, as both N and T go to infinity. The variance of the MG estimator $\hat{\beta}_{MG}$ is computed directly from the individual estimates $\hat{\beta}_1, \ldots, \hat{\beta}_N$ as

$$\mathrm{Var}(\hat{\beta}_{MG}) = \frac{1}{N(N-1)} \sum_{i=1}^{N} (\hat{\beta}_i - \hat{\beta}_{MG})^2,$$

[12]We also estimated a generalized model which included six lagged first differences in sales in equation (11). This had negligible effect on the coefficient on the contemporaneous first difference. Because the interpretation of the coefficients on lagged first differences is not clear to us, we do not include these results in the text.

which can be proven to be a consistent estimator of Var($\hat{\beta}_{MG}$) under fairly general conditions.

The second modification of equation (9)—instead of allowing random variation in the sales coefficient across firms—restricts the parameter β to be common to all firms in a specific industry, but allows a different coefficient on sales for each industry. Specifically, let I_{im} denote an indicator function that equals one if firm i is industry m and zero otherwise. The second specification is given by

$$\Delta H_{it} = \alpha_i + I_{im}\beta X_{it} + d_{mt} + \epsilon_{it}. \tag{17}$$

After eliminating fixed firm and fixed industry-specific time effects with appropriate transformations, equation (17) is estimated with OLS.

3.2 Euler Equation Estimation

3.2.1 Industry-Level Estimation

The presence of unit roots in sales and inventories has important implications for the estimation of Euler equations at the industry level. Furthermore, the possibility of cointegration between sales and inventories affects estimation of the intertemporal first-order conditions. If both sales and inventories are $I(0)$, then equation (14) can be estimated in levels (including a trend term). Even if sales and inventories are $I(1)$ but cointegrated, equation (14) can be estimated in levels, as the parameter estimates will remain asymptotically normal (see West (1986, 1995)).

However, if sales and inventories are not cointegrated, then equation (14) must first be differenced for estimation to proceed along standard lines. Although initially surprising, the lack of cointegration can be rationalized in the L-Q model by assuming that the cost shock u_t follows a nonstationary process. Given that we find very scant evidence of cointegration across trade industries—a result also found by Granger and Lee (1989)—we decided to estimate equation (14) in first differences.

We estimate the differenced equation (14) using standard GMM techniques. Under the assumption that the cost shock u_t is a random walk, the residual term in the differenced version of (14) will follow an MA(1) process. Valid instruments, therefore, would be first differences of inventories and sales lagged at least one period. We allow for the possibility of additional serial correlation by using first differences of sales and inventories lagged at least two periods.

The variance-covariance matrix of the parameters is estimated using the quadratic spectral (QS) kernel with the "plug-in" bandwidth parameter (see Andrews (1991)). The structural cost parameters associated with the estimated parameter vector $\hat{\gamma}$ are then calculated as in equation (15) and their asymptotic standard errors are calculated using the delta method.

3.2.2 Firm-Level Estimation

To ensure consistency with the specifications used to test predictions of the (S, s) model, the estimable Euler equation (14) is augmented with fixed firm and fixed industry-specific time effects. It is well known that the standard technique of eliminating individual-specific effects—by transforming all variables to deviations from their respective individual means—is inappropriate in a context of a dynamic model with unobservable individual effects (see Nickell (1981), for example).[13] The theoretically correct way to estimate a dynamic model with individual effects is first to difference the data—to eliminate the individual-specific effect—and then to estimate the differenced equation using an instrumental variables procedure like GMM (see Holtz-Eakin, Newey, and Rosen (1988), for example).

An alternative to first differencing that is very useful in the context of dynamic panel data models is the orthogonal deviations transformation proposed by Arellano and Bover (1995). The advantage of the orthogonal deviations transformation is that it gives an equivalent to a within-group estimator while preserving the orthogonality among the transformed errors. That is, individual effects are eliminated by subtracting the mean of all available future observation from the first $T-1$ observations in the sample:

$$x_{it}^{*} = \sqrt{\left[\frac{T-t}{T-t+1}\right]} \times \left[x_{it} - \frac{1}{(T-t)}(x_{it+1} + \cdots + x_{iT})\right]; \quad t = 1, \ldots, T-1,$$

where x_{it}^{*} denotes the transformed variable, and $(T-t)/(T-t+1)$ is the weighting factor that equalizes the variances.[14]

We use the orthogonal deviations transformation to eliminate the unobservable firm-specific effects from the firm-level Euler equation. Because the error term, ν_{it+2} in the Euler equation is, by construction, serially correlated, orthogonal deviations transformation, consequently, induces higher-order serial correlation in the error term. Under the assumption that the original error term ν_{it+2} follows an MA(1) process, a valid set of moment restrictions for period t in the transformed equation is given by $E[z_{it}\nu_{it}^{*}] = 0$, where $z_{it} = (H_{i1}, \ldots, H_{it-3}, X_{i1}, \ldots, X_{it-3}, D_{mt})$ is a vector of valid instruments for period t, ν_{it}^{*} is the transformed error term, and D_{mt} denotes the relevant industry-specific time dummies. A complete set of moment restrictions for firm i is given by $E[Z_i\nu_i^{*}] = 0$, where

$$Z_i = \text{diag}[H_{i1}, \ldots, H_{is}, X_{i1}, \ldots, X_{is}, D_{mt}]; \quad s = 1, \ldots, T_i - 3,$$

[13] An OLS or an IV estimator obtained from data that have been transformed in this manner is inconsistent, for finite T, because of the asymptotic correlation that exists between the transformed lagged endogenous variables and the transformed error term.

[14] This transformation can be regarded as first differencing the equation to eliminate individual-specific effects, followed by a GLS transformation to remove the serial correlation induced by differencing.

and diag[·] represents a block-diagonal IV matrix of the type discussed in Arellano and Bond (1991); and ν_i^* is a $(T_i \times 1)$ vector of transformed errors for firm i.

Because the panel is unbalanced, $\dim(Z_i) = \dim(Z_j)$ if and only if firm i and firm j are in the sample the same number of periods. An IV matrix for the complete transformed system is obtained by stacking up the relevant firm-specific IV matrices, $Z = (Z_1', \ldots, Z_N')'$, and adding columns of zeros where necessary to ensure conformability. The resulting transformed equation is estimated with an asymptotically efficient two-step GMM estimator of the type presented in Arellano and Bond (1991).[15] As in the case of industry-level data, the structural parameters of the L-Q model are obtained from equation (15), and their asymptotic standard errors are computed by the delta method.

4 Data

4.1 Industry-Level Data

The source for the industry-level data on sales, end-of-period inventories, and inventory investment is the Bureau of Economic Analysis, U.S. Department of Commerce. These monthly, seasonally adjusted data are in billions of 1992 chained-weighted dollars. Deliveries are calculated using the accounting identity $D_t = X_t + \Delta H_t$.

The data are available from January 1959 through August 1997 for nine categories of retail establishments, as well as for the aggregate retail trade and the durable and nondurable sectors. For the aggregate wholesale sector—as well as total nondurable goods and total durable goods—the data also are available from January 1959 through August 1997. For the 18 three-digit SIC wholesale categories,the data are available from January 1967 through August 1997.[16]

[15] An asymptotically efficient GMM estimator would exploit all (linear) moment restrictions. Given that our panel has a long time series dimension, using all moment restrictions would result in an IV matrix Z with several thousands columns. For computational reasons it is clearly impractical to use all of the available instruments. In addition, given the actual sample size, the finite-sample properties of the estimator are likely to be affected by the use of an excessive number of instruments. Consequently, only lags 3 to 5 were used as instruments. As a robustness check, we extended the lag length to 6 without affecting any of the results.

The estimation was carried out by DPD.sas—a set of general panel data estimation routines written in SAS by the Egon Zakrajšek—that are based on the GAUSS version of a similar program written by Arellano and Bond (1988).

[16] Much of the industry-level analysis was repeated using data from January 1976 through December 1996, which matches the time period of the firm-level data. This had little substantive effect on our results.

4.1.1 Unit Root and Cointegration Issues

As discussed in the industry-level econometric methodology section, unit roots in sales and inventories and the fact that inventory levels and sales may be cointegrated could have a significant effect on the estimation and inference of our models. In this section, we briefly discuss these issues. For the sake of brevity, we do not report any of these results, which are available upon request.

We test for the presence of unit roots at the industry-level using the generalized augmented Dickey-Fuller (ADF) procedure developed by Im, Pesaran, and Shin (1995).[17] This allows us to examine the univariate time series properties of the industry panel in a compact and relatively simple manner, while allowing us to exploit the advantages of the panel structure of the data. Using this procedure, we find that we cannot reject the null hypothesis of an unit root for the log-level of inventories and sales, but we can reject the unit root hypothesis for the growth rates of inventories and sales and for inventory investment. We thus conclude that inventories and sales in the industry-level data are $I(1)$, while inventory investment is $I(0)$.[18]

The presence of cointegration between sales and inventories has a significant effect on Euler equation estimation. Given the very preliminary state of testing for cointegration in panels (see Pedroni (1997)), we have decided to be inconsistent with our panel data unit root tests, and examine cointegration for each trade industry and the aggregates separately, using the Johansen (1991) methodology.[19]

The test statistics indicate that in most industries and in the aggregate sales and inventories are not cointegrated—in addition, there is no discernible pattern across industries for which we find the evidence of cointegration.[20] The fact that sales and inventories in so many industries are not cointegrated led us to decide to estimate the Euler equation of the L-Q model in first differences.

[17] The tests were performed on separate panels for retail and wholesale trade, because the time dimensions of the series in the two sectors differ. The data are in logs with the exception of inventory investment. The panel version of the ADF regression for an arbitrary variable q_{it} is $\Delta q_{it} = \alpha_i + \phi_i q_{it-1} + \sum_{j=1}^{p_i} \theta_i \Delta q_{it-j} + \delta_i t + d_t + \varepsilon_{it}$, where i indexes industries and t indexes time. Unobservable common shock, d_t, is eliminated by transforming all variables as deviations from their time-specific means; we set $p_i = 12, \forall i$. The null hypothesis of a unit root is $H_0 : \phi_i = 0, \forall i$, against the alternative of trend stationarity, $H_A : \phi_i < 0, \forall i$.

[18] Examination of the separate ADF regressions for each trade industry and aggregate largely confirms these results. Only for sales of retail nondurables and the metals and minerals industry in the wholesale sector is the unit root hypothesis rejected at a conventional significance level.

[19] The number of lags included in the underlying VAR model for the test is six.

[20] The results here are similar to those of Granger and Lee (1989) for trade industries. The one major difference is in retail automotive category—Granger and Lee (1989) find no cointegration for this industry, but we find cointegration.

4.2 Firm-Level Data

The firm-level data used in this paper come from the Compustat quarterly P/S/T, Full Coverage and Research data files. The data set used in the analysis is an unbalanced panel of 824 trade firms covering the time period 1976:Q1 to 1996:Q4 (84 quarters); the minimum tenure in the panel is 12 quarters and the longest is 84 quarters, yielding a total of 24,995 observations. The exact selection procedure and the construction of all variables are described in the Data Appendix.

In Table 1, we provide summary statistics for some of the relevant variables. Measured by assets, the median firm size in our sample is almost $150 million, which by trade sector standards is a fairly large firm—the distribution of firm size is also heavily skewed as indicated by the difference between the mean and the median. Investment in inventories—measured in arithmetic changes or in growth rates—is on average positive and extremely volatile, with standard deviation exceeding the mean by several orders of magnitude. The median firm quarterly inventory-sales ratio is about 0.50, which is only slightly above the average quarterly inventory-sales ratio for the aggregate trade sector.

5 The Relative Variability of Deliveries and Sales

We begin our analysis by examining whether our data are consistent with elementary predictions of the (S, s) model—that the variance of deliveries is greater than the variance of sales and that the correlation between inventory investment and sales is zero.

5.1 Industry-Level Results

Because deliveries and sales at the industry-level are $I(1)$, we examine a number of alternative versions of the variance ratio to be sure that the results are robust to the presence of unit roots. The three versions which are presented in the tables are: (1) $\frac{\text{Var}(D)}{\text{Var}(X)}$, where the levels of deliveries and sales are detrended using linear and quadratic time trends as in Mosser (1988, 1991).[21] (2) $\frac{\text{Var}(\Delta D)}{\text{Var}(\Delta X)}$, where the first differences were detrended using a linear trend to be consistent with the detrending used in the first ratio.[22] (3) $1 + \frac{E(D^2 - X^2)}{\text{Var}(\Delta X)} \simeq \frac{\text{Var}(D)}{\text{Var}(X)}$, a ratio calculated by Ramey and West (1997), which is robust to the presence of unit roots. In the tables, we also present the correlation between detrended inventory investment and detrended level of sales.

[21] We also examined detrending the industry-level data using a broken linear trend as in Ramey and West (1997). The results were not affected in any substantial way.

[22] We also examined some alternatives to the above detrending choices: first differences of the raw data with no detrending and first differences of the detrended data (using linear and quadratic time trends as in (1)). The results were not substantially different from those presented in the paper.

These variance ratios and correlations using industry-level data are presented in Table 2A for the retail sector and Table 2B for the wholesale sector. Uniformly across trade industries and aggregates, each version of the ratio indicates that deliveries are more volatile than sales, which consistent with the predictions of the (S, s) model. In addition, the correlation between inventory investment and sales presented in the last column is small (and mostly positive) for almost all categories. These results may not be surprising given those of Mosser (1988, 1991) and the results using aggregate data from the US and other countries (see Ramey and West (1997)), but they do indicate that further examination of the (S, s) model for trade industries is warranted.

5.2 Firm-Level Results

Although unit roots are not an issue at the firm level, we computed the three versions of the variance ratio, as well as the correlation between inventory investment and sales, for each of the 824 firms in our panel. Each variable was demeaned firm-by-firm prior to computing these statistics, which is consistent with the statistics reported for the industry-level data.

In Table 3, we present measures of the sample distribution—mean, variance, median, and quantiles—across firms for each of these statistics.[23] Given the consistent pattern of the relative variability of sales and deliveries in the aggregate and industry-level data, there is considerable cross-sectional heterogeneity for each of the measures of the variance ratio. Still, by any measure of the ratio, the variance of deliveries exceeds or is close to the variance of sales for a significant fraction—more than 50 percent—of firms in the sample.[24] Furthermore, the correlation between inventory investment and sales is not significantly different from zero for most firms.[25] This is consistent with many firms in the sample following (S, s) inventory policies.

For both the industry- and the firm-level data, the variance ratios are largely consistent with the predictions of the (S, s) model. Armed with this preliminary evidence, we turn to a more thorough analysis of whether trade sector inventory behavior is consistent with the (S, s) model.

[23] These statistics computed across the cross-section of firms are not weighted. Weighting by the tenure of the firm in the sample does not have any material effect on the results.

[24] A cursory examination of the variance ratios by industry indicated that the distribution of the statistics did not differ much across 2-digit SICs.

[25] If the calculated firm-specific sample correlation was not significantly different from zero at the 10 percent significance level, the correlation was recorded as zero.

6 The (S, s) Regressions

6.1 Industry-Level Results

As discussed in Section 3, we estimate two different specifications of the (S, s) regression model using industry-level data. The first specification is the generalized model with delivery lags estimated in levels, equation (10). The number of lags of sales included in the model is six.[26] The results of estimating this regression are presented in Table 4A (retail trade) and in Table 4B (wholesale trade).

The first thing to note is that exclusion tests indicate that the coefficients on lagged sales are not jointly zero in many industries, which is consistent with the presence of delivery lags in the (S, s) model. This is especially true for durable goods retailers and wholesalers, where the null hypothesis that $\beta_1 = \ldots = \beta_6 = 0$ can be rejected at the 5 percent significance level in 3 out of 4 retail categories and in 7 out of 9 wholesale industries. For nondurable goods retailers and wholesalers, the rejections of the exclusion restrictions are less frequent.[27]

The estimated coefficients are largely consistent with the predictions of the generalized (S, s) model. For almost all categories in Tables 4A and 4B, the coefficient on contemporaneous sales is statistically not different from zero or is negative; the sum of the coefficients on contemporaneous and lagged sales—even when statistically significant—is very close to zero. The major exceptions are lumber and building materials and furniture and home furnishings in the retail sector, and furniture and hardware in the wholesale sector. In these categories, the evidence—in particular, the positive coefficient on contemporaneous sales and the quantitatively small sum of all the sales coefficients—points to significantly negative coefficients on lagged sales.[28] This is contrary to the prediction that the coefficients on lagged sales should be nonnegative. It is not clear to us why this is so, but the strongly positive coefficient on contemporaneous sales would be difficult to explain in a simple delivery smoothing model also.

The second specification we estimated, equation (11), takes into account that sales are nonstationary. The results presented in Tables 5A (retail trade) and 5B (wholesale trade) are largely in line with the predictions of the (S, s) model. For most trade industries, the coefficient on the first difference of sales is zero or even positive.[29]

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[26] Six lags were chosen in order to be comparable to Mosser (1988, 1991); the regressions also include linear and quadratic time trends.

[27] The exclusion restrictions can be rejected in 2 out of 5 nondurable goods retail categories and in 2 out of 9 nondurable goods wholesale industries (6 out of 9 at the 10 percent significance level).

[28] For two other wholesale industries, groceries and petroleum products, there are similar indications, but the exclusion restrictions on lagged sales coefficients can only be rejected at the 10 percent significance level.

[29] The latter include retail lumber and furniture and wholesale furniture and hardware, where we had observed a positive coefficient on contemporaneous sales in the levels regression.

The one exception to this pattern is an admittedly large one, the retail automotive group, where the coefficient on the first difference of sales is significantly negative.[30] Given the close relationship between automobile dealers and manufacturers, it is not surprising that this industry could provide results which differs from other trade industries; for example, see Blanchard's (1983) study of inventories in the automotive industry.

Nevertheless, our overall results using the industry-level data largely confirm the results of Mosser (1988, 1991). We next turn to a more thorough analysis of the firm-level data to examine whether the behavior of these firms is consistent with the predictions of the (S, s) model.

6.2 Firm-Level Results

Because firm heterogeneity induces heteroskedasticity in the error term, we divide both sides of every regression by a lag of (real) total assets. Table 6 presents estimates of a random coefficients model given in equation (16). The estimated mean of the sales coefficients across firms is 0.04, and is highly statistically significant. This estimate is consistent with the (S, s) model where firms change their targets periodically based on recent sales behavior. In addition, this estimate is quantitatively larger than most of the industry-level estimates from the differenced specification in Tables 5A and 5B.

The second model we estimate allows the slope coefficient to vary across industries. The results of estimating this specification are presented in Table 7. For most industries, the sales coefficient is nonnegative, which is consistent with the (S, s) model. Although the estimates of the sales coefficient are more tightly bunched across industries and have smaller magnitudes in this regression than they do at the industry level, there remain some noticeable differences across industries. For example, the slope coefficients for the two wholesale categories are positive, statistically highly significant, and larger than those in the retail categories. In addition, the coefficient on sales for the furniture and home furnishings category is significantly positive, as was the case in the industry-level regression.

There is one industry were the estimated sales coefficient is not consistent with the simple predictions of the (S, s) model. The department stores category has a negative and a statistically significant slope coefficient of -0.05, which is consistent with delivery smoothing. From an economic perspective, we find this result surprising, because department stores commonly are not thought to be smoothing deliveries. Moreover, the industry-level regressions do not suggest that data from this industry should be inconsistent with the steady-state predictions of the (S, s) model.

Contrast the results of this industry with those of the automotive group retail sector—an industry where the industry-level regressions indicate possible delivery

[30] The effect of the retail automotive group is large enough so that the coefficient on sales difference for total retail sector as well as for total durable goods retail sector is negative.

smoothing and one which is thought to have unique characteristics conducive to delivery smoothing. The coefficient for the automotive group, however, is essentially zero, and so it surprisingly does not provide evidence of delivery smoothing at the firm level.

The reasons for these surprising results for department stores and the automotive group will require further study. Nevertheless, the preliminary conclusion we derive from both the industry-level and firm-level (S, s) regressions is that both the industry- and firm-level data are consistent with the steady-state predictions of the (S, s) model. These predictions, however, are simple reduced-form relationships which, although not compatible with simple delivery smoothing models, could be compatible with more complicated L-Q models. To examine this possibility, we now turn to the Euler equation estimation of the L-Q model.

7 The L-Q Model Estimates

7.1 Industry-Level Results

In this section, we examine how well does the L-Q model fits the industry-level trade data. As discussed in Section 3, the Euler equation (14) is estimated in first differences. Because the residual in the differenced form of equation (14) follows at least an MA(1) process, we use a constant, lags two through four of the first difference in sales and lags two through four of the first difference in inventories as instruments in the GMM estimation. The results from this estimation are presented in Tables 8A (retail trade) and 8B (wholesale trade).

Although there are few outright rejections of the over-identifying restrictions, the estimates of the structural parameters indicate that the L-Q model with convex adjustment costs does not fit the data very well.[31] The parameter a_1/c, which measures the increasing marginal costs of deliveries, is positive and statistically significant for only three retail categories and three wholesale industries. For most of the other industries, the parameter is statistically not different from zero, suggesting that marginal costs are linear in deliveries—consistent with the cost structure of the (S, s) model.[32]

The coefficient a_2/c, which measures the strength of inventory holding costs, is the most precisely estimated parameter of the L-Q model using the industry-level data. It is positive—its theoretical sign—and statistically significant in 6 retail categories

[31] We can reject the overidentifying restrictions for only 2 out of 9 retail categories and 6 out of 18 wholesale industries.

[32] In one retail category (other durable goods stores) and three wholesale industries, the estimate of this coefficient is negative, which also suggests nonconvex costs and delivery bunching. Since the estimated $|a_1|$ is small relative to the estimated a_2 in these industries, the linear-quadratic problem would still be well-posed; see Ramey (1991) for more on nonconvex costs in these models.

and 13 wholesale industries; in remaining industries, the parameter estimates are not significantly different from zero. This suggests that inventory holding costs are important for these industries. In addition, note that for most of those industries where the parameter a_1/c is positive, the ratio a_1/a_2 tends to be relatively large, indicating that the model is trying to capture the persistence of the inventory-sales relationship. On the other hand, the ratio a_1/a_2 tends to be relatively small in those industries where the parameter estimates point to a nonconvex costs structure—for these industries, the model appears to be trying to capture the procyclical behavior of inventories.

The parameter a_3, which measures the relative strength of the stockout motive to hold inventories, is imprecisely estimated. It is positive—its theoretical sign—and statistically significant in only 4 retail categories and 2 wholesale industries. It is statistically not different from zero in the rest of the industries, although there are several industries with negative point estimates. The fact that the parameter capturing the stockout avoidance motive is not strongly positive in most industries implies that it would be difficult to explain procyclical movements in inventories at the industry-level by appealing to stockout costs—an argument advanced by Blinder (1986) and Kahn (1987) to explain procyclical behavior of inventories in L-Q models.

We take the fact that the estimates of the Euler equation across industries are diverse with many "nonsensical" parameters to indicate that the L-Q model is having a hard time matching the industry-level trade data. This suggests that such a model with convex costs, which implies delivery smoothing, is a poor representation of trade inventories, at least at the industry level. We next turn to the firm-level data to see whether the model can have more success at the firm level.

7.2 Firm-Level Results

Estimates of the structural cost parameters obtained from the firm-level Euler equation estimation are presented in Table 9. In contrast to the industry-level results, estimates of the cost parameters from the firm-level data are consistent with a slightly convex delivery cost function, significant inventory holding costs, and a strong accelerator motive.

The estimate of a_1/c, which captures the curvature and the slope of the delivery cost function, is 0.04, statistically highly significant, and indicates that the marginal delivery cost function is upward sloping. Coupled with the statistically significant estimate of 0.98 for the parameter a_2/c—which measures the relative strength of inventory holding costs—the estimated ratio of delivery-to-holding costs, a_1/a_2, is approximately 0.04, indicating that the accelerator term in the cost function will dominate the overall dynamics of inventory investment.

The relative size of these two parameters and the economically and statistically significant estimate of the stockout parameter, a_3, is consistent with the variance condition given in equation (7) and procyclical movements in inventories, both of which we observe at the firm level. The point estimate of the stockout parameter, a_3, is 0.17, implying a target-level of 17 percent of quarterly sales for the stockout avoidance motive, which to us seems like a sensible estimate.[33]

Despite what seem like economically plausible estimates of the structural cost parameters, the over-identifying restrictions imposed on the model can be rejected at a two percent significance level, casting some doubt on the validity of the L-Q model. While tests of the first-order (m_1) and second-order (m_2) serial correlation indicate residual serial correlation of at least order two, both sales and inventories lagged at least three periods were used as instruments. We re-estimated the model with instrument lagged four periods and more, which had no appreciable affect on the parameter estimates, although we can now reject the over-identifying restrictions only at a (marginal) seven percent significance level. This result is consistent with a cost shock process that is highly autocorrelated and which induces higher-order MA process in the Euler equation error term.

8 Concluding Remarks

In this paper, we have examined the (S, s) and linear-quadratic (L-Q) models of trade inventory behavior using both industry- and high-frequency firm-level data. For both of our data sets, we could not reject the steady-state reduced-form predictions of Caplin for the (S, s) model. In addition, estimates of the structural cost parameters of the L-Q model at the industry level are mostly of the "wrong" sign and are imprecisely estimated.

At the firm level, however, the estimates of the underlying cost parameters of the L-Q model are economically meaningful and statistically highly significant. The estimated cost parameters are consistent with a slightly convex delivery cost function, economically significant inventory holding costs, and a strong stockout avoidance motive. The relative magnitude of the estimated cost parameters implies that inventory holding costs will dominate the overall inventory dynamics, which coupled with the strong stockout avoidance motive will generate procyclical inventory movements, highly persistent inventory-sales ratio, and the variance of deliveries exceeding the variance of sales.

The dynamics implied by the estimated cost parameters at the firm level are observationally equivalent to the steady-state probability relationships of inventories, sales, and deliveries derived from the (S, s) model. The economically meaningful estimates of the structural cost parameters obtained from the firm-level data suggest that aggregation may be in part responsible for the failure of the L-Q model at the

[33] We also estimated the Euler equation for the retail and wholesale trade firm separately and obtained virtually identical parameter estimates.

industry level.

To provide a more definitive answer about which model may best explain the behavior of trade inventories will require further refinement of both models. In particular, future research will have to examine structural estimates of the (S, s) model and the dynamics implied by it. High-frequency firm-level data may prove particularly useful in this exercise, because it allows us, for example, to examine the evolution of the cross-sectional distribution of inventories over time.

A Data Appendix

This section describes the construction of variables and the selection rules used to construct of the firm-level panel data set for our analysis.

A.1 Construction of Variables

- **Inventories**: The Compustat data report the book value of total inventories. In the trade sector, inventories consist almost entirely of finished goods inventories (see Blinder and Maccini (1991)). Many retailers are thought to follow first in, first out (FIFO) pricing practices; namely, once a finished good is placed on shelves, it is given a price tag that remains on the item regardless of what subsequently happens to the price of newly produced goods (see Okun (1981), pp. 155-60). Although the firm-level Compustat data does provide limited information on the inventory accounting practices, we assumed that all inventory stocks are evaluated using the FIFO method, so that the replacement value of inventory stocks equals their book value. To convert nominal reported value of inventories to real terms, inventory stocks were deflated by the chain-weighted sectoral (i.e., retail and wholesale) inventory deflator; real inventory investment was define as the first difference in real inventories.

- **Sales**: To construct a real measure of sales, the reported nominal value of sales was deflated by the industry-specific (2-digit SIC) chain-weighted sales deflator for the retail trade sector.

- **Deliveries**: Using real sales and real inventory investment, deliveries were constructed from the accounting identity $D = X + \Delta H$; any remaining variables used in the analysis (e.g., total assets) were deflated by the chain-weighted 1992 GDP price deflator.

A.2 Selection Rules

From the P/S/T, Full Coverage, and Research Compustat data files, we selected all firms with at least 12 continuous quarters of data between 1976:Q1–94:Q4. This procedure yielded a sample of 1,054 firms. To avoid results that are driven by a small number of extreme observations, three criteria were used to eliminate firms with substantial outliers or obvious errors:

1. If a firm's estimate of deliveries from the accounting identity $D = X + \Delta H$ was negative at any point during a firm's tenure in the sample, a firm was eliminated in its entirety.

2. If a firm's growth rate of (real) inventories was below the 0.50th or above the 99.50th percentile of the distribution at any point during a firm's tenure in the sample, a firm was eliminated in its entirety.
3. If a firm's growth rate of (real) sales was below the 0.50th or above the 99.50th percentile of the distribution at any point during a firm's tenure in the sample, a firm was eliminated in its entirety.

As a consequence of these selection rules, 230 firms were eliminated, leaving 824 firms in the final data set.[34] By sector, 293 firms belong to the wholesale trade sector, and 531 firms belong to the retail trade sector.

[34]Subsequent analysis of firms that were deleted from the sample revealed severe anomalies in their data (e.g., quarterly growth rates of sales and inventories in excess of 200%.

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Figure I
Share of Trade Inventories

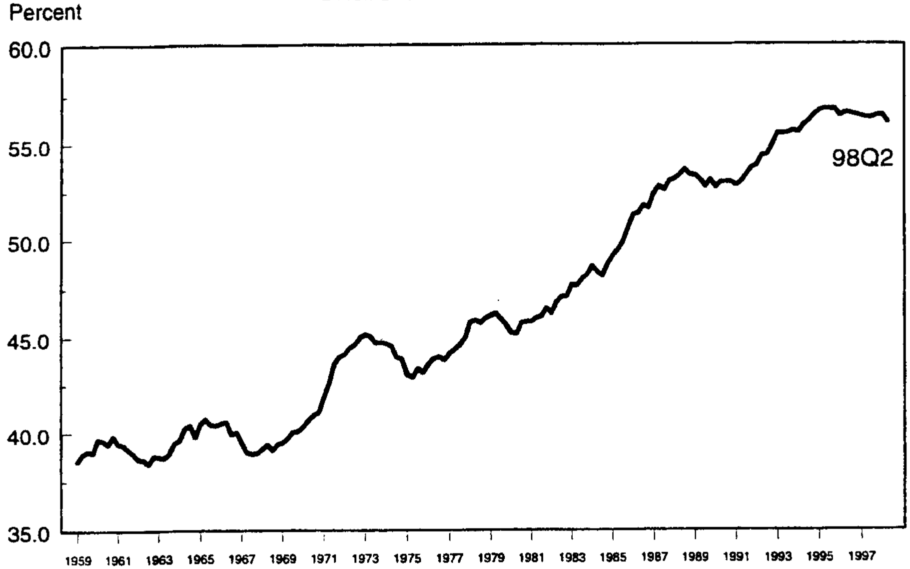
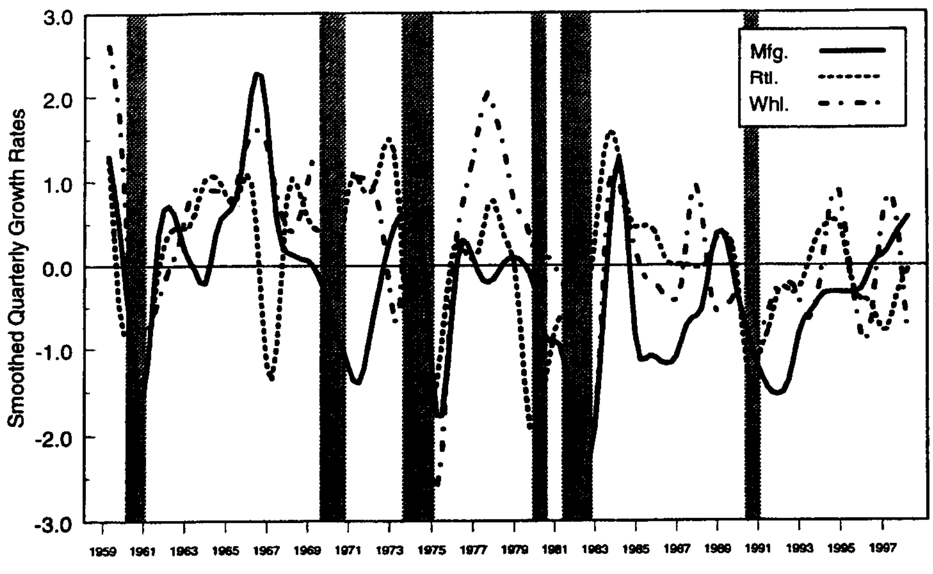


Figure II
Inventory Growth Rates



Note: The shaded regions represent N.B.E.R. recessions.

Table 1

Firm-Level Data
Summary Statistics

Variable	*Mean*	*Std. Dev.*	*Median*
Inventories	160.1	489.6	39.9
Net Sales	351.2	1017.4	81.8
Deliveries	360.0	1030.7	85.0
Total Assets	729.0	4048.3	147.4
Inv/Sales Ratio	0.59	0.44	0.52
Inv. Investment	2.48	73.3	0.12
Inv. Growth Rate (%)	1.79	15.9	1.68
Sales Growth Rate (%)	1.76	21.2	2.02
No. of Firms	824		
Max. Tenure	84		
Min. Tenure	12		
Avg. Tenure	30.3		
Observations	24,995		

Notes: Sample period: 1976:Q1–96:Q4. All variables are in millions of 1992 chain-weighted dollars.

Table 2A

Retail Trade
Relative Variability of Deliveries and Sales

Industry Classification	$\frac{\text{Var}(D)^a}{\text{Var}(X)}$	$\frac{\text{Var}(\Delta D)^b}{\text{Var}(\Delta X)}$	$1+\frac{E[D^2-X^2]^c}{\text{Var}(\Delta X)}$	$\text{Corr}(\Delta H, X)^d$
Retail Trade	1.09	1.57	2.91	0.05
Durable Goods	1.15	1.49	2.54	0.06
Automotive Group	1.21	1.50	2.00	0.01
Lumber & Building Materials	1.27	5.71	4.61	0.11
Furniture & Home Furnishings	1.03	6.43	4.94	-0.07
Other Durables	1.58	10.9	7.50	0.06
Nondurable Goods	1.05	1.88	2.41	-0.05
Food Stores	1.07	1.26	1.95	0.05
Apparel Stores	1.27	3.44	2.74	-0.02
Department Stores	1.11	4.42	3.29	-0.06
General Merch. Stores	1.16	5.11	4.31	0.01
Miscellaneous Retail	1.03	2.32	2.55	-0.04

Notes: Sample Period: 1959:01–97:08. The data are seasonally adjusted in millions of 1992 chain-weighted dollars; D denotes deliveries, X denotes sales, and ΔH denotes inventory investment. All variables are linked by the identity $D = X + \Delta H$.

[a]Detrended levels.

[b]Detrended first-differences.

[c]This term is essentially $\text{Var}(D)/\text{Var}(X)$, computed under the assumption that both D and X are non-stationary; see Ramey and West (1997) for details

[d]Detrended first-difference and detrended level.

Table 2B

Wholesale Trade
Relative Variability of Deliveries and Sales

Industry Classification	$\frac{\text{Var}(D)^a}{\text{Var}(X)}$	$\frac{\text{Var}(\Delta D)^b}{\text{Var}(\Delta X)}$	$1 + \frac{E[D^2 - X^2]^c}{\text{Var}(\Delta X)}$	$\text{Corr}(\Delta H, X)^d$
Wholesale Trade	1.08	1.64	2.66	0.12
Durable Goods	1.12	2.16	2.17	0.18
Motor Vehicles	1.27	3.06	2.60	0.11
Furniture	1.46	3.46	2.38	0.09
Lumber	1.11	2.00	2.06	0.09
Professional Equip.	1.01	3.62	2.22	-0.04
Metals, Minerals (ex. Petroleum)	1.23	2.32	2.97	0.25
Electrical Goods	1.17	3.75	4.66	0.14
Hardware	1.37	3.94	3.67	0.18
Machinery	1.29	4.50	4.99	0.20
Other Durables	1.07	1.66	1.52	-0.06
Nondurable Goods	1.08	1.68	1.45	0.02
Paper Products	1.18	2.53	2.31	0.05
Drugs & Sundries	1.25	6.32	4.04	0.06
Apparel	1.47	2.86	2.56	0.13
Groceries	1.13	1.63	1.43	0.12
Farm products	1.14	1.61	1.35	0.02
Chemical & Allied Products	1.10	1.94	1.67	-0.00
Petroleum Products	1.08	1.29	1.28	0.09
Alcoholic Beverages	1.43	1.80	1.64	0.05
Other Nondurables	1.13	1.92	1.35	-0.04

Notes: For the wholesale trade and durable and nondurable categories the sample period is 1959:01–97:08; for the 2-digit SICs, the sample period is 1967:01–97:08. The data are seasonally adjusted in billions of 1992 chain-weighted dollars; D denotes deliveries, X denotes sales, and ΔH denotes inventory investment. All variables are linked by the identity $D = X + \Delta H$.

[a]Detrended levels.

[b]Detrended first-differences.

[c]This term is essentially $\text{Var}(D)/\text{Var}(X)$, computed under the assumption that both D and X are nonstationary; see Ramey and West (1997) for details

[d]Detrended first-difference and detrended level.

Table 3

Firm-Level Trade Data
Relative Variability of Deliveries and Sales

Statistic	$\frac{\mathrm{Var}(D)}{\mathrm{Var}(X)}$	$\frac{\mathrm{Var}(\Delta D)}{\mathrm{Var}(\Delta X)}$	$1+\frac{E[D^2-X^2]^a}{\mathrm{Var}(\Delta X)}$	$\mathrm{Corr}(\Delta H, X)^b$
Mean	1.03	1.48	1.43	-0.08
Std. Dev.	0.49	1.75	1.71	0.29
Maximum	7.23	30.9	34.7	0.75
75% Q3	1.11	1.65	1.38	0.00
Median	1.00	1.08	1.04	0.00
25% Q1	0.87	0.79	0.92	0.00
Minimum	0.25	0.06	-0.20	-0.92
$N = 824$				

Notes: Sample Period: 1976:Q1–96:Q4. The data are in millions of 1992 chain-weighted dollars and have been demeaned firm-by-firm; D denotes deliveries, X denotes sales, and ΔH denotes inventory investment. The variables are linked by the identity $D = X + \Delta H$.

[a] This term is essentially $\mathrm{Var}(D)/\mathrm{Var}(X)$, computed under the assumption that both D and X are nonstationary; see Ramey and West (1997) for details

[b] If the firm-specific correlation coefficient was not different from zero at a 10 percent significance level, the correlation was set to zero.

Table 4A

Estimated Equation for Retail Trade:

$$\Delta H_t = \alpha + \sum_{k=0}^{6} \beta_k X_{t-k} + \delta_1 t + \delta_2 t^2 + \epsilon_t$$

Industry Classification	α	β_0	$\sum_{k=0}^{6} \beta_k$	*Excl.*[a]	*Adj.* R^2	*D-W*
Retail Trade	-0.39	-0.10	0.01	0.00	0.08	1.71
	(0.61)	(0.05)	(0.01)			
Durable Goods	-0.44	-0.16	0.03	0.00	0.08	1.57
	(0.24)	(0.08)	(0.02)			
Automotive Group	-0.33	-0.19	0.04	0.00	0.06	1.58
	(0.19)	(0.10)	(0.02)			
Lumber & Building Materials	-0.08	0.17	0.02	0.00	0.04	2.51
	(0.06)	(0.06)	(0.02)			
Furniture & Home Furnishings	0.07	0.18	-0.04	0.00	0.11	2.06
	(0.04)	(0.11)	(0.02)			
Other Durables	-0.03	-0.02	0.04	0.14	0.00	2.13
	(0.04)	(0.11)	(0.03)			
Nondurable Goods	0.76	-0.06	-0.02	0.00	0.04	1.99
	(0.62)	(0.04)	(0.02)			
Food Stores	-0.16	0.01	0.01	0.75	-0.01	1.91
	(0.18)	(0.03)	(0.01)			
Apparel Stores	0.04	-0.09	-0.01	0.01	0.01	2.01
	(0.08)	(0.08)	(0.03)			
Department Stores	0.16	-0.17	-0.04	0.00	0.07	1.99
	(0.06)	(0.10)	(0.02)			
General Merch. Stores	0.01	-0.03	0.00	0.27	0.00	1.92
	(0.05)	(0.08)	(0.02)			
Miscellaneous Retail	0.29	0.03	-0.01	0.13	0.02	2.21
	(0.17)	(0.04)	(0.01)			

Notes: Estimation Period: 1959:07–97:08. The data are seasonally adjusted in billions of 1992 chain-weighted dollars. All regression include linear and quadratic time trends (not reported) and are estimated with OLS, with heteroscedasticity and autocorrelation consistent asymptotic standard errors reported in parenthesis.

[a]Probability value for the Wald test of the null hypothesis that lagged sales coefficients are jointly zero: $H_0 : \beta_1 = \ldots = \beta_6 = 0$.

Table 4B

Estimated Equation for Wholesale Trade:

$$\Delta H_t = \alpha + \sum_{k=0}^{6} \beta_k X_{t-k} + \delta_1 t + \delta_2 t^2 + \epsilon_t$$

Industry Classification	α	β_0	$\sum_{k=0}^{6} \beta_k$	*Excl.*	*Adj.* R^2	*D-W*
Wholesale Trade	-0.33	0.05	0.01	0.24	0.04	2.02
	(0.45)	(0.03)	(0.01)			
Durable Goods	-0.40	-0.03	0.03	0.01	0.06	2.23
	(0.23)	(0.04)	(0.01)			
Motor Vehicles	0.16	-0.02	0.05	0.01	0.03	2.15
	(0.13)	(0.07)	(0.03)			
Furniture	-0.02	0.16	0.02	0.01	0.04	2.37
	(0.02)	(0.05)	(0.02)			
Lumber	-0.01	0.06	0.01	0.12	0.01	2.29
	(0.04)	(0.04)	(0.01)			
Professional Equip.	0.16	-0.03	-0.01	0.24	0.06	2.63
	(0.06)	(0.10)	(0.01)			
Metals & Minerals	-0.13	0.01	0.07	0.01	0.03	2.07
	(0.09)	(0.05)	(0.02)			
Electrical Goods	-0.06	0.09	0.03	0.01	0.09	2.36
	(0.05)	(0.06)	(0.02)			
Hardware	-0.06	0.23	0.03	0.00	0.15	2.31
	(0.05)	(0.06)	(0.02)			
Machinery	0.06	0.23	0.06	0.01	0.06	2.29
	(0.12)	(0.16)	(0.02)			
Other Durables	0.22	-0.02	-0.04	0.01	0.01	2.16
	(0.08)	(0.04)	(0.02)			

Table 4B (Continued)

Industry Classification	α	β_0	$\sum_{k=0}^{6}\beta_k$	*Excl.*[a]	*Adj.* R^2	*D-W*
Nondurable Goods	0.24	0.01	-0.01	0.00	0.03	1.96
	(0.27)	(0.03)	(0.01)			
Paper Products	0.02	0.03	0.00	0.06	0.09	2.24
	(0.07)	(0.06)	(0.03)			
Drugs & Sundries	-0.00	0.11	0.01	0.01	0.10	2.41
	(0.08)	(0.08)	(0.02)			
Apparel	-0.12	0.15	0.06	0.13	0.02	2.24
	(0.08)	(0.09)	(0.04)			
Groceries	-0.17	0.10	0.02	0.06	0.03	2.33
	(0.10)	(0.03)	(0.02)			
Farm Products	0.01	0.02	0.01	0.31	-0.00	1.60
	(0.12)	(0.03)	(0.02)			
Chemical & Allied Products	0.02	-0.01	-0.01	0.01	0.00	2.49
	(0.19)	(0.05)	(0.01)			
Petroleum Products	0.03	0.06	0.00	0.06	0.02	2.09
	(0.05)	(0.03)	(0.01)			
Alcoholic Beverages	0.01	0.03	0.00	0.08	0.03	2.33
	(0.03)	(0.04)	(0.03)			
Other Nondurables	0.01	0.01	-0.01	0.31	0.02	2.22
	(0.13)	(0.03)	(0.02)			

Notes: For the wholesale trade and durable and nondurable categories the estimation period is 1959:07–97:08; for the 2-digit SICs, the estimation period is 1967:07–97:08. The data are seasonally adjusted in billions of 1992 chain-weighted dollars. All regression include linear and quadratic time trends (not reported) and are estimated with OLS, with heteroscedasticity and autocorrelation consistent asymptotic standard errors reported in parenthesis.

[a]Probability value for the Wald test of the null hypothesis that lagged sales coefficients are jointly zero: $H_0 : \beta_1 = \ldots = \beta_6 = 0$.

Table 5A

Estimated Equation for Retail Trade:

$$\Delta H_t = \alpha + \beta_0 \Delta X_t + u_t$$

Industry Classification	α	β_0	*Adj.* R^2	*D-W*
Retail Trade	0.53	-0.09	0.01	1.56
	(0.09)	(0.04)		
Durable Goods	0.30	-0.17	0.04	1.52
	(0.07)	(0.06)		
Automotive Group	0.17	-0.18	0.04	1.57
	(0.05)	(0.07)		
Lumber & Building Materials	0.02	0.15	0.01	2.43
	(0.01)	(0.07)		
Furniture & Home Furnishings	0.04	0.19	0.01	1.98
	(0.01)	(0.09)		
Other Durables	0.06	-0.01	-0.00	2.09
	(0.01)	(0.11)		
Nondurable Goods	0.24	-0.04	0.00	1.86
	(0.03)	(0.03)		
Food Stores	0.05	0.00	-0.00	1.90
	(0.01)	(0.00)		
Apparel Stores	0.03	-0.12	0.01	1.99
	(0.01)	(0.07)		
Department Stores	0.10	-0.15	0.01	1.83
	(0.02)	(0.08)		
General Merch. Stores	0.01	-0.05	-0.00	1.89
	(0.01)	(0.08)		
Miscellaneous Retail	0.04	0.01	-0.00	2.19
	(0.01)	(0.04)		

Notes: Estimation Period: 1959:02–97:08. The data are seasonally adjusted in billions of 1992 chain-weighted dollars. All regressions are estimated with OLS, with heteroscedasticity and autocorrelation consistent asymptotic standard errors reported in parenthesis.

Table 5B

Estimated Equation for Wholesale Trade:

$$\Delta H_t = \alpha + \beta_0 \Delta X_t + \epsilon_t$$

Industry Classification	α	β_0	*Adj.* R^2	*D-W*
Wholesale Trade	0.45	0.05	0.00	1.95
	(0.06)	(0.03)		
Durable Goods	0.30	0.00	-0.00	2.10
	(0.04)	(0.04)		
Motor Vehicles	0.05	0.01	-0.00	2.11
	(0.02)	(0.06)		
Furniture	0.01	0.14	0.02	2.36
	(0.00)	(0.06)		
Lumber	0.01	0.04	0.00	2.23
	(0.05)	(0.04)		
Professional Equip.	0.07	0.07	0.00	2.53
	(0.01)	(0.10)		
Metals & Minerals	0.02	0.02	0.00	1.91
	(0.01)	(0.05)		
Electrical Goods	0.05	0.10	0.00	2.26
	(0.01)	(0.06)		
Hardware	0.02	0.21	0.04	2.20
	(0.01)	(0.07)		
Machinery	0.05	0.19	0.02	2.18
	(0.03)	(0.07)		
Other Durables	0.03	-0.04	0.00	2.10
	(0.01)	(0.03)		

Table 5B (Continued)

Industry Classification	α	β_0	*Adj.* R^2	*D-W*
Nondurable Goods	0.15	0.10	0.03	1.95
	(0.02)	(0.02)		
Paper Products	0.02	0.04	-0.00	2.13
	(0.00)	(0.06)		
Drugs & Sundries	0.03	0.16	0.00	2.25
	(0.00)	(0.06)		
Apparel	0.03	0.12	0.01	2.21
	(0.01)	(0.06)		
Groceries	0.03	0.08	0.03	2.31
	(0.01)	(0.03)		
Farm Products	0.02	0.01	-0.00	1.59
	(0.01)	(0.03)		
Chemical & Allied Products	0.01	-0.03	-0.00	2.46
	(0.00)	(0.05)		
Petroleum Products	0.01	0.05	0.02	2.06
	(0.00)	(0.03)		
Alcoholic Beverages	0.01	-0.06	0.00	2.27
	(0.00)	(0.06)		
Other Nondurables	0.03	-0.03	0.00	2.19
	(0.01)	(0.00)		

Notes: For the wholesale trade and durable and nondurable categories the estimation period is 1959:02–97:08; for the 2-digit SICs, the estimation period is 1967:02–97:08. The data are seasonally adjusted in billions of 1992 chain-weighted dollars. All regressions are estimated with OLS, with heteroscedasticity and autocorrelation consistent asymptotic standard errors reported in parenthesis.

Table 6

Mean-Group Parameter Estimates
Estimated Equation:

$$\Delta H_{it} = \alpha_i + \beta_i X_{it} + d_{mt} + \epsilon_{it}$$

Estimate	*Std. Error*	*Adj.* R^2	N	T	*Obs.*
$\beta = 0.04$	0.01	0.24	824	29.3	24,171

Notes: Estimation Period: 1976Q2–96:Q4. The data are in millions of 1992 chain-weighted dollars. Both sides of the equation are divided by (real) total assets from period $t-1$ to control for heteroscedasticity. The regression includes fixed firm and industry-specific time effects (not reported) and is estimated by the Mean-Group procedure developed by Pesaran, Smith, and Im (1996).

Table 7

Industry-Specific Sales Coefficients
Estimated Equation:

$$\Delta H_{it} = \alpha_i + I_{im}\beta X_{it} + d_{mt} + \epsilon_{it}$$

Industry Classification	*Estimate*	*Std. Error*
Wholesale Durables	0.09	0.01
Wholesale Nondurables	0.05	0.01
Retail Trade		
Automotive Group	-0.00	0.03
Lumber & Building Materials	0.01	0.02
Furniture & Home Furnishings	0.05	0.02
Other Durables	-0.00	0.02
Food Stores	0.02	0.00
Apparel Stores	-0.00	0.02
Department Stores	-0.05	0.02
Eating & Drinking Places	0.00	0.00
Other Nondurables	0.01	0.01
Adj. $R^2 = 0.24$		
$N = 824$		
$\bar{T} = 29.3$		
$Obs = 24,171$		

Notes: Estimation Period: 1976Q2–96:Q4. The data are in millions of 1992 chain-weighted dollars. $I_{i,m}$ denotes the indicator function, which equals 1 if firm i is industry m and 0 otherwise. Both sides of the equation are divided by (real) total assets from period $t-1$ to control for heteroscedasticity. The regression includes fixed firm and industry-specific time effects (not reported) and is estimated with OLS. Standard errors have been corrected for heteroscedasticity.

Table 8A

Euler Equation Estimates for Retail Trade

Industry Classification	a_1/c	a_2/c	a_3	a_1/a_2	*Prob* $> J^a$
Durables					
Automotive Group	0.44	0.12	-4.06	3.68	0.71
	(0.12)	(0.24)	(7.18)		
Lumber & Building Materials	-0.13	1.27	1.49	-0.10	0.04
	(0.22)	(0.44)	(0.59)		
Furniture & Home Furnishings	-0.23	1.46	0.73	-0.15	0.02
	(0.19)	(0.38)	(0.31)		
Other Durables	-0.36	1.73	0.32	-0.21	0.17
	(0.15)	(0.31)	(0.15)		
Nondurables					
Food Stores	0.01	0.99	0.11	0.01	0.43
	(0.08)	(0.16)	(0.14)		
Apparel Stores	0.40	0.21	-2.75	1.89	0.11
	(0.13)	(0.26)	(5.41)		
Department Stores	0.64	-0.27	2.99	-2.35	0.72
	(0.27)	(0.54)	(2.52)		
General Merch. Stores	0.04	0.93	-2.55	0.04	0.25
	(0.18)	(0.36)	(2.23)		
Miscellaneous Retail	-0.36	1.73	0.32	-0.21	0.44
	(0.54)	(0.31)	(0.15)		

Notes: Estimation Period: 1959:06–97:06. The data are seasonally adjusted in billions of 1992 chain-weighted dollars. All regressions are in first-differences and include a constant term (not reported) and are estimated with GMM using $\Delta H_{t-2}, \Delta H_{t-3}, \Delta H_{t-4}, \Delta X_{t-2}, \Delta X_{t-3}$, and ΔX_{t-4} as instruments. Heteroscedasticity and autocorrelation consistent asymptotic standard errors of the structural cost parameters are computed according to the delta method and are reported in parenthesis.

[a]Probability value for the test of the over-identifying restrictions; the J-statistic is distributed as χ^2 with four degrees of freedom (see Hansen (1982)).

Table 8B

Euler Equation Estimates for Wholesale Trade

Industry Classification	a_1/c	a_2/c	a_3	a_1/a_2	$Prob > J$
Durables					
Motor Vehicles	0.14	0.73	-0.65	0.19	0.12
	(0.17)	(0.34)	(0.78)		
Furniture	0.12	0.76	-0.63	0.16	0.31
	(0.45)	(0.92)	(1.13)		
Lumber	0.05	0.91	-0.02	0.05	0.50
	(0.14)	(0.27)	(0.35)		
Professional Equip.	-0.47	1.93	0.40	-0.24	0.20
	(0.09)	(0.18)	(0.16)		
Metals & Minerals	0.29	0.42	-1.24	0.69	0.01
	(0.09)	(0.18)	(0.74)		
Electrical Goods	0.30	0.41	0.96	0.73	0.00
	(0.17)	(0.34)	(0.74)		
Hardware	-0.01	1.03	-0.67	-0.01	0.01
	(0.12)	(0.24)	(0.49)		
Machinery	-0.30	1.60	0.13	-0.19	0.00
	(0.15)	(0.30)	(0.30)		
Other Durables	0.02	0.96	0.34	0.02	0.54
	(0.15)	(0.30)	(0.25)		

Table 8B (Continued)

Industry Classification	a_1/c	a_2/c	a_3	a_1/a_2	$Prob > J^a$
Nondurables					
Paper Products	0.49	0.03	15.2	16.3	0.75
	(0.31)	(0.62)	(284.9)		
Drugs & Sundries	-0.02	1.05	0.14	-0.02	0.04
	(0.15)	(0.31)	(0.33)		
Apparel	0.56	-0.12	0.35	-4.67	0.94
	(0.28)	(0.57)	(2.58)		
Groceries	-0.30	1.60	0.28	-0.19	0.61
	(0.14)	(0.27)	(0.12)		
Farm Products	0.56	-0.12	0.35	-4.67	0.72
	(0.28)	(0.57)	(2.58)		
Chemical & Allied Products	-0.28	1.58	0.05	-0.18	0.02
	(0.19)	(0.38)	(0.31)		
Petroleum Products	0.12	0.77	-0.23	0.16	0.35
	(0.17)	(0.35)	(0.39)		
Alcoholic Beverages	-0.17	1.35	0.05	-0.13	0.66
	(0.17)	(0.34)	(0.44)		
Other Nondurables	0.03	0.95	-0.14	0.03	0.39
	(0.12)	(0.24)	(0.30)		

Notes: Estimation Period: 1967:06–97:06. The data are seasonally adjusted in billions of 1992 chain-weighted dollars. All regressions are in first-differences and include a constant term (not reported) and are estimated with GMM using $\Delta H_{t-2}, \Delta H_{t-3}, \Delta H_{t-4}, \Delta X_{t-2}, \Delta X_{t-3}$, and ΔX_{t-4} as instruments. Heteroscedasticity and autocorrelation consistent asymptotic standard errors of the structural cost parameters are computed according to the delta method and are reported in parenthesis.

[a]Probability value for the test of the over-identifying restrictions; the J-statistic is distributed as χ^2 with four degrees of freedom (see Hansen (1982)).

Table 9

Firm-Level Euler Equation Estimates

a_1/c	a_2/c	a_3	a_1/a_2	$Prob > J^a$	$m_1/m_2{}^b$
0.04	0.98	0.17	0.04	0.02	9.21/10.83
(0.00)	(0.01)	(0.00)			
$N = 824$					
$\bar{T} = 25.3$					
$Obs = 20,875$					

Notes: Estimation Period: 1976:Q4–96:Q3. The data in millions of 1992 chain-weighted dollars. Both sides of the estimable Euler equation specification are divided by (real) total assets in period $t-1$ to control for heteroscedasticity. The regression equation includes fixed firm effects (eliminated using orthogonal deviations) and industry-specific time effects (not reported) and is estimated with GMM using $H_{it-3}, H_{it-4}, H_{it-5}, X_{it-3}, X_{it-4}$, and X_{it-5} as instruments. Heteroscedasticity and autocorrelation consistent asymptotic standard errors of the structural cost parameters are computed according to the delta method and are reported in parenthesis.

[a]Probability value for the test of the over-identifying restrictions; the J-statistic is distributed as χ^2 with 474 degrees of freedom (see Hansen (1982)).

[b]Generalized test for the first-order (m_1) and second-order (m_2) serial correlation. The m_1- and m_2-statistics are distributed asymptotically as $N(0,1)$; see Arellano and Bond (1991)