

# An Empirical Investigation of Fluctuations in Manufacturing Sales and Inventory within a Sticky-Price Framework

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**T**he macroeconomics literature has recently witnessed a resurgence of interest in issues related to nominal price rigidities. In particular, advances in computational methods have allowed for the analysis of fully articulated quantitative general equilibrium models with inflexible prices.<sup>1</sup> Because nominal price rigidities create predictable variations in sales, these models provide a natural setting for the study of inventory behavior. Specifically, firms that face increasing marginal costs wish to smooth production and, given predictable variations in sales, can naturally use inventories to accommodate any difference between a smooth production volume and sales.

Hornstein and Sarte (1998) study the implications of sticky prices for inventory behavior under different assumptions about the nature of the driving process. Regardless of whether the economy is driven by nominal demand or real supply shocks, the authors find that an equilibrium model with inflexible prices can replicate the main stylized facts of inventory behavior. Namely, production is more volatile than sales while inventory investment is positively correlated with sales at business cycle frequencies. More importantly, their study also makes specific predictions about the dynamic adjustment of inventories and sales to these shocks. In response to a permanent positive money growth

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<sup>1</sup> See Goodfriend and King (1997) for a survey of recent work.

innovation, both sales and inventories contemporaneously rise before gradually returning to the steady state. In contrast, a permanent positive technology shock leads to a rise in sales and a fall in inventories on impact. As time passes by, sales increase monotonically and eventually reach a new higher steady-state level.

In this article, we estimate a structural vector autoregression (SVAR), where money is constrained to be neutral in the long run, in order to gauge the degree to which these theoretical dynamic adjustment paths hold in the data. Using manufacturing data, we find that the impulse response of sales and inventories to nominal shocks is generally consistent with the predictions of a sticky-price model. Furthermore, both sales and inventories also behave as predicted in the long run in response to a technology shock. Contrary to theory, however, we find that inventories contemporaneously rise in response to a positive innovation in technology. In all cases, the data indicate significantly more sluggishness in the dynamic adjustment of sales and inventories to shocks than implied by current models with sticky prices. The latter finding is consistent with earlier work by Feldstein and Auerbach (1976), as well as Blinder and Maccini (1991), using stock-adjustment equations. More recently, Ramey and West (1997) also find that the inventory:sales relationship is unusually sluggish. They are able to explain this result by appealing either to persistent shocks to the cost of production or to a strong accelerator motive within a linear quadratic framework.

Although the earlier analysis in Hornstein and Sarte (1998) makes specific predictions regarding the dynamic response of sales and inventories to various shocks, it does not assess the relative importance of these shocks as sources of fluctuations. Here we use our estimated VAR to acquire some insight into the significance of both real and nominal shocks in generating fluctuations in sales and the inventory:sales ratio. We find that nominal shocks generally contribute little to the forecast error variance in the latter variables at both short and long horizons. Instead, consistent with earlier work such as King, Plosser, Stock, and Watson (1991), fluctuations in real variables tend to be dominated by real disturbances. Moreover, these empirical findings tend to hold consistently throughout different historical episodes at the business cycle frequency. One exception concerns monetary disturbances that play a noticeably more important role in generating inventory:sales ratio fluctuations in the early 1990s.

This article is organized as follows. We first set up and motivate an empirical model that is consistent with generic restrictions implied by an equilibrium model of inventory behavior. In particular, we assume that money is neutral in the long run and that the inventory:sales ratio is a stationary process without trend. Note that we do not impose any a priori restrictions that are directly tied to the assumption of sticky prices. The next section examines various integration and cointegration properties of the data under consideration. We then analyze the impulse responses of sales and the inventory:sales ratio to various shocks. We also try to gauge the relative importance of these shocks

as sources of fluctuations in the latter variables. After that, we offer some cautionary remarks regarding the specific empirical implementation in this article. The final section concludes the analysis.

## 1. INVENTORY FLUCTUATIONS: THEORETICAL MOTIVATION

To set the stage and notation for the econometric specification, we will provide some theoretical background on the behavior of inventories. The basic framework we have in mind is one in which firms use inventories to smooth production in a setting with staggered nominal prices.<sup>2</sup> The assumption of inflexible price adjustment provides a natural role for production smoothing as the underlying factor driving inventory behavior. In particular, nominal price rigidity creates predictable variations in sales. Suppose, for instance, that the nominal price set by a given firm is fixed over some time interval. If the general price level increases over that time interval, then the firm's relative price correspondingly falls and its sales rise, all else being equal. Given this rising sales path, the firm also attempts to minimize total production costs by keeping production relatively smooth. Inventories can then be used to make up for the differences between production and sales. In addition to identifying this sticky-price motive, we, like Khan (1987), assume that firms may also hold inventories to avoid costly stock-outs.

Within the context of this framework, the dynamic adjustment of inventories and sales to various shocks will generally depend on how preferences and technology are specified. In the long run, however, the model exhibits basic neoclassical properties that can be used for the purposes of identification. One of these properties suggests that money is neutral and, moreover, that changes in the steady-state level of sales ultimately arise from innovations in technology. With this in mind, we let the long-run component of the sales process evolve according to

$$s_t^* = \delta_s + s_{t-1}^* + \Phi_s(L)a_t, \quad (1)$$

where  $s_t^*$  denotes the log level of sales and  $a_t$  captures shocks to technology. The lag polynomial  $\Phi_s(L)$ , as well as all other polynomials described below, is assumed to have absolutely summable coefficients with roots lying outside the unit circle. Observe that equation (1) implicitly assumes that the sales process possesses a unit root. We formally test this assumption later in this article.

In principle, the steady-state level of inventories can be thought of as being determined by the two forces we described previously. Note that in a

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<sup>2</sup> See Hornstein and Sarte (1998) for details of the model.

model with rigid prices, firms naturally wish to hold inventories to accommodate any difference between predictable variations in sales and a smooth production volume. Moreover, by using inventories to avoid costly stock-outs, firms generally target some appropriate inventory:sales ratio in the long run. Although the short- and medium-run dynamics of inventories typically depend on both these forces, Hornstein and Sarte (1998) note that in the steady state, the level of inventories reflects almost exclusively the stock-out avoidance motive. Accordingly, we may express long-run inventories as

$$n_t^* = s_t^* + \xi, \quad (2)$$

where  $n_t^*$  denotes the log level of inventories and  $\xi$  is some target inventory:sales ratio. It immediately follows from (1) and (2) that inventories and sales share a common stochastic trend whose growth rate is  $\delta_s + \Phi_s(L)a_t$ . Furthermore, as we make clear below, the inventory:sales ratio becomes a stationary stochastic process.

Since in this article we are partly interested in how monetary shocks affect the dynamics of inventories and sales, we must specify our beliefs about the behavior of money. To this end, we let the long-run component of money evolve according to

$$m_t^* = \delta_m + \Phi_m(L)[a_t, \eta_t]', \quad (3)$$

where  $m_t^*$  is the log level of money and  $\eta_t$  denotes money innovations. Note that, as in Gali (1999), we allow monetary policy to respond permanently to long-run changes in technology,  $a_t$ . This assumption captures the idea that the Federal Reserve reacts to permanent real changes in the economic environment in its effort to keep prices stable. We further assume that  $a_t$  and  $\eta_t$  are serially and mutually uncorrelated shocks.

While we have assumed that long-run changes in sales are ultimately determined by technological considerations, sales may actually respond to a variety of economic shocks in the short run. More specifically, the level of sales,  $s_t$ , may deviate temporarily from its long-run value because of money shocks or transitory real demand shocks. Such real shocks may include temporary changes in tastes, for instance. Therefore, a complete process for sales can be described as

$$s_t = s_t^* + \psi_s(L)[a_t, \eta_t, e_t]', \quad (4)$$

where  $e_t$  captures a mixture of temporary real demand shocks. These are assumed to be serially uncorrelated as well as uncorrelated with  $a_t$  and  $\eta_t$ . In principle, the fact that  $s_t$  depends on all shocks in the model allows for flexible short-run dynamics. The aim of our empirical exercise is, in part, to gauge whether these short-run dynamics are consistent with the predictions of a model with nominal price rigidities. Taking the first difference in equation (4) and

substituting equation (1) into it yields

$$\Delta s_t = \delta_s + \Phi_s(L)a_t + (1 - L)\psi_s(L)[a_t, \eta_t, e_t]', \quad (5)$$

which represents one of the structural equations to be estimated.

As in (4), one generally expects the level of inventories to be sensitive to all shocks in the short run. Consequently, we may write the following stochastic process for inventories:

$$n_t = n_t^* + \psi_n(L)[a_t, \eta_t, e_t]'. \quad (6)$$

Note that the theoretical framework we have been using predicts a testable cointegrating restriction. In particular, while (1) and (2) suggest that both inventories and sales are integrated of order one (often denoted  $I(1)$ ), these equations combined with (4) also suggest that the difference between inventories and sales is stationary (or  $I(0)$ ). Formally, we can use (6) along with equations (1), (2), and (4) to show that

$$n_t - s_t = \xi + \{\psi_n(L) - \psi_s(L)\}[a_t, \eta_t, e_t]'. \quad (7)$$

The above equation clearly indicates that the inventory:sales ratio will deviate from its long-run value at high and medium frequency. By construction, these deviations are never permanent.

To complete the econometric specification, we allow monetary policy to respond to various shocks not only in the long run but also in the short run. The latter assumption along with equation (3) yields

$$\Delta m_t = \delta_m + \Phi_m(L)[a_t, \eta_t]' + (1 - L)\psi_m(L)[a_t, \eta_t, e_t]'. \quad (8)$$

At this point, we wish to stress that the identifying restrictions made in this section are, in fact, quite generic and unrelated to the notion of sticky prices per se. Therefore, if the results below turn out to be consistent with the notion of nominal rigidities, this outcome will not be as a direct consequence of the identifying strategy used. It remains that different identification strategies may yield different results. Because our restrictions are relatively general, however, they encompass a broad range of models.<sup>3</sup>

## 2. ECONOMETRIC METHOD AND DATA ANALYSIS

### Using Long-Run Restrictions for the Purpose of Identification

We can summarize our model thus far in the form of a vector moving average,

$$\mathbf{Y}_t = T(L)\varepsilon_t, \quad (9)$$

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<sup>3</sup> See Cooley and Dwyer (1998) for a thorough discussion of the pitfalls associated with the identification of SVARs.

where  $\mathbf{Y}_t = (\Delta s_t, \Delta m_t, n_t - s_t)'$  and  $\varepsilon_t = (a_t, \eta_t, e_t)$ . The matrix polynomial  $T(L)$  consists of the polynomials  $\Phi_a(L)$ ,  $\Phi_m(L)$ ,  $\psi_s(L)$ ,  $\psi_n(L)$ , and  $\psi_m(L)$  in equations (1) through (8). In addition, embedded in  $T(L)$  are long-run restrictions implied by our model that can be used to identify each of the three structural shocks. Specifically, the matrix of long-run multipliers,  $T(1)$ , may be written as

$$T(1) = \begin{bmatrix} a_{11} & 0 & 0 \\ a_{12} & a_{21} & 0 \\ a_{31} & a_{32} & a_{33} \end{bmatrix}. \quad (10)$$

Thus, the first row of  $T(1)$  reflects our restriction that only technology shocks alter the level of sales in the long run (in the steady state, sales should equal production). Money, therefore, is neutral, and we can appropriately constrain the estimation of the sales growth equation to identify technology shocks. To see how to impose the restrictions contained in  $T(1)$ , note first that under the assumption that  $T(L)$  is invertible,  $T(1)^{-1}$  is also lower block triangular. In estimating the sales growth equation, therefore, it suffices to set the long-run elasticity of  $\Delta s_t$  with respect to both  $\Delta m_t$  and  $n_t - s_t$  to zero.

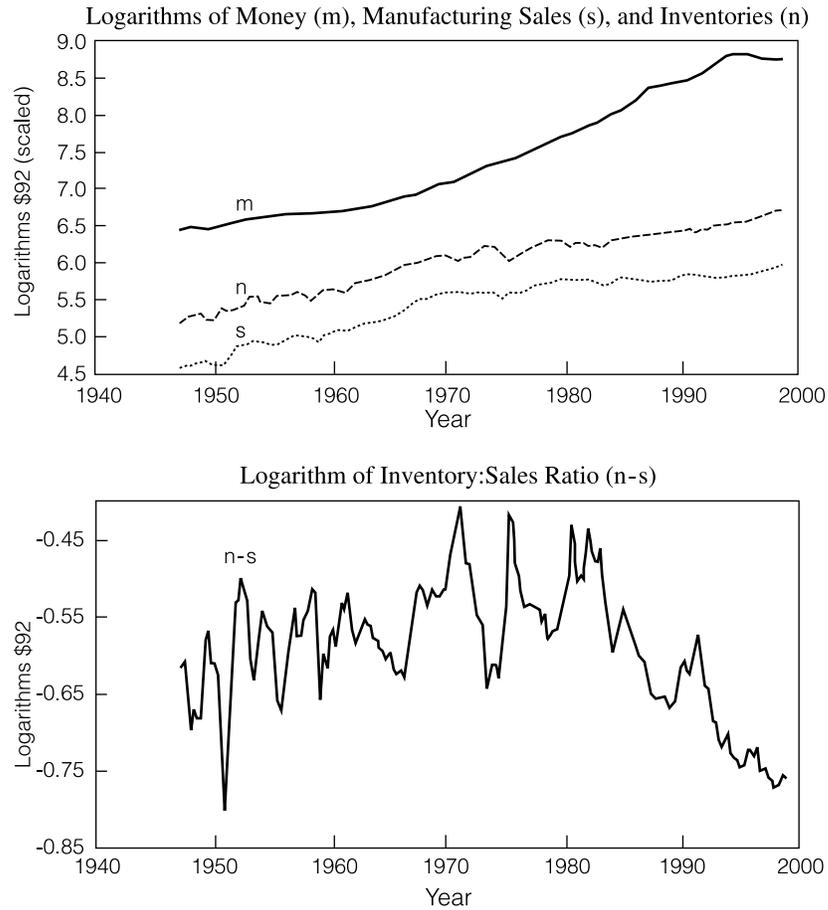
Real transitory demand shocks cannot, by definition, have long-run effects on any of the variables in the model. As the second row of  $T(1)$  suggests, this restriction, already imposed in estimating the sales growth regression, can be used to identify money shocks. In other words, except for permanent changes in technology, long-run changes in money are associated only with their own innovations, as equation (3) illustrates. To uncover money innovations, therefore, we estimate the money growth equation subject to the restriction that the long-run elasticity of  $\Delta m_t$  with respect to  $n_t - s_t$  be set to zero. It remains that the long-run elasticity of  $\Delta m_t$  with respect to  $\Delta s_t$  will generally not be zero. To account for the presence of this contemporaneous endogenous variable in the money growth regression, we use the fact that the structural disturbances are assumed to be mutually uncorrelated and use the residual from the sales growth regression as an instrument. The econometric methodology used here, therefore, follows that of Shapiro and Watson (1988), Blanchard and Quah (1989), King, Plosser, Stock, and Watson (1991), as well as many others.

It follows that the last remaining innovation captures real temporary demand shocks. In particular, the third row of  $T(1)$  suggests that the latter shocks can simply be uncovered by estimating the inventory:sales ratio equation without any restrictions. We use the residuals from both the sales growth and money growth regressions to instrument for  $\Delta s_t$  and  $\Delta m_t$  in this last regression.

### Cointegration Properties of the Data

Before proceeding with the estimation, we first investigate the cointegrating restriction implied by (7). As with the majority of the empirical literature on inventory behavior, this article focuses mainly on manufacturing inventories.

**Figure 1**



More specifically, the notion of production smoothing applies best to manufactured goods, as pointed out in Hornstein (1998). In Section 4, we shall take the research one step further by showing that the econometric specification above may be ill-suited to both the retail and service sectors. We add one cautionary note, however, regarding our assumption that money may respond to long-run innovations in technology (recall equation [3]). In all likelihood, this assumption is most relevant for aggregate shocks rather than sectoral shocks. Our model does not allow us to disentangle these shocks. Consequently, shocks captured by  $a_t$  should be interpreted as a linear combination of both aggregate and sectoral innovations.

**Table 1 Cointegration Statistics—1947:1–1998:3**

<b>a. Results from Unrestricted Levels Vector Autoregression: Largest Eigenvalues of Estimated Companion Matrix</b>		
VAR(6) with constant and trend		
Real	Imaginary	Modulus
0.98	0.04	0.98
0.98	−0.04	0.98
0.85	0.15	0.86
0.85	−0.15	0.86
0.63	0.47	0.78
0.63	−0.47	0.78

<b>b. Multivariate Unit-Root Statistics: Stock and Watson <math>q^f</math> Statistic</b>		
<b>H0: 3 unit roots vs. H1: at most 2 unit roots</b>		
Number of Lags	$q^f(3, 2)$ statistic	<i>P</i> value
1	−42.51	2.75
2	−45.10	1.75
3	−42.27	2.75
4	−34.68	9.75
5	−31.89	14.75

<b>H0: 2 unit roots vs. H1: at most 1 unit root</b>		
Number of Lags	$q^f(2, 1)$ statistic	<i>P</i> value
1	−8.99	83.25
2	−11.94	67.50
3	−9.39	81.25
4	−8.69	85.00
5	−7.87	88.75

Figure 1 shows the logarithms of money, as defined by M1 (i.e., currency and demand deposits), manufacturing inventories, and sales of finished goods. The data are quarterly U.S. observations spanning the period 1947:1 to 1998:3. Early figures for M1 were obtained from the Monetary Statistics of the United States since they were unavailable from the Board of Governors dataset. The inventory and sales data were downloaded from the National Income and Products Accounts on February 19, 1999. Regressions were run over the period 1948:3 to 1998:3 to allow for six lags. The plots of the variables display familiar, clear upward trends with inventories being the most volatile component. Note that inventories and sales indeed seem to share the same trend over the period considered. Figure 1 also plots the logarithm of the inventory:sales ratio,  $(n - s)$ , which appears relatively stable. One possible exception concerns the period

**Table 1 Cointegration Statistics—1947:1–1998:3 (cont.)**

<b>Johansen’s Likelihood Ratio Statistics</b>		
	$2(\mathcal{L}_1 - \mathcal{L}_0)$	5% critical value
H0: $h = 0$ vs. H1: No restrictions:	$-T \sum_{i=1}^3 \log(1 - \lambda_i) = 41.97$	29.51
H0: $h = 0$ vs. H1: $h = 1$ :	$-T \log(1 - \lambda_1) = 25.99$	20.77
H0: $h = 1$ vs. H1: No restrictions:	$-T \sum_{i=2}^3 \log(1 - \lambda_i) = 15.98$	15.20
H0: $h = 1$ vs. H1: $h = 2$ :	$-T \log(1 - \lambda_2) = 12.95$	14.03

Notes:  $T = 201$ , where  $T$  is the sample size,  $\lambda_1 = 0.1213$ ,  $\lambda_2 = 0.0624$ , and  $\lambda_3 = 0.0148$ , where the  $\lambda_i$ 's refer to the square of the canonical correlations.

<b>Saikkonen’s Estimator for Cointegrated Regressions</b>		
Variable	Null Hypothesis	Estimates
$s$	-1	-1
$m$	0	0
$n$	1	0.95 (0.02)

Wald Test for the Cointegrating Vector  $(-1, 0, 1)$ :  $\chi^2_{[1]} = 12.08$ .

beginning in the early 1990s in which this ratio seems to have started to fall.<sup>4</sup> On the whole, however, it would be difficult to argue that the inventory:sales ratio does not fluctuate around a constant mean. Alternatively, Figure 1 loosely suggests that inventories and sales are cointegrated.

A univariate analysis of the three variables plotted in Figure 1 suggests that they can each be characterized as an I(1) process with positive drift. Our concern, however, is mostly with a multivariate analysis of the relationship described by (9). Accordingly, Tables 1a and 1b present a number of statistics that relate to the three-variable system,  $\tilde{Y}_t = (s_t, m_t, n_t)'$ .

Panel a of Table 1 shows the largest eigenvalues of the companion matrix associated with a VAR(6) estimated with a constant and a linear trend. Under the assumption that only one cointegrating restriction links the variables in  $\tilde{Y}_t$ , the companion matrix should have two unit eigenvalues corresponding to two common stochastic trends. All other eigenvalues should be less than one in modulus. These results follow directly from Stock and Watson’s (1988) common trends representation. The point estimates displayed in Table 1a indeed

<sup>4</sup> Regressions were also run over the period 1947:1 to 1990:1 to check for robustness with respect to this feature of the data. Our empirical results, however, were largely unaffected.

support the hypothesis of two common trends or, alternatively, that there exists a single cointegrating restriction in our three-variable system.

Panel b presents more formal tests of cointegration developed by both Stock and Watson (1988) and Johansen (1988). Stock and Watson's  $q_{\tau}^f(k, m)$  statistic tests the null of  $k$  unit roots against the alternative of  $m$ , ( $m < k$ ), unit roots using Stock and Watson's (1989) dynamic Ordinary Least Squares (OLS) procedure. Specifically, if there are  $n$  variables and  $h$  cointegrating vectors, the procedure estimates  $h$  regression equations containing a constant,  $n - h$  regressors in levels, as well as leads and lags of the first differences in these regressors as right-hand-side variables. The  $\tau$  subscript indicates that a linear trend is included in the regressions. In panel b of Table 1, we note that the  $q_{\tau}^f(3, 2)$  statistic is consistent with rejecting the null of no cointegrating restrictions against the alternative of at least one cointegrating restriction. In particular, the  $P$  values are generally small regardless of the number of lags used in the dynamic OLS equations. In addition, the  $q_{\tau}^f(2, 1)$  statistic suggests rejecting the alternative of two cointegrating restrictions against the null of one cointegrating vector. Put together, these results provide evidence of only one cointegrating vector in our three-variable system.

Panel b also presents results obtained from Johansen's Likelihood Ratio Trace and Maximum Eigenvalue statistics. For these statistics, we can think of the number of unit roots as the number of variables less the number of cointegrating relations. Consider first the likelihood ratio test for the null of zero cointegrating relation against the alternative of three cointegrating relations. For this test, the likelihood ratio statistic,  $2(\mathcal{L}_1 - \mathcal{L}_0)$ , is 41.97, which is greater than 29.51. Therefore, the null hypothesis is rejected at the 5 percent significance level. Similarly, the test statistic for the null of zero cointegrating restriction against the alternative of one restriction is  $25.99 > 20.77$ . It follows that the null hypothesis of no cointegration is rejected by this second test as well.

To see whether a second cointegrating relation potentially exists, consider the likelihood ratio test for the null of  $h = 1$  against the alternative of  $h = 3$ . In this case, the test statistic is  $15.98 > 15.20$  so that the null hypothesis is, in fact, rejected at the 5 percent significance level. However, the likelihood ratio test statistic for the null of one cointegrating relation against the alternative of two relations is  $12.95 < 14.03$ . Therefore, although the Johansen tests generally suggest one cointegrating relation, they also offer conflicting evidence as to the presence of a second cointegrating restriction.

Finally, panel b gives an estimate of the cointegrating relation associated with the vector of variables  $(s_t, m_t, n_t)$  using Saikkonen's (1991) procedure.<sup>5</sup>

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<sup>5</sup> This procedure is essentially that of dynamic OLS. In this case, the regression involves the level of sales as the dependent variable; as right-hand-side variables it involves the level of inventories, a constant but no deterministic trend, as well as leads and lags of the differences in inventories.

Although the Wald Statistic suggests rejecting the null hypothesis that the cointegrating vector is proportional to  $(-1, 0, 1)$ , the point estimates are broadly consistent with the notion that the inventory:sales ratio is stationary.

### 3. ESTIMATION OF A THREE-VARIABLE SYSTEM

The results presented in this section are based on the estimation of the Vector Error Correction Model (VECM) implied by equation (9). Each regression equation is estimated using six lags of  $\Delta s_t$ ,  $\Delta m_t$ , the error-correction term  $n_t - s_t$ , as well as a constant. As we indicated earlier, the triangular nature of the long-run multiplier matrix and the assumption that the structural error terms are mutually uncorrelated allows us to recursively estimate each equation in the system. In estimating the money growth equation, the residual from the sales growth regression was used to instrument for contemporaneous endogenous variables. Similarly, in estimating the inventory:sales ratio equation, the residual from the money growth regression was added to the list of instruments.<sup>6</sup>

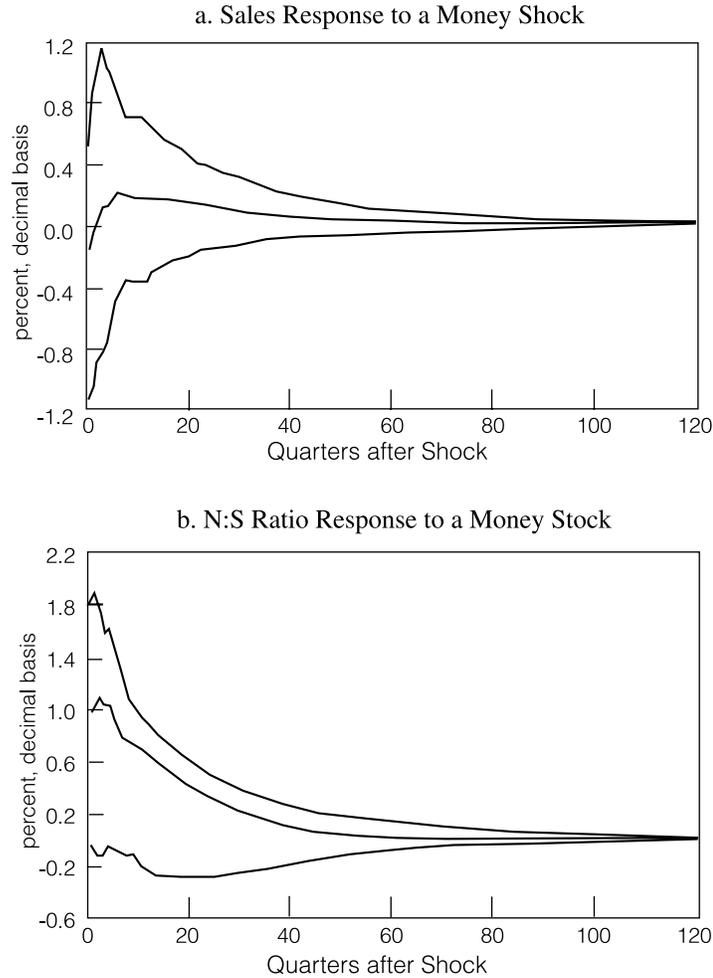
#### Estimated Structural Impulse Responses

Figure 2 displays the estimated impulse response function obtained from the system summarized by (9). The 95 percent confidence bands also displayed in Figure 2 were computed using Monte Carlo simulations. These simulations were carried out by using draws from the normal distribution for the technology, money growth, and temporary real demand innovations. One thousand Monte Carlo draws were completed.

We now interpret these impulse response functions in terms of a production-smoothing model with nominal rigidities. Let us first focus our attention on the effect of a money growth innovation. In a framework with staggered prices, Hornstein and Sarte (1998) suggest that in response to a money growth shock, sales should contemporaneously rise before gradually reverting back to the steady state. To see why this is true, note that a firm that does not adjust its price following an increase in nominal demand naturally sees its sales rise on impact. Moreover, its relative price continues to decline as long as its nominal price remains fixed. These results occur because other firms eventually increase their price so that the price level rises. Firms that do adjust their price immediately following the money growth innovation set their price high enough so that their sales initially fall. In the aggregate, however, the latter firms typically represent a small fraction of the total number of firms and aggregate sales initially rise. Looking at the point estimates of the sales response to a money

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<sup>6</sup> See Shapiro and Watson (1988) for details of how to estimate just-identified SVARs using an instrumental variables approach.

**Figure 2**

innovation in Figure 2a, we see that sales actually fall when the shock occurs. However, immediately following this initial response, sales increase before reverting back to the steady state. This dynamic adjustment in sales, therefore, is almost compatible with the predicted response in Hornstein and Sarte (1998). The main difference lies in the contemporaneous response that appears negative in the data. On the one hand, this difference may be evidence that a relatively nontrivial fraction of firms actually do adjust their price at the time of the shock. On the other hand, the upper bound of the confidence interval suggests

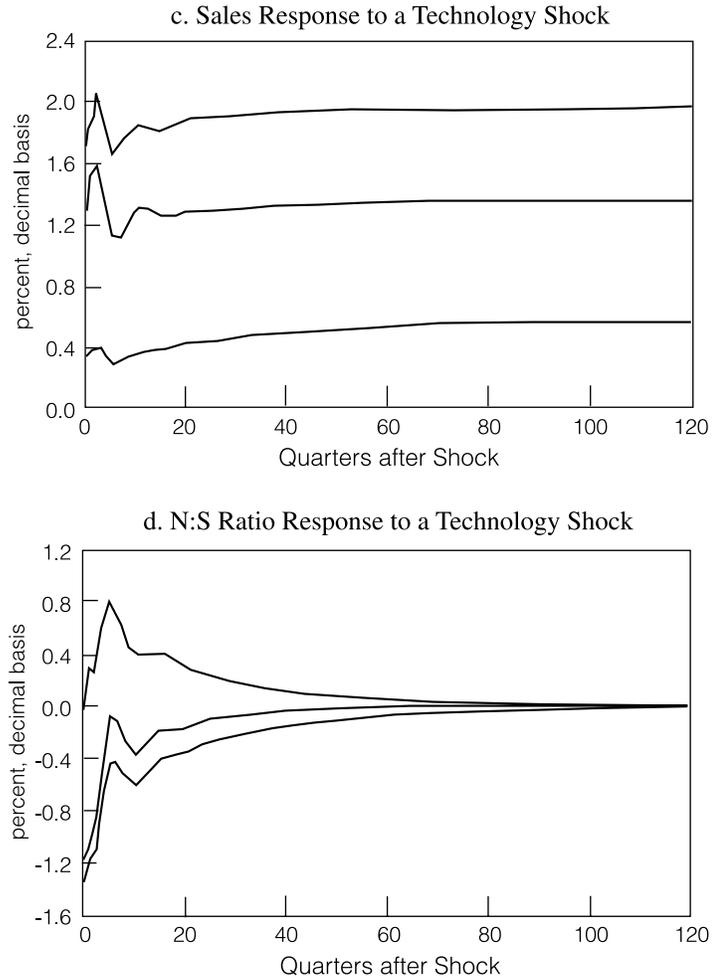
a positive initial response of sales as expected. Furthermore, the subsequent dynamic adjustment in sales is consistent with that of a sticky-price model.

We now turn to the dynamic response of the inventory:sales ratio to a money growth innovation. In theory, the combination of production smoothing and sticky-price forces predicts that inventories should rise on impact in response to a positive nominal shock. Because the inventory:sales ratio is constant in the steady state, and nominal shocks have no long-run effect on sales, inventories then gradually fall back so as to meet some target inventory:sales ratio. Alternatively, changes in the inventory:sales ratio fall back to zero. To understand the nature of this dynamic adjustment, recall that a firm that does not adjust its price in response to a nominal shock initially experiences a rise in sales. Afterwards, sales continue to rise as long as its price remains unchanged. Given that this firm also smooths production over its pricing cycle, it must initially increase production by *more* than sales. This large initial increase in production effectively allows output to grow relatively slowly over the remainder of the firm's pricing cycle. Therefore, firms that keep their price fixed following a money growth shock increase their inventory holdings at the outset. Now, what about firms that do change their price at the time the shock occurs? Since these firms also smooth production over their pricing cycle, they initially reduce output by *less* than the fall in sales they experience. Consequently, inventory holdings increase for the latter firms as well. In the aggregate, therefore, inventory holdings should *unambiguously rise* on impact in response to a positive nominal demand shock. Looking at the response of the inventory:sales ratio to a money shock in Figure 2b, we see that it rises on impact by approximately 1 percent. Since sales contemporaneously fall by 0.4 percent in response to the same shock, the level of inventories does indeed rise at the outset by about 0.6 percent as suggested by our sticky-price framework.<sup>7</sup>

When examining the dynamic adjustment of sales and inventories to a technology shock, Hornstein and Sarte (1998) suggest that total sales should contemporaneously rise in response to a technology shock. This result is mainly driven by the firms that respond to the innovation. In particular, a productivity increase implies a fall in the marginal cost of production. Firms that immediately respond to the shock, therefore, lower their price and see their sales increase. Furthermore, during the transition, aggregate sales continue to rise monotonically to a higher steady state as more firms also reduce their price. The sales response in Figure 2c indeed broadly suggests that sales first increase in response to a technology shock and eventually reach a new higher steady-state level. The dynamic adjustment, however, is not monotonic. Specifically, sales appear to overshoot the new steady state twice during the early portion

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<sup>7</sup> Letting  $n:s$  denote the inventory:sales ratio, observe that the change in inventories is then given by  $\Delta n = \Delta n:s + \Delta s = 0.01 - 0.004 = 0.06$ .

**Figure 2**


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of the transition phase. This oscillatory impulse response in sales is somewhat difficult to reconcile with a standard sticky-price model. It may suggest that some firms find it difficult to know exactly where to set a new price following the shock. In particular, the overshooting suggests that these firms may initially set their price too low. The subsequent corrective rise in price that would then occur causes a temporary decline in sales. It remains that, as expected, sales ultimately rise in the long run relative to their initial level.

As with the dynamic adjustment to a monetary innovation, the response of inventories to a technology shock hinges on the production-smoothing behavior of firms. Consider first the behavior of firms that adjust their price immediately following the shock. As we have just seen, these firms initially lower their price so that their sales at first increase. However, these firms then face declining sales over the remainder of their pricing cycle. This result stems from the fact that, following the initial adjustment, their price remains fixed while the price level continues to fall. Therefore, firms that adjust their price on impact also raise production but by a lesser amount than the initial sales increase. These firms consequently experience a fall in inventory holdings.

For the firms that do not adjust their price at the time the shock occurs, sales initially decrease as adjusting firms cause the aggregate price level to fall. Since these firms anticipate further declines in sales while their price remains fixed, they reduce production on impact by more than the initial decline in sales. Therefore, inventory holdings contemporaneously fall for the latter firms as well. It follows that aggregate inventory holdings should *unambiguously decline* immediately following the technology shock. As sales eventually rise to a higher steady state, inventories should then rise by the same amount in the long run to keep the inventory:sales ratio constant.

When we examine the inventory:sales ratio response to a technology shock in Figure 2d, we see that it falls by approximately 0.8 percent on impact in response to the innovation. Given the 1.2 percent rise in sales that contemporaneously follows the same technology shock, inventories then rise by about 0.4 percent at the time the shock hits. Since, on the contrary, a framework with sticky prices predicts an unambiguous initial decline in inventory holdings, the implied initial reaction of inventories in the data represents evidence against such a framework. However, we note that the lower bound of the 95 percent confidence interval for the impact response of sales is relatively small at about 0.35 percent. Because of the contemporaneous fall in the inventory:sales ratio by 0.8 percent, the level of inventories would also fall if we were to use the lower bound on the contemporaneous sales response. The latter observation mitigates the evidence against a sticky-price framework implied by the point estimates.

Thus far, the dynamic adjustment of sales and the inventory:sales ratio to both nominal demand and technology shocks are roughly consistent with what might have been predicted from a rigid price framework. The two main exceptions are (1) the implied initial response of inventories to technology shocks, and (2) the extremely sluggish dynamic adjustment of both sales and the inventory:sales ratio to shocks, as shown in Figure 2. In the case of the inventory:sales ratio's response to a money innovation, for instance, the half-life of the impulse is approximately 25 quarters or more than six years. While typical sticky-price models deliver nowhere near this kind of sluggishness in real variables, Ramey and West (1997) also note that the inventory:sales

relationship exhibits a very high degree of persistence. In fact, these findings turn out to be a reflection of a well-known problem in the empirical literature on inventory behavior. Specifically, Feldstein and Auerbach (1976) point out early on the incongruity inherent to the notion that firms may take years to adjust to a sales shock, while the widest swings in inventory levels seldom amount to more than a few days' production. More recently, Blinder and Maccini (1991, p. 81) write that "one major difficulty with stock-adjustment models is that adjustment speeds turn out to be extremely low," a comment referring to the estimation of stock-adjustment equations generally.<sup>8</sup> They further note that "a natural reaction is that the slow estimated adjustment speeds must be an artifact of econometric biases. One potential source of such bias is omitted variables." As with the estimation of stock-adjustment equations, we should be conscious that the structural equations we estimate may also be subject to the latter source of bias.

### Forecast Error Variance Decompositions

Having investigated the way in which the variables in (9) empirically respond to various structural shocks, we now wish to gauge the importance of each of these shocks in determining short-run variations in the data. We have seen that the dynamic adjustment of sales and the inventory:sales ratio, and hence inventories, to a money shock is generally consistent with the predictions of a sticky-price framework in which firms also smooth production. In some sense, however, this concept may be of secondary importance to a monetary policymaker if money shocks only play a small role in determining real variables. King, Plosser, Stock, and Watson (1991), for example, present compelling evidence to that effect in the case of aggregate variables. Of primary importance is the role played by each structural shock in determining short- and medium-run fluctuations in the data, as reflected when decomposing the variance of the  $k$ -step-ahead forecast errors.

Consider the moving-average process given by (9) and let  $T(L) = T_0 + T_1L + T_2L^2 + \dots + T_kL^k + \dots$ ,  $L^j x_t = x_{t-j}$ , while  $E(\varepsilon_t \varepsilon_t') = \Sigma_\varepsilon$ . Then, we may write the  $k$ -step-ahead forecast error in  $\mathbf{Y}$  as

$$\mathbf{Y}_{t+k} - E_{t-1} \mathbf{Y}_{t+k} = \sum_{j=0}^k T_k \varepsilon_{t+k-j}. \quad (11)$$

For our purposes, what we wish to assess is the fraction of variance in the left-hand side of equation (11) that is attributable to each of the structural shocks. In other words, we ask the question: To the degree that the actual data differ from the optimal forecast, which of the structural shocks is most

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<sup>8</sup> See Lovell (1961) for instance.

**Table 2 Decompositions of Forecast Error Variance**

<b>a. Fraction of Sales Forecast Error Variance Attributed to Shocks</b>			
<b>Horizon</b>	<b>Technology Shock</b>	<b>Money Shock</b>	<b>Real Demand Shock</b>
1	0.70 (0.21)	0.22 (0.16)	0.08 (0.13)
4	0.92 (0.17)	0.06 (0.12)	0.02 (0.12)
8	0.97 (0.13)	0.02 (0.09)	0.01 (0.07)
12	0.99 (0.11)	0.01 (0.08)	0.00 (0.05)
16	0.99 (0.09)	0.01 (0.07)	0.00 (0.05)
20	0.99 (0.07)	0.01 (0.05)	0.00 (0.02)
$\infty$	1.00 (0.00)	0.00 (0.00)	0.00 (0.00)

<b>b. Fraction of Inventory:Sales Ratio Forecast Error Variance Attributed to Shocks</b>			
<b>Horizon</b>	<b>Technology Shock</b>	<b>Money Shock</b>	<b>Real Demand Shock</b>
1	0.90 (0.27)	0.08 (0.26)	0.02 (0.21)
4	0.85 (0.26)	0.01 (0.25)	0.14 (0.24)
8	0.79 (0.22)	0.01 (0.25)	0.20 (0.24)
12	0.75 (0.22)	0.05 (0.24)	0.20 (0.24)
16	0.73 (0.21)	0.06 (0.25)	0.21 (0.24)
20	0.72 (0.21)	0.09 (0.24)	0.18 (0.24)
$\infty$	0.69 (0.20)	0.14 (0.24)	0.17 (0.25)

responsible for this difference? Note that our identifying restrictions imply that 100 percent of the sales forecast error variance is explained by the technology shock at the infinite horizon. At shorter horizons, however, both nominal and real demand disturbances are allowed to contribute to fluctuations in sales. Table 2, panel a, shows that in fact, this contribution is relatively minor.<sup>9</sup> At the one-quarter horizon, technology shocks already explain 70 percent of the forecast error variance in sales. The bulk of the remaining variance is attributable to money growth shocks while real demand disturbances play a very small role. At the four-quarter horizon, technology shocks account for 92 percent of the variation in sales. At the three-year horizon, virtually all of the forecast error fluctuations in sales can be explained by technology shocks.

Focusing on fluctuations in the inventory:sales ratio, we again find that they tend to be dominated by real disturbances. In this case, however, it is interesting that as the forecast horizon lengthens, the important role played by technology

<sup>9</sup> Standard errors are in parentheses.

innovations diminishes somewhat at the expense of real demand disturbances. Also, by contrast to sales above, forecast errors in the inventory:sales ratio are not restricted to be uniquely driven by real disturbances in the long run. As a result, we find that at the infinite horizon, monetary disturbances explain approximately 14 percent of the forecast error in the inventory:sales ratio. While this number may not be too consequential, it is slightly larger than most other findings concerning the role of nominal shocks in determining the behavior of real variables. Gali (1992), for example, finds that after 20 quarters, money supply shocks only explain 9 percent of the variation in aggregate output.

### Historical Decompositions

The variance decompositions in Table 2 show the relative importance of each structural shock in explaining variations in both sales and the inventory:sales ratio *on average*. It is also interesting to note that these shocks may matter more or less during various historical episodes. Figures 3 and 4 plot the historical forecast error decompositions in sales and the inventory:sales ratio at the 12-quarter horizon. This 12-quarter horizon concept of the business cycle is adopted from King, Plosser, Stock, and Watson (1991).

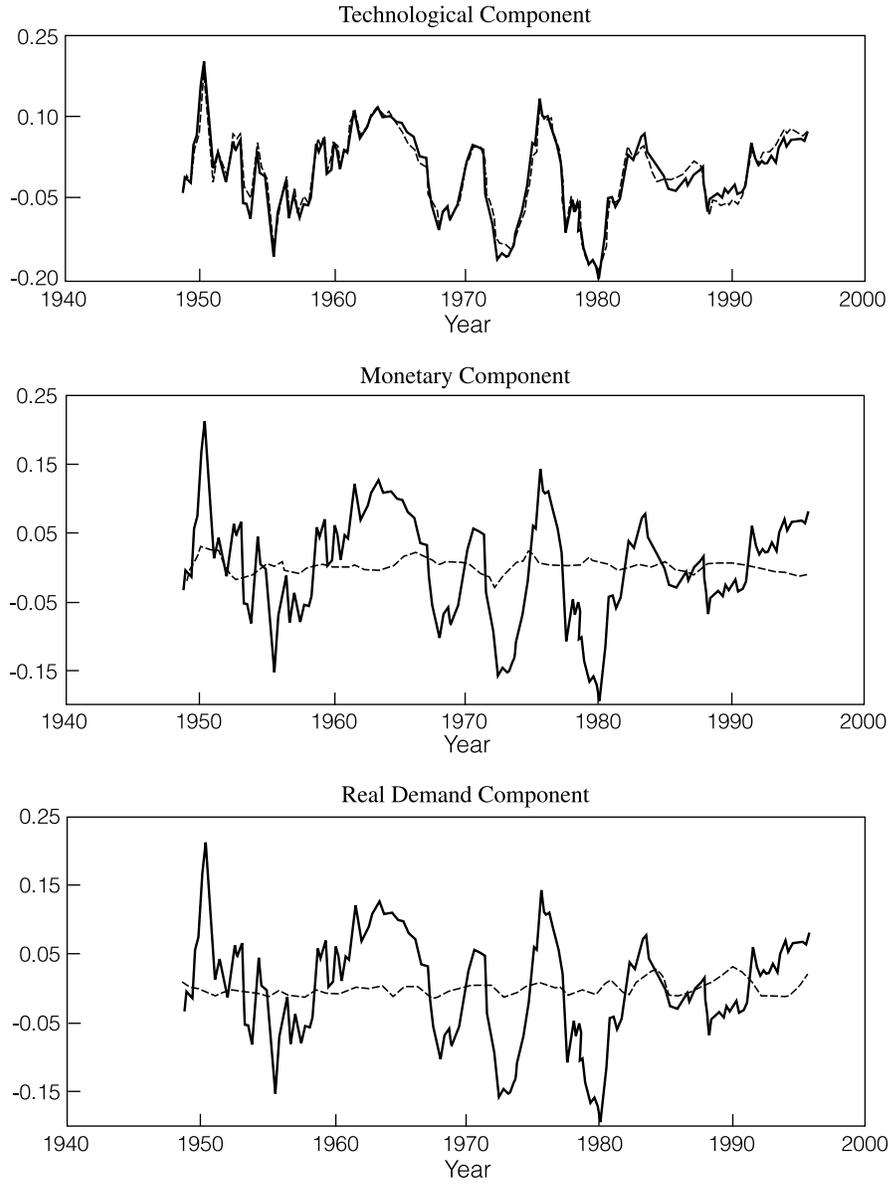
Figure 3 confirms that while money shocks have historically played a small role in explaining fluctuations in sales, technology shocks have played a more substantial role. Interestingly, this finding appears to remain consistent throughout the entire sample period considered. Temporary real demand disturbances take on relatively more importance in explaining sales fluctuations in the 1990s. On the whole, the largest forecast errors occur in the mid-1970s and, as might have been expected, coincide with the oil price shock of 1973.

The latter observation also applies to the forecast errors in the inventory:sales ratio as suggested by Figure 4. Again we note that money generally plays a small role in driving inventory:sales ratio fluctuations, as implied by the variance decompositions in Table 2. In contrast, we also find that the importance of the monetary component, even if small on average, noticeably increases in the early 1990s. Put another way, Figure 4 suggests that even if monetary fluctuations have traditionally represented a small portion of fluctuations in the inventory:sales ratio, this does not imply that monetary disturbances are always unimportant.

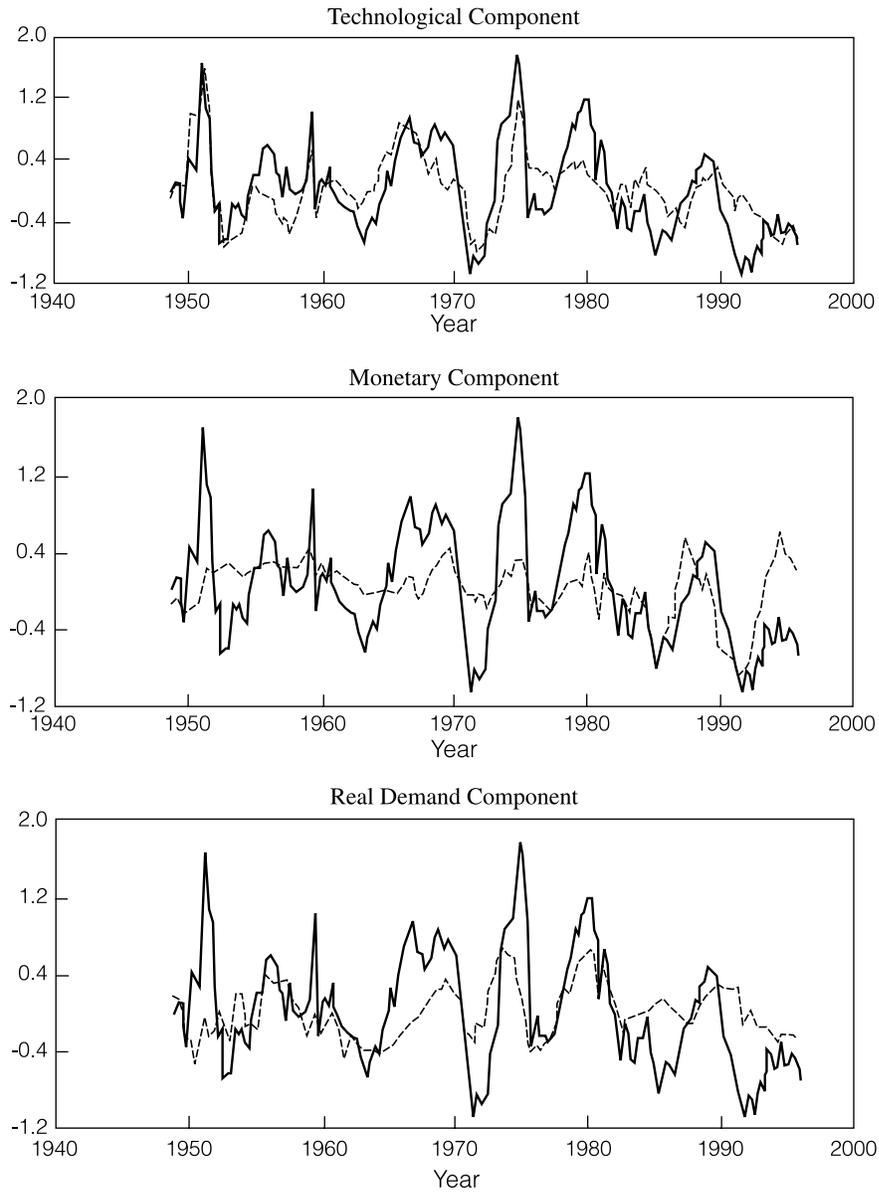
## 4. CAUTIONARY REMARKS

An important part of the empirical analysis above has been the assumption that the inventory:sales ratio is stationary around a constant mean. As we have seen, various cointegration tests have generally confirmed this hypothesis for manufacturing inventories. Moreover, the notion of a stationary ratio is typically explained on the grounds that stock-outs are costly and, therefore, that

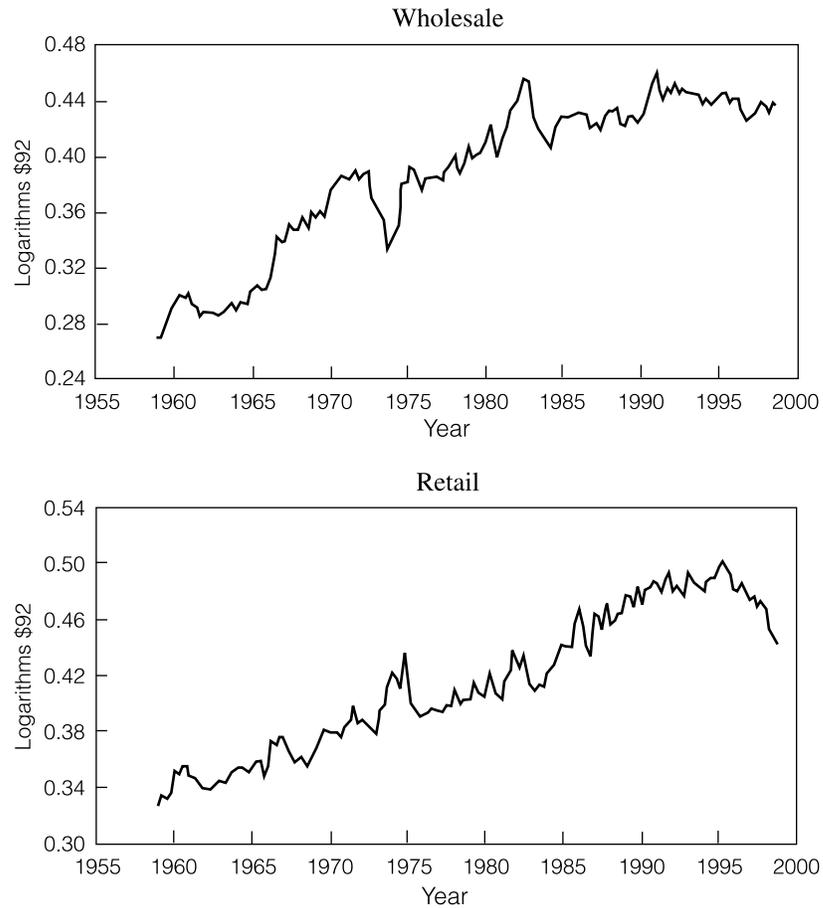
**Figure 3 Historical Forecast-Error Decomposition: Sales**



**Figure 4 Historical Forecast-Error Decomposition: N:S Ratio**



**Figure 5** Logarithm of the Inventory:Sales Ratio ( $n-s$ )



firms generally try to meet some target inventory:sales ratio in the long run. The fall in the inventory:sales ratio that begins in the early 1990s (Figure 1) is sometimes taken as evidence of the just-in-time inventory method taking hold in the United States. The inventory:sales ratio in both the wholesale and retail sectors, however, reveals a much different story. Figure 5 suggests that for much of the period under consideration, the inventory:sales ratio in both these sectors has actually trended *upwards*. Both the ratios seem to stabilize in the early 1990s, perhaps again because of the widespread emergence of the just-in-time method. Nevertheless, it remains that much of the increase in the inventory:sales ratio up to the early 1990s, in both the wholesale and retail sectors, represents somewhat of a puzzle.

To explain this puzzle, one can speculate that, over time, consumers have gained easier access to a wide variety of goods through improved means of communication and transportation. As a result, back orders for any one business are less likely to arise since consumers can simply acquire the same goods elsewhere. So not having goods on hand more readily results in lost sales, which effectively drives up the cost of stock-outs and, consequently, inventory:sales ratios. Alternatively, consistent improvements in technology may simply have reduced storing costs over time. This would have made it easier for wholesalers and retailers to avoid stock-outs and is directly consistent with increasing inventory:sales ratios. Food products, for instance, have become increasingly storable because of consistent innovations in preservatives technology. Whatever the case may be, Figure 5 makes it clear that traditional theories of inventory behavior need to be amended to account for the data in the wholesale and retail sectors. Perhaps a focus away from production smoothing is even necessary.

## 5. CONCLUSIONS

We have used an SVAR to acquire some insight into the dynamic responses of manufacturing sales and inventories to both nominal demand and real supply shocks. We assumed that money is neutral in the long run and, moreover, that the inventory:sales ratio can be properly characterized as a stationary process without trend. We then found that the estimated dynamic adjustments to nominal demand and real supply shocks are generally consistent with those of an equilibrium model of inventory behavior with inflexible prices. However, the degree of sluggishness exhibited by both sales and the inventory:sales ratio, and hence inventories, in response to these shocks is much greater than that suggested by current sticky-price models. The latter findings confirm earlier observations by Blinder and Maccini (1991) and, more recently, Ramey and West (1997).

We also used our empirical framework to gauge the relative importance of both nominal and real disturbances as sources of fluctuations in the manufacturing sector. The results indicate that nominal shocks generally contribute little to the forecast error variance in both sales and the inventory:sales ratio at all horizons. Instead, fluctuations in real variables are mainly driven by real disturbances. In addition, the latter results appeared to hold consistently at the business cycle frequency throughout the sample period under consideration.

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