

Inventories and the Information Revolution: Implications for Output Volatility

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Abstract

The U.S. economy has experienced a significant decline in the volatility of real output since the early 1980's. A key feature of the contraction in output volatility is that it has occurred both absolutely and relative to the volatility of final demand. This relative contraction is most pronounced in the durable goods sector. In this paper, we highlight the role of inventories in the durable goods sector in accounting for the increased stability in that sector as well as in the aggregate economy. We then provide a model in which technological change in the form of improved information about final demand leads to less volatile output, both absolutely and relative to final demand.

1 Introduction

The standard deviation of quarterly U.S. real GDP growth over the last fifteen years is less than half that of the rest of the post-war period. By comparison, the instability of the 1970's and early 1980's represents a relatively modest and brief episode. A key feature of the contraction in output volatility is that it has occurred both absolutely and relative to the volatility of final demand. This relative contraction is most pronounced in the durable goods sector.

In this paper we argue that changes in inventory behavior stemming from improvements in information technology have played an important role in reducing real output volatility. The idea is that even if the magnitude of the exogenous shocks hitting the economy is unchanged, the role of inventory investment in magnifying or propagating those shocks has moderated significantly. Thus even a large swing in final demand would be expected to produce a smaller swing in production now than it would have twenty or thirty years ago.

Our view that technological change is primarily responsible for the reduced volatility of output is formed largely by two important features of the data. First, in a growth accounting sense, most of the reduction in aggregate variability can be explained by a corresponding reduction in the variability of output in the durable goods sector. The nondurables, services and structures sectors of the economy do not contribute importantly to the increased aggregate stability, nor are these sectors themselves significantly more stable.¹ Second, the dramatic decline in the volatility of durables production is not accompanied by a similar reduction in the variability of durables final sales. In fact the ratio of output variability to sales variability in that sector drops sharply after the early 1980's.

Alternatives to the information hypothesis, namely that the reduced volatility is a product of some combination of improved monetary policy or good luck, seem more difficult to reconcile with the above features of the data. In particular, the view

¹See McConnell and Perez-Quiros (MPQ) (2000) for details.

that policy alone brought about the increased stability would have to explain why policy affected the volatility of production so much more than final sales, and why the phenomenon of increased stability has been concentrated in the durable goods sector. In other words, both the good policy and good luck hypothesis would have to explain why the impact was felt primarily in durable goods inventories.

In Section 2 we provide an overview of the changing volatility of macro data. In Section 3 we present a model in which improved information about final demand leads to less volatile output, both absolutely and relative to final demand. Section 4 concludes.

2 The Changing Variability of Real Activity

In this section we document the changing volatility of the U.S. macroeconomy over the post-war period 1952:3 to 2000:2. Figure reffig-GDP plots real GDP growth over period 1953:2 to 2000:2. The sharp decline in volatility after the early 1980's is immediately evident. The top panel of Table 1 reports the standard deviation of GDP growth and its components for our three sample periods.² The first is 1953:2 to 1968:4, corresponding to the first 15 years of the post-war sample, the second is the fifteen-year period from 1969:1 to 1983:4, with the end date here corresponding to the date MPQ find for the break in the volatility of output growth, and the last is 1984:1 2000:2. Focusing first on aggregate GDP, we see the unconditional standard deviation of real growth in the 1970's is not markedly different from that of 1950's and 1960's, and that the latter period is more stable than either of the earlier two.³

²The numbers reported here are the standard deviations of the growth rates of the individual components, and not of the growth contributions.

³McConnell and Perez-Quiros (MPQ) (2000) use tests for structural change of the type described in Andrews (1993) and Andrews and Ploberger (1994) to estimate a break in the residual variance of an AR(1) specification for real GDP growth in 1984:1. They also test for additional breaks within each of the periods 1953:2 to 1983:4 and 1984:1 to 1999:2 and find no evidence of additional breaks. Hence it is the date 1984:1 on which we base our split between the second and third sample periods, and it is only this date that we view as relevant for the behavior of output volatility. The distinction between the first and second sample periods is made purely to illustrate that the 1970's were not significantly different from the 1950's and 1960's.

An analysis of the components of real GDP growth reveals that the behavior of durables volatility most closely mimics the behavior of aggregate volatility. In particular, the magnitudes of the standard deviations in each of the early two periods are similar and are more than twice as high as the standard deviation in the later period. This is precisely the pattern observed in the aggregate data, and it is matched in no sector other than durables. The volatility of the nondurables and structures sectors is high in period (2) relative to the earlier and later periods.⁴ Finally, there is sizable reduction in services volatility in the latter two periods relative to the early period.⁵

Thus the durables sector experienced a 50 percent decline in the standard deviation of its output roughly contemporaneously with the decline in overall GDP volatility. The share of the durables sector in GDP is only about 20 percent, however, so it does not necessarily follow that its impact on aggregate volatility would be large. To gauge the potential role of the durables sector in accounting for the behavior of aggregate volatility, we undertake an experiment like one presented in MPQ. Drawing on their finding of a structural break in the residual variance of an AR(1) specification for durables growth in 1985:1, we generate an artificial series for durable goods growth under the counterfactual assumption that the residual variance post-1985 is equal to its average value in the pre-1985 period. We then aggregate to construct an artificial GDP series under this counterfactual assumption and compare the volatility of this series to the actual. Table 2 reports the results of this exercise. It shows that the volatility reduction in the durables sector is large enough to account for over two-thirds of the decline in aggregate volatility.

⁴Kahn, McConnell and Perez Quiros point out that the volatility pattern in the nondurable and services sectors matches that of aggregate inflation volatility.

⁵Since Table 1 presents only the standard deviation of the growth rates of each of these sectors, it doesn't provide an assessment of the effects of changes in the composition of nominal GDP. There has in fact been some shift in composition over time, with the average shares of the goods, services and structures sectors changing from 0.47, 0.42 and 0.11, respectively, in the pre-1984 period to 0.39, 0.52 and 0.09 in the recent period. A second experiment that holds sectoral shares constant shows that the standard deviation of output would have declined to 2.6, very close to the actual value of 2.2. See MPQ (2000) for a more detailed discussion of the sectoral data.

2.1 Output, Final Sales and Inventories

Having established that the magnitude of the durables sector’s decline in volatility is sufficient to account for much of the decline in aggregate volatility since the early 1980’s, we can then ask what factor within durables—and perhaps within nondurables as well—has contributed to stabilizing output. The primary question we seek to answer in this section is whether or not the dramatic increase in output stability simply reflects greater stability in aggregate final demand. In other words, does it appear that producers are simply facing more stable demand and thus are able to stabilize output, or alternatively, have there been changes in production behavior (and thus inventory behavior) that appear to be independent of any changes in final demand. Sorting through these two stories seems crucial to understanding whether the current stability of the real economy can be mainly attributed to technologically induced changes inventory behavior or instead to policy- or even luck-induced stability in final demand.

In this section we work only with data from the goods sector. We do so for two reasons. First, the evidence presented in Table 1 indicates that this sector (in particular, the durable goods sector) is responsible for the bulk of the stability of overall GDP. Further, the distinction between production, final sales and inventories that we wish to exploit in this section is only meaningful in the goods sector.⁶

Table 3 provides a summary of the data from the goods sector, splitting the sample according to the MPQ breakdate, 1984:Q1. We see that the unconditional standard deviation of output and final sales has fallen in both the overall goods sector and each of the durable and nondurables sectors, though the decline is most dramatic for durable goods output. We also see, however, that one important feature of the data from the early sample, namely that the ratio of output to final sales variability is uniformly greater than one, is no longer true for the durable sector in the later

⁶Aggregate GDP and final sales both include the services and structures sectors of the economy. Since inventories are not held in these sectors, it is not meaningful to examine changes in inventory behavior in response to movements in these components of aggregate final sales.

sample.⁷ Thus the durables sector (and also the overall goods sector) has experienced a contraction not only in overall output volatility, but in output volatility *relative* to sales volatility. The contraction in this ratio points to a change in inventory behavior.

To illustrate the role of inventory behavior in explaining output volatility in a simple growth accounting framework, Table 4 decomposes the variance of output growth in the goods sector into the variance of the growth contributions of sales and inventory investment along with their covariance. In the goods sector as a whole (top panel) as well as for nondurables and durables separately (bottom two panels), the percentage of the decline in output volatility *not* accounted for by a reduction in sales volatility (reported in the last column) is large—78.3 percent in the overall goods sector and 86.8 percent in the durables sector. Thus, particularly in durables, we find an important role for the variance of the growth contribution of inventory investment, as well as for the decline in the covariance between the growth contributions of inventories and sales, in explaining the reduction in output volatility.⁸

2.2 Other Evidence on Changing Inventory Behavior

The behavior of inventory-to-sales (I/S) ratios in the goods producing sectors of the economy suggest that firms are increasingly economizing on their inventory holdings. The bottom panel of Figure 2 plots the ratio of real nonfarm inventories to final sales of goods starting in 1947.⁹ There is little drift in this ratio until the early 1980's, when it begins to trend downward.¹⁰ The upper panel of Figure 2 plots the ratios separately

⁷The value of this ratio in the early period is not surprising, as a large literature exists documenting and seeking to understand the reasons that production is more volatile than sales.

⁸Golob (2000) also points out the change in the covariance across these two samples and suggests that this is evidence of greater production smoothing behavior. Whether firms are indeed smoothing production (relative to sales) more now or instead simply trying to match sales more closely remains an empirical question.

⁹Because these plots are ratios of two chain-weighted series, the level of the inventory ratio is not meaningful, but movements in the ratio are. Nominal ratios yield the same general picture.

¹⁰In 1991 Blinder and Maccini wrote 'Contrary to popular belief, inventories are not leaner now than they were decades ago. Despite the alleged revolution in inventory practices brought about by computerization, the economy-wide ratio of real inventories to real sales has been trendless for 40 years'. Thus, even by 1991 it was not apparent to many that inventory-sales ratios had begun to

for durables and nondurables. The durables ratio has no discernible drift through the early 1980's, and then begins to drop precipitously, down roughly 30 percent by the end of the sample during a timespan of less than 20 years. In nondurables, meanwhile, the ratio has only a slight downward drift over the entire sample period, on the order of a 10 percent total decline over a span of more than 50 years. While we do not establish in this paper a direct link between the *level* of the inventory-sales ratio and output volatility, the decline in the ratio does provide circumstantial evidence of a structural change in the durable goods sector around the same time as the decline in volatility.

In addition to the decline in the target I/S ratio, the data suggest that variation around this target has fallen. Figure 3 shows the movement of the actual inventory sales ratio around a smoothed trend designed to capture the target. The reduction in the size of deviations from the target after 1984:1 indicates that firms are making smaller mistakes now than before.¹¹

Another piece of circumstantial evidence can be found from a simple vector autoregression on the growth rates of final sales and inventories. Tables 5 presents results from the durable goods sector for the pre- and post-1984 sample periods (real 1996 chain-weighted dollars, in growth rates). While there is a modest decline in the volatility of the dependent variables, what is striking is the increase in the R^2 for the sales equation, apparently due to the increased explanatory role of lagged inventories—As seen in the bottom panel, inventories explain only 5% of the variance in sales in the early period, but 15% in the later period. At the same time, lagged sales play *less* of a role in explaining inventory investment. Both of these findings are consistent with the story that inventory investment incorporates better information—and is therefore better able to anticipate sales—in the later sample period.

Finally, we note that the concentration of the phenomenon in the durable goods sector may be an artifact of differences in the speed at which information technology

come down.

¹¹The “target” was estimated by Kalman filter methods, assuming a permanent and transitory component, and allowing for the variance reductions post-1984. See Appendix B for details.

has disseminated across sectors. One measure of this might be the differentials in investment in information technology (IT) across the durable and nondurable sectors of the economy. Data from the Bureau of Economic Analysis on investment in IT capital indicate that the durables sector invested in twice as much IT capital per worker (in nominal terms) over the period 1965 to 1985 than did the nondurable sector.¹²

A survey of manufacturing, wholesale and retail trade publications from the mid-to-late 1980's on topics such as flexible manufacturing, 'just-in-time' inventory management, and computer numerically controlled machine tools reveals numerous references to dramatic changes in production techniques in the late 1970's and early 1980's in the durable goods sector, with particular emphasis on motor vehicles, aerospace, primary metals and electrical and industrial equipment, though there are also examples from industries such as lumber and furniture. Virtually all of these references emphasize the fact that these manufacturing techniques have the desired effect of reducing the inventory-to-sales ratios across all stages of fabrication. Figures 4 and 5, which plot inventory-to-sales ratios for materials and works-in-process inventories suggest that this reduction is indeed evident across a wide range of durable manufacturing industries. Finally, data from the National Association of Purchasing Manager's survey indicates that there has been a reduction in the lead time for ordering production materials since the early 1980's.¹³

¹²'Information technology' capital refers to mainframe computers, personal computers, direct access storage devices, computer printers, computer terminals, computer tape drives, computer storage devices photocopy equipment, instruments, communication equipment, and other information equipment. The source data for this calculation is the 'Fixed Reproducible Tangible Wealth of the United States, 1925-96'. U.S. Department of Commerce, Economics and Statistics Administration, Bureau of Economic Analysis. Unfortunately this data does not include information on investment in capital such as computer numerically controlled machine tools.

¹³See Mosser, McConnell and Perez Quiros (1999).

3 The Model

In this section we explore the implications of better information technology using a model of the macro economy. Our results illustrate how increased information on the part of the firm can reduce output volatility with no change in the underlying volatility of the shocks hitting the economy. The effect of this is to lower the ratio of output volatility to sales volatility.

3.1 Inventories and Output

We now describe a model that illustrates the effect of increasing the amount of information that producers have about final demand at the moment that they make their production decisions. The key feature of the model is that firms make decisions regarding production before they know final demand for the period. To the extent that sales deviate from their expectations there will be unintended inventory accumulation or decumulation. These movements in inventories push firms away from their target inventory-to-sales ratios and force them to alter production in the following period to accommodate both the change in demand and the recovery of inventories toward their target.

Figure 7 illustrates this basic point. As shown in the top panel, firms enter period 1 with sales of 50 units and a target inventory-to-sales ratio (I/S) of 2, i.e. 100 units of inventories. To understand the effect of firms having to commit to their production levels before knowing demand in the period, we trace out the effects of an unanticipated permanent increase in final demand. This scenario is reported on the left-hand side of the figure. Since the firm does not know the level of demand in the period before it commits to production, it will choose to produce the expected value of final demand (in this example, 50 units). Later in the period, a permanent increase in demand to 75 is revealed to the firm. To meet this demand, the firm initially draws down its inventories, leaving it with 75 units of inventories at the end of the period. The increase in the expected value of demand in future periods causes the firm to

raise its target level of inventories from 100 to 150, in order to maintain I/S at 2. In period 2 then, the firm must produce 150 units, 75 to meet the new higher demand in that period, and 75 to get the firm back to its desired I/S target. Finally, in period 3 the firm enters the period with desired inventories equal to their target and simply produces the expected value of inventories in that period.¹⁴

The model has two other potentially important simplifications. First, the steady-state I/S ratio is essentially determined by a parameter of the utility function θ . Consequently the improvements in information technology do not translate into a lower I/S ratio in the model, even though they appear to do so in the data. This would only be important if the ratio itself has implications for volatility, which we can check for in the context of the model by changing θ .

The second simplification is that the produced good is modeled as a nondurable good in terms of how it enters into consumer utility. While the qualitative implications of the model are unlikely to be affected, quantitative issues arise in calibrating the model to real world data that we discuss below.

3.2 Model Setup

We now incorporate inventories into a simple stochastic dynamic general equilibrium model. To simplify the analysis we leave physical capital out of the story. We also depart from the approach of Kydland and Prescott (1982) and Christiano (1988), who put inventories in the production function. To stay closer to the spirit of much of the empirical inventory literature, which focuses more on inventories' role in facilitating sales,¹⁵ we put inventories in the utility function. The idea is that a larger stock of inventories enables consumers either to match their tastes more effectively

¹⁴This simple example makes the extreme assumption that the firm adjusts its inventories to target within one period upon learning of the demand change. The full general equilibrium model described below allows for the more realistic case in which the response is optimally spread out over time. But the essential results concerning volatility carry over to that case.

¹⁵See, for example, Bills and Kahn (2000). Even the standard linear-quadratic inventory model, which puts inventories in the cost function, usually does so in terms of their deviation from expected sales, and motivates it by the desire to avoid lost sales from stockouts.

(what might be called the Baskin-Robbins effect), or to economize on shopping costs. Although non-finished goods (i.e. works-in-process and materials) comprise a significant share of inventories, the same argument applies: A manufacturer with a large inventory of paint colors ultimately facilitates the consumer ending up with a product that provides the most satisfaction.

Consider a representative consumer and producer with an inherited stock of inventories \tilde{I}_{t-1} , choosing how much to produce and consume at date t . (Variables with a “~” are those that will grow in a steady state, and therefore will be normalized below.) We will assume for now that production for period t gets chosen before complete information about demand arrives. (This will be related later to our notion of “progress.”)

We will solve for the equilibrium by examining a planner’s problem. The planner solves

$$\max_{\{c,n\}} E_0 \left\{ \sum_{t=0}^{\infty} \beta^t U(\tilde{c}_t, n_t; \tilde{I}_{t-1}, \zeta_t) \right\}$$

subject to

$$\tilde{I}_t = \tilde{I}_{t-1} + A_t f(n_t) - \tilde{c}_t \tag{1}$$

where n_t is work effort at t , \tilde{c}_t consumption, \tilde{I}_t the stock of inventories at the end of period t , A_t a technology shock, and ζ_t a taste shock (in the form of a shock to the marginal rate of substitution between leisure and goods.)¹⁶

We assume that U and f take the following forms:

$$\begin{aligned} U(\tilde{c}_t, n_t; \tilde{I}_{t-1}, \zeta_t) &= \log \left[\theta \tilde{c}_t^{1-\rho} + (1-\theta) \tilde{I}_{t-1}^{1-\rho} \right]^{\frac{1}{1-\rho}} \zeta_t - n_t^{1+\delta} \\ f(n_t) &= n_t^{1-\alpha}. \end{aligned}$$

where $E_{t-1}\{\xi_t\} = E_{t-1}\{v_t\} = E_{t-1}\{w_t\} = 1$. The first term in U captures the idea that a larger inventory stock increases the marginal utility of any given purchase c_t ,

¹⁶While such shocks are rather ad hoc, Hall (1997) argues persuasively that it is difficult to account for a large part of high-frequency movements in aggregate data without resort to this type of shock to the marginal rate of substitution between consumption and leisure.

either by reducing transactions costs (e.g. shopping time) or by better matching the consumer’s tastes. The parameter ρ is the inverse of an elasticity of substitution, which will dictate the degree to which consumption and inventories are linked. The second term is a standard disutility of labor, with $\delta > 0$.¹⁷

For the shock processes, we have

$$A_t = (1 + g)A_{t-1}\xi_t\tau_t/\tau_{t-1}$$

for the technology shock. This process contains a permanent shock ξ_t and a transitory shock, τ_t . For the preference shock ζ_t we consider two possibilities:

$$\begin{aligned}\zeta_t &= \zeta_{t-1}^\phi v_t w_t \\ \zeta_t &= \zeta_{t-1}^\phi v_{t-1} w_t\end{aligned}$$

In either case the the combined shock vw is i.i.d., but part of it (the v) is observable before the other (the w). This time structure is illustrated in Figure 6. In the first case, which we will refer to as “Contemporaneous Information” (CI), producers learn something about period t demand in time to adjust n_t (and hence y_t and end-of-period inventories I_t), but too late to do anything about inventories going into period t , I_{t-1} .¹⁸ In the second case, which we will refer to as “Early Information” (EI), the information arrives in time to adjust the inventory stock I_{t-1} through the choice of n_{t-1} .

¹⁷This combination of CES utility in consumption plus an additive disutility of labor would appear to violate the balanced growth conditions given by King, Plosser, and Rebelo (1988). They do not in this case because there is no capital, and the state variable \tilde{I} enters the utility function. Qualitatively similar results can be obtained with logarithmic utility.

¹⁸In an earlier draft, the preference shock specification was $\zeta_t = \zeta_{t-1}^\phi v_t w_t$, i.e. the information about period t demand was received in time to adjust y_t (and hence end-of-period inventories I_t), but not I_{t-1} . This also has the effect of reducing volatility, but only by enabling producers to offset forecast errors better, not by enabling them to forecast better in the first place. Consequently it has the implication of increasing rather decreasing the covariance of inventory investment growth and production growth, contrary to what was found in the data.

If we define $c_t \equiv \tilde{c}_t/A_{t-1}$, and $I_{t-1} \equiv \tilde{I}_{t-1}/A_{t-1}$, then we have

$$U(\tilde{c}_t, n_t; \tilde{I}_{t-1}, \zeta_t) = A_{t-1} + U(c_t, n_t; I_{t-1}, \zeta_t).$$

The resource constraint becomes

$$A_t I_t = A_{t-1} I_{t-1} + A_t n_t^{1-\alpha} - A_{t-1} c_t$$

$$(I_t - n_t^{1-\alpha})(1+g)z_t - I_{t-1} + c_t = 0$$

where $z_t \equiv \xi_t \tau_t / \tau_{t-1}$. With this normalization, I , c , and n will be constant in steady state.

We can express the first-order conditions as

$$\left[\theta c_t^{1-\rho} + (1-\theta) I_{t-1}^{1-\rho} \right]^{-1} \theta c_t^{-\rho} \zeta_t - q_t = 0 \quad (2)$$

$$(1+\delta)n_t^\delta - n_t^{-\alpha}(1+g)^{-1} E_{t-1} \{q_t z_t | v_t\} = 0 \quad (3)$$

$$E_t \left\{ \beta \left[\theta c_{t+1}^{1-\rho} + (1-\theta) I_t^{1-\rho} \right]^{-1} (1-\theta) I_t^{-\rho} \zeta_{t+1} - q_t(1+g) + \beta q_{t+1} \right\} = 0 \quad (4)$$

where q_t is the normalized shadow price of consumption goods at date t , and $E_{t-1} \{q_t z_t | v_t\}$ refers to the expectation given period $t-1$ information plus v_t . These conditions can be solved for their steady-state implications. Ignoring uncertainty, we have, for example:

$$\frac{I}{c} = \left[\frac{\beta(1-\theta)}{\theta(1+g-\beta)} \right]^{1/\rho} \quad (5)$$

$$\frac{n^{1-\alpha}}{I} = \frac{g}{1+g} + \frac{1}{1+g} \left[\frac{\theta(1+g-\beta)}{\beta(1-\theta)} \right]^{1/\rho}. \quad (6)$$

This means that for c/I to be near one, θ should be near β .

It will be useful to consider a market equilibrium corresponding to the solution to the above system. In this case we would want to consider a real interest rate. According to standard asset pricing theory (e.g. Lucas, 1978), we can compute the

equilibrium risk-free rate of return from the price of a risk-free asset, which will be

$$\beta E_t \{U_{\tilde{c}_{t+1}}\} / U_{\tilde{c}_t}.$$

Thus the equilibrium risk-free rate of return is equal to the inverse of this, i.e.

$$1 + r_t = \frac{U_{\tilde{c}_t}}{\beta E_t \{U_{\tilde{c}_{t+1}}\}} = \frac{(1 + g)q_t z_t}{\beta E_t \{q_{t+1}\}}.$$

Thus in a deterministic steady state this return would equal $(1 + g)/\beta$.

Next we can log-linearize the system by writing it in terms of first-order approximations of log deviations from the steady state. First, define

$$\mu \equiv \frac{\theta c^{1-\rho}}{\theta c^{1-\rho} + (1 - \theta)I^{1-\rho}},$$

a function of steady-state I/c (and usually close in value to θ). Replacing all the variables by their log deviations from steady state, we have

$$-(1 - \rho)[\mu c_t + (1 - \mu)I_{t-1}] - \rho c_t + \zeta_t - q_t = 0 \quad (7)$$

$$E_{t-1} \{(\alpha + \delta)n_t - q_t - z_t | v_t\} = 0 \quad (8)$$

$$I_t - (1 + g)^{-1}I_{t-1} + \frac{c}{I(1 + g)}c_t - \frac{n^{1-\alpha}}{I} [(1 - \alpha)n_t + z_t] + z_t = 0 \quad (9)$$

$$E_t \left\{ -(1 - \rho)[\mu c_{t+1} + (1 - \mu)I_t] - \rho I_t + \zeta_{t+1} - \frac{q_t + z_t - \beta(1+g)^{-1}q_{t+1}}{1 - \beta(1+g)^{-1}} \right\} = 0 \quad (10)$$

and

$$r_t = q_t - E_t \{q_{t+1}\}$$

for the real interest rate.

Note that (7) and (10) can be combined to yield

$$E_t \left\{ -\rho(I_t - c_{t+1}) - \frac{q_t + z_t - q_{t+1}}{1 - \beta(1 + g)^{-1}} \right\} = 0$$

or

$$E_t \{I_t - c_{t+1}\} = - \left(\frac{1}{\rho} \right) \frac{r_t}{1 - \beta(1 + g)^{-1}},$$

which says that the inventory-sales ratio responds negatively to the real interest rate in proportion to $1/\rho$, the elasticity of substitution between I and c in utility.

We will assume that the permanent and transitory components of the supply shock \hat{z}_t are not separately observable. In that case \hat{z}_t can be represented as an $MA(1)$ process $\eta_t - \nu\eta_{t-1}$, with

$$\nu = \begin{cases} 1 + \frac{1}{2} \frac{\sigma_\xi^2}{\sigma_\tau^2} - \frac{1}{2} \sqrt{4 \frac{\sigma_\xi^2}{\sigma_\tau^2} + \left(\frac{\sigma_\xi^2}{\sigma_\tau^2} \right)^2} & \sigma_\tau^2 > 0 \\ 0 & \sigma_\tau^2 = 0 \end{cases}$$

and

$$E_t \{z_{t+1}\} = -\nu(z_t - E_{t-1}\{z_t\})$$

which is the standard rational expectations updating rule for extracting the permanent part of a mixture of permanent and transitory shocks.

3.3 Equilibrium

We can solve the system (7)-(10) using a variant of the method of underdetermined coefficients. The difference in available information between the choice of n_t and the choice of c_t requires some extra apparatus. First, define a variable called \bar{n}_{t-1} , which is the *ex ante* choice for n_t . Then “guess” that $n_t = \bar{n}_{t-1} + hv_t$ for some h . We replace (8) by

$$E_{t-1} \{(\alpha + \delta)\bar{n}_{t-1} - q_t - z_t\} = 0 \tag{11}$$

$$n_t - \bar{n}_{t-1} - hv_t = 0. \tag{12}$$

Equations (8) and (11) imply that

$$n_t = \bar{n}_{t-1} + (\alpha + \delta)^{-1}(E_{t-1}\{q_t|v_t\} - E_{t-1}\{q_t\}).$$

In other words, n_t is revised to the extent that v_t changes the expected value of q_t .

We can describe the full set of first-order conditions in terms of a state vector (I_t, n_t, \bar{n}_t) , a vector of “jump variables” (c_t, q_t) , exogenous variables $(\zeta_t, \eta_t, \eta_{t-1}, \tau_t, v_t)$ and shocks (either $(w_{t+1} + v_{t+1}, \xi_{t+1} + \tau_{t+1}, 0, \tau_{t+1}, v_{t+1})$ under CI, or $(w_{t+1}, \xi_{t+1} + \tau_{t+1}, 0, \tau_{t+1}, v_{t+1})$ under EI—see the Appendix for more details). We obtain a solution (conditional on the choice of h) of the form

$$\begin{bmatrix} I_t \\ n_t \\ \bar{n}_t \end{bmatrix} = P \begin{bmatrix} I_{t-1} \\ n_{t-1} \\ \bar{n}_{t-1} \end{bmatrix} + Q \begin{bmatrix} \zeta_t \\ \eta_t \\ \eta_{t-1} \\ \tau_t \\ v_t \end{bmatrix} \quad (13)$$

$$\begin{bmatrix} c_t \\ q_t \end{bmatrix} = R \begin{bmatrix} I_{t-1} \\ n_{t-1} \\ \bar{n}_{t-1} \end{bmatrix} + S \begin{bmatrix} \zeta_t \\ \eta_t \\ \eta_{t-1} \\ \tau_t \\ v_t \end{bmatrix} \quad (14)$$

where P, Q, R , and S are matrices of coefficients determined from (7), (9)-(10), (11), (12). Under CI, the shock processes are described by

$$\begin{bmatrix} \zeta_{t+1} \\ \eta_{t+1} \\ \eta_t \\ \tau_{t+1} \\ v_{t+1} \end{bmatrix} = N \begin{bmatrix} \zeta_t \\ \eta_t \\ \eta_{t-1} \\ \tau_t \\ v_t \end{bmatrix} + \begin{bmatrix} w_{t+1} + v_{t+1} \\ \xi_{t+1} + \tau_{t+1} \\ 0 \\ \tau_{t+1} \\ v_{t+1} \end{bmatrix}. \quad (15)$$

where

$$N = \begin{bmatrix} \phi & 0 & 0 & 0 & 0 \\ 0 & \nu & 0 & -1 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}.$$

Under EI, we have

$$\begin{bmatrix} \zeta_{t+1} \\ \eta_{t+1} \\ \eta_t \\ \tau_{t+1} \\ v_{t+1} \end{bmatrix} = N \begin{bmatrix} \zeta_t \\ \eta_t \\ \eta_{t-1} \\ \tau_t \\ v_t \end{bmatrix} + \begin{bmatrix} w_{t+1} \\ \xi_{t+1} + \tau_{t+1} \\ 0 \\ \tau_{t+1} \\ v_{t+1} \end{bmatrix}. \quad (16)$$

where

$$N = \begin{bmatrix} \phi & 0 & 0 & 0 & 1 \\ 0 & \nu & 0 & -1 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}.$$

Finally, we also have

$$a_{t+1} = a_t + z_{t+1} \quad (17)$$

where $a_t \equiv \log(A_t)$. For details of the solution method, see the Appendix.

Given the solution (13)-(14), we have under CI

$$E_{t-1}\{q_t|v_t\} - E_{t-1}\{q_t\} = S[2, 1] + S[2, 5],$$

and under EI

$$E_{t-1}\{q_t|v_t\} - E_{t-1}\{q_t\} = S[2, 1].$$

A complete solution requires $h = (\alpha + \delta)^{-1}[E_{t-1}\{q_t|v_t\} - E_{t-1}\{q_t\}]$. We then iterate, updating the choice of h until convergence is achieved.

3.4 Progress

Because of the nature of the inventory problem, in which forecast errors carry over into current production decisions, improvements in information technology or inventory management can reduce output volatility. There has been a wealth of anecdotal and case study evidence to suggest that information about final sales travels upstream much more quickly than it used to, because of advances in information technology.

To understand how better information works to reduce output volatility in our model, we now suppose that rather than waiting until the after it has committed to production, the firm gets a signal about the upcoming demand shock prior to making its production decision. An extreme example of this scenario, one in which the firm knows the exact demand shock, is shown on the right-hand side of Figure 7. In this example, we assume that the firm finds out the magnitude of the demand shock in advance of making its production decision, and hence it chooses to produce 125 units of the good—75 of which will meet current demand and the other 50 of which will be added to inventories, raising the stock to 150 and keeping the firm at its target ratio of 2.

To see the effect of better information on the volatility of production, compare the movements in output under our two scenarios. As shown in the top panel of Figure 8, for the same underlying demand shock (shown in the bottom panel), production jumps by 100 units under the low information scenario, but only by 75 units under the high information scenario (note that Figure 8 depicts the first differences of the movements described in Figure 7). The demand increase is identical in both cases, so the reduction in volatility is entirely a product of the technological change that allows firms to know more in advance about the likely realization of demand for that period.

We will consider two types of information improvement: Recall that we have

n_t chosen based on knowledge of v_t but not w_t . Thinking of v as a signal of the total shock $v + w$, we model progress as an increase in the ratio σ_v^2/σ_w^2 , holding $\sigma_v^2 + \sigma_w^2$ constant. This corresponds to an improvement in the quality of the signal. Figures 9 and 10 provide some structural impulse responses to illustrate this for the two cases $\zeta_t = \phi\zeta_{t-1} + v_t + w_t$ and $\zeta_t = \phi\zeta_{t-1} + v_{t-1} + w_t$, respectively. In the first case, information about the current shock is revealed before current production decisions have to be made. In the second case, information about the shock is revealed before decisions have to be made about the previous period's production (early enough to adjust the inventory stock going into the period in which the shock will occur). The shocks are to v and w at $t = 5$, such that $v + w = 0.1$. In each figure, the three panels show the effect of increasing $v/(v + w)$ from 0 to 0.4 to 0.8. We can clearly see that the impulse to y is moderated relative to that of c as the shock becomes more anticipated. The reason is that to the extent the demand shock is foreseen, output responds in anticipation, to moderate the impact on inventories and to reduce marginal cost (which is proportional to y).

Comparing Figures 9 and 10 allows us to understand the effect of information arriving earlier, holding fixed the signal quality. This corresponds to going from, say, the $s/n = 0.4$ case in Figure 9 to the corresponding case in Figure 10. With the earlier arrival of information, inventories are built up ahead of the sales increase, and get drawn down when the “shock” arrives.

Note that in either case the reductions in production volatility occur without any change in the actual shocks (ζ_t, ξ_t, τ_t) hitting the economy. It is only the information about the shocks that is reaching decision-makers in a more timely fashion.¹⁹ But to an observer who only sees the output data, for example, it might appear that the magnitude of the shocks has diminished.

Another aspect of better information could be a decline in inventory-sales ratios, as determined by the parameter θ . In stockout-avoidance models (e.g. Kahn, 1987),

¹⁹An alternative interpretation is that production is more “flexible,” so that firms can wait longer (i.e. obtain more information) before making production decisions.

the average inventory-sales ratio would typically be related to one-period-ahead uncertainty about sales. While we have not modeled this relationship explicitly, we can allow for the impact of declining ratios on output volatility as well by recalibrating the model according to observed ratios.

3.5 Information: Earlier or Better?

As described above, the difference between the two specifications of the ζ process has to do with when the information is received. In an earlier draft, the preference shock specification was $\zeta_t = \zeta_{t-1}^\phi v_t w_t$, i.e. the information about period t demand was received in time to adjust y_t (and hence end-of-period inventories I_t), but not I_{t-1} . This also has the effect of reducing volatility, but only by enabling producers to offset forecast errors better, not by enabling them to forecast better in the first place. Consequently it has the implication of increasing rather decreasing the covariance of inventory investment growth and production growth, contrary to what was found in the data. [Incomplete]

3.6 Monte Carlo Simulations

Table 6 presents the results of a Monte Carlo simulation of our model. [Incomplete]

4 Summary

In this paper we document the increased stability of U.S. output growth since 1984 and show that inventory investment, particularly in the durable goods sector, plays at least a passive role in that stability. Specifically, final sales has shown substantially less increased stability compared to output.

Our structural model, incorporating both inventories and information technology, illustrates how better information about demand leads to lower output volatility, both absolutely and relative to final demand. However, the quantitative effects of

better information in the model are modest, suggesting that other factors may have contributed to the increased stability, or that further refinements to the model are necessary. For example, the model does not allow for durability of the goods for consumers. It also does not allow for endogenous reductions in inventory-sales ratios as part of the response to better information technology. The results suggest that these would be fruitful areas for further research.

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Table 1: The Changing Variability of Real Activity

	(1)	(2)	(3)
	53:2 - 68:4	69:1 - 83:4	84:1 - 00:2
Output Growth			
Aggregate	4.5	4.8	2.2
Durables	18.1	17.9	8.0
Nondurables	5.9	7.9	4.8
Services	3.4	1.5	1.4
Structures	7.0	13.6	8.6

Note: The numbers reported in columns marked (1) through (3) are the standard deviation of the variable listed in the left-hand column. Output growth is measured as the percent change in chainweighted 1996 dollars at an annual rate.

Table 2: Explaining the Changing Variability of Real Activity

	53:2 - 84:4	85:1 - 00:2
Actual	4.7	2.2
‘Durables’ Experiment	4.7	3.9

Note: The numbers reported are the standard deviation of the variable listed in the left-hand column. ‘Durables’ Experiment refers to an artificial GDP series constructed under the counterfactual assumption that the volatility of output in the durable goods sector did not decline after 1985:1. Output growth is measured as the percent change in chainweighted 1996 dollars at an annual rate.

Table 3: Output and Final Sales Growth in the Goods Sector - 1953:2 to 2001:1

	1953:2 - 1983:4	1984:1 - 2001:1
Goods		
Output	8.2	4.6
Final Sales	5.7	4.3
Ratio	1.4	1.1
Durables		
Output	17.9	8.1
Final Sales	10.7	8.4
Ratio	1.7	1.0
Nondurables		
Output	6.9	4.8
Final Sales	4.7	3.0
Ratio	1.5	1.6

Note: The numbers reported in the first two rows of each panel are the standard deviation of the annualized quarterly growth rate (chain-weighted 1996\$) of the variable listed in the left-hand column. “Ratio” is the ratio of the standard deviation of output growth to final sales growth.

Table 4: The Role of Inventories in Lower Output Volatility

Component	59:1-83:4	84:1-00:3	% of $\Delta\text{var}(\hat{y})$	
Goods				
$\text{var}(\hat{y})$	3.73	1.14	100	
$\text{var}(\hat{s})$	1.58	1.02	21.7	
$\text{var}(\widehat{\Delta I})$	2.26	1.15	43.4	
$2\text{cov}(\widehat{\Delta I}, \hat{s})$	-0.12	-1.02	35.0	
Durable Goods				
$\text{var}(\hat{y})$	17.46	3.70	100	
$\text{var}(\hat{s})$	5.68	3.91	13.2	
$\text{var}(\widehat{\Delta I})$	9.11	3.92	38.2	
$2\text{cov}(\widehat{\Delta I}, \hat{s})$	2.68	-4.12	48.5	
Nondurable Goods				
$\text{var}(\hat{y})$	2.94	1.39	100	
$\text{var}(\hat{s})$	1.12	0.52	38.1	
$\text{var}(\widehat{\Delta I})$	2.37	0.99	87.7	
$2\text{cov}(\widehat{\Delta I}, \hat{s})$	-0.56	-0.12	-25.8	

Note: We work with growth contributions because the data are chain-weighted. \hat{y} refers to the quarterly (not annualized) growth rate of output, while \hat{s} is the quarterly growth contribution of sales, and $\widehat{\Delta I}$ is the quarterly growth contribution of inventory investment. We approximate the growth contribution of sales by its lagged nominal share multiplied by its growth rate. The growth contribution of inventory investment is defined as a residual, so that $\hat{y} = \hat{s} + \widehat{\Delta I}$.

Table 5: Durable Goods Sector

VAR Estimates				
	53:1-83:4		84:1-00:2	
	Sales _t	Inventories _t	Sales _t	Inventories _t
Sales _{t-1}	0.152 (0.089)	0.142 (0.041)	-0.212 (0.129)	0.132 (0.054)
Sales _{t-2}	0.138 (0.089)	0.116 (0.041)	-0.138 (0.112)	0.173 (0.047)
Inventories _{t-1}	0.445 (0.206)	0.390 (0.094)	1.007 (0.286)	0.446 (0.121)
Inventories _{t-2}	-0.551 (0.190)	-0.030 (0.087)	0.082 (0.319)	-0.038 (0.135)
R^2	0.132	0.422	0.275	0.410
s.d. dependent	0.025	0.015	0.020	0.010
Variance Decomposition				
	53:1-83:4		84:1-00:2	
Sales	94.6%	37.8%	84.1%	18.2%
Inventories	5.4	62.2	14.9	81.8%

Note: The numbers reported in the top panel are the results of a VAR on the growth rates (change in the log, not annualized) of final sales and inventories for the durable goods sector. The bottom panel reports the results of a variance decomposition after 10 periods with sales placed first in the ordering.

Table 6: Monte Carlo Simulations

		1953-1983	1984-2000
Goods	$\text{var}(\hat{y})$	3.73	1.14
	$\text{var}(\hat{s})$	1.58	1.02
	$\sigma_{\Delta y}/\sigma_{\Delta s}$	2.36	1.12
	$\text{var}(\widehat{\Delta I})$	2.26	1.15
	$2\text{cov}(\widehat{\Delta I}, \hat{s})$	-0.12	-1.02
Durables	$\text{var}(\hat{y})$	17.46	3.70
	$\text{var}(\hat{s})$	5.68	3.91
	$\sigma_{\Delta y}/\sigma_{\Delta s}$	3.07	0.95
	$\text{var}(\widehat{\Delta I})$	9.11	3.92
	$2\text{cov}(\widehat{\Delta I}, \hat{s})$	2.68	-4.12
		CI	EI
$s/n = 0$	$\text{var}(\hat{y})$		0.140
	$\text{var}(\hat{s})$		0.029
	$\sigma_{\Delta y}/\sigma_{\Delta s}$		4.83
	$\text{var}(\widehat{\Delta I})$		0.167
	$2\text{cov}(\widehat{\Delta I}, \hat{s})$		-0.056
$s/n = 0.4$	$\text{var}(\hat{y})$	0.126	0.099
	$\text{var}(\hat{s})$	0.038	0.058
	$\sigma_{\Delta y}/\sigma_{\Delta s}$	3.31	1.71
	$\text{var}(\widehat{\Delta I})$	0.105	0.155
	$2\text{cov}(\widehat{\Delta I}, \hat{s})$	-0.018	-0.114
$s/n = 0.8$	$\text{var}(\hat{y})$	0.114	0.059
	$\text{var}(\hat{s})$	0.047	0.087
	$\sigma_{\Delta y}/\sigma_{\Delta s}$	2.43	0.68
	$\text{var}(\widehat{\Delta I})$	0.044	0.144
	$2\text{cov}(\widehat{\Delta I}, \hat{s})$	0.022	-0.172

Note: The top panel reports the actual data. The third panel shows the baseline case of no information about shocks until the period in which the shock occurs. Reading across the bottom two panels of the table gives the effects of earlier arrival of information (holding the amount fixed), while reading down the columns gives the effects of a better signal regarding the upcoming shock, holding the period of the arrival of that signal fixed.

Figure 1: U.S. Real GDP Growth: 1953:2 to 2000:2

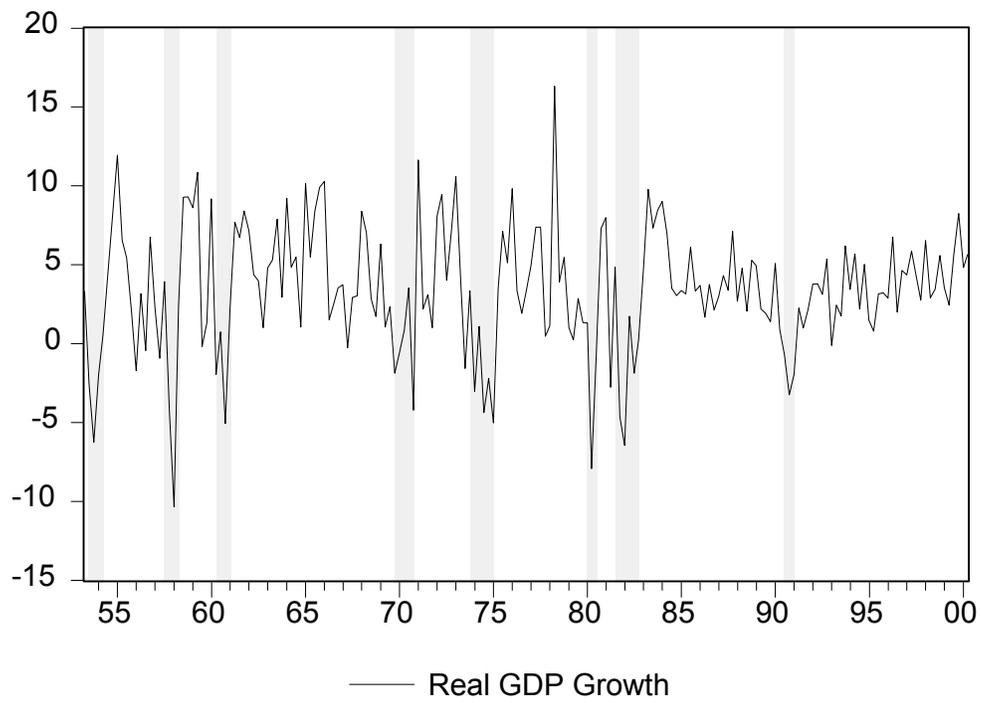


Figure 2: Postwar Inventory-to-Sales Ratios

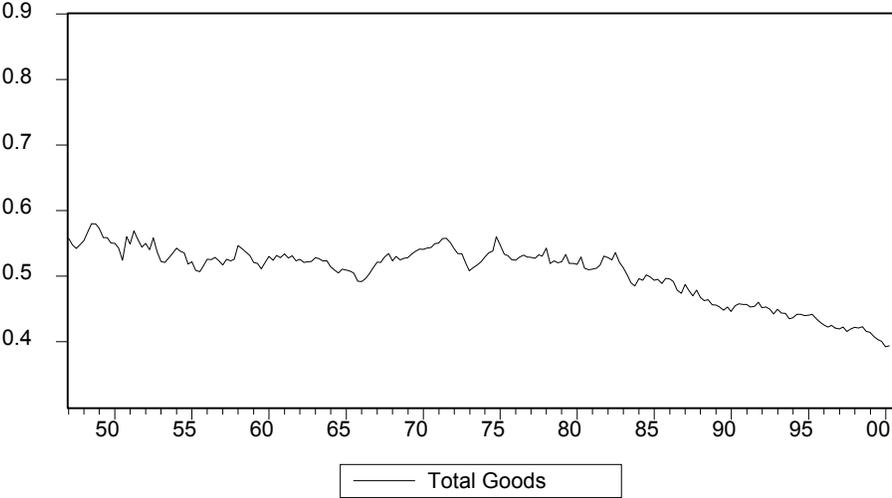
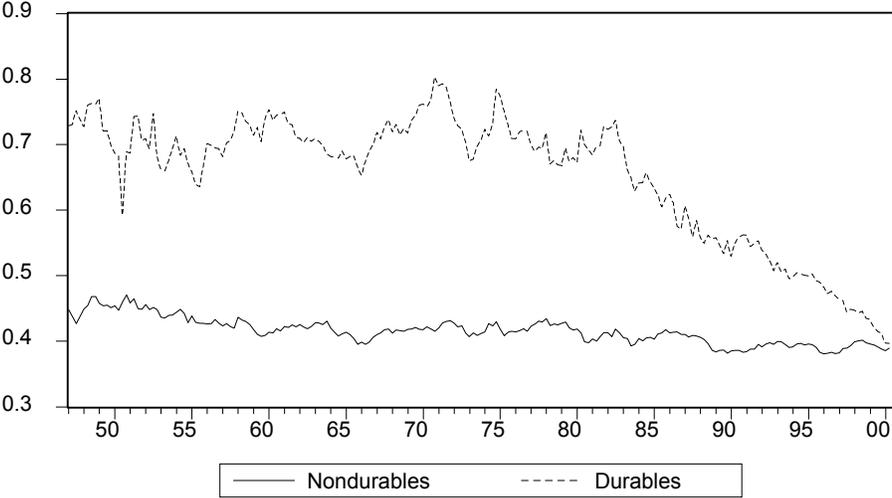


Figure 3: Durables I/S, Target I/S and Deviations from Target

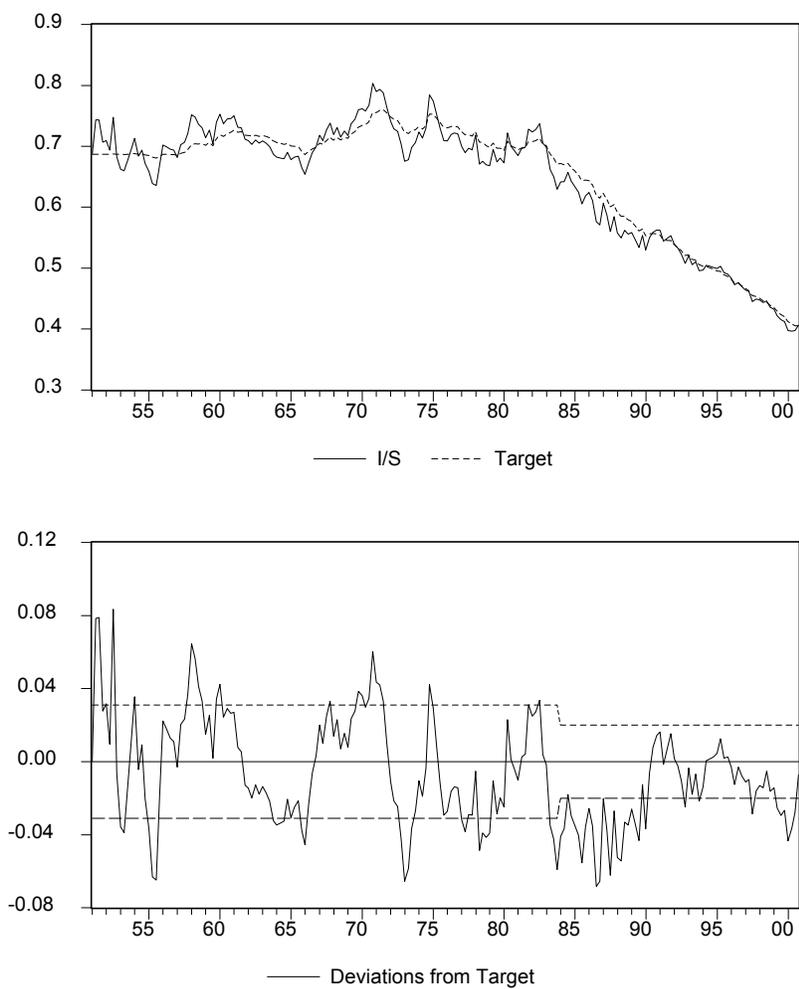


Figure 4: Materials Inventory-to-Sales Ratios - Durable Manufacturing

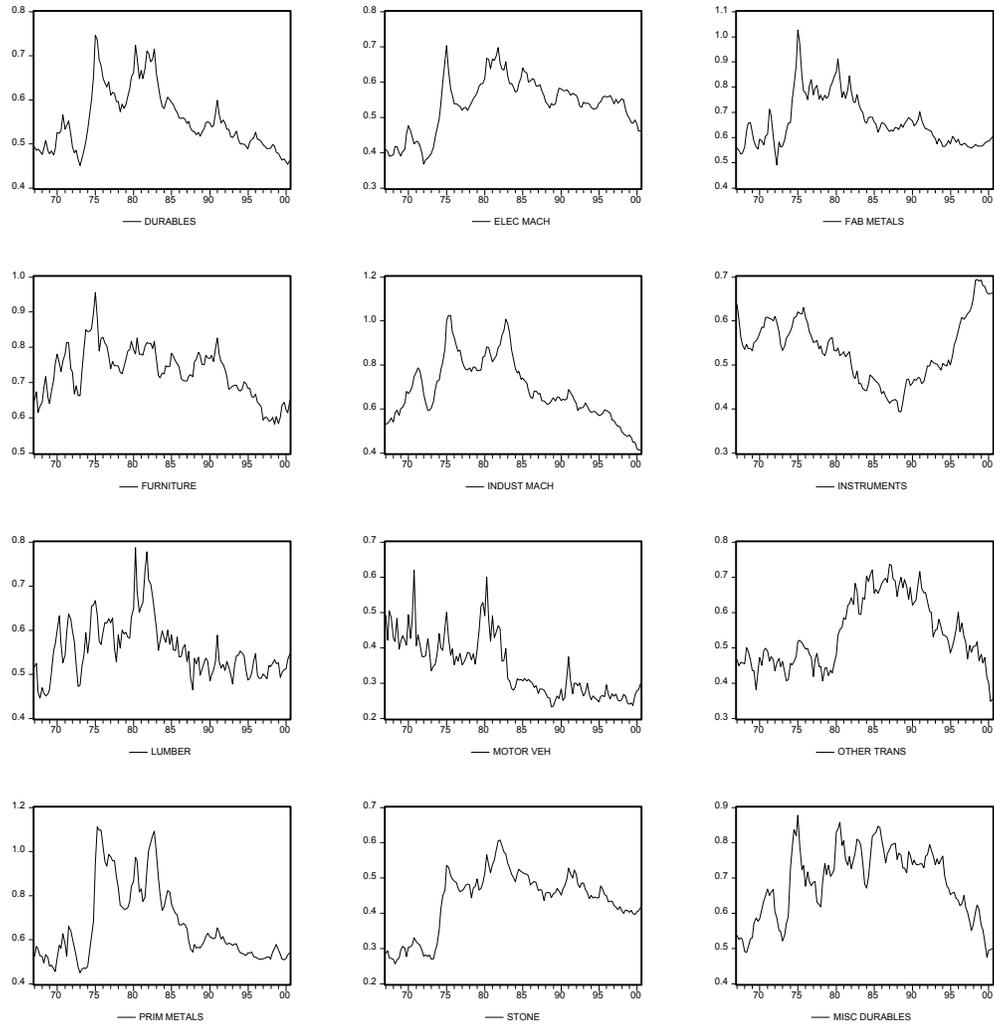


Figure 5: Works-in-Process Inventory-to-Sales Ratios - Durable Manufacturing

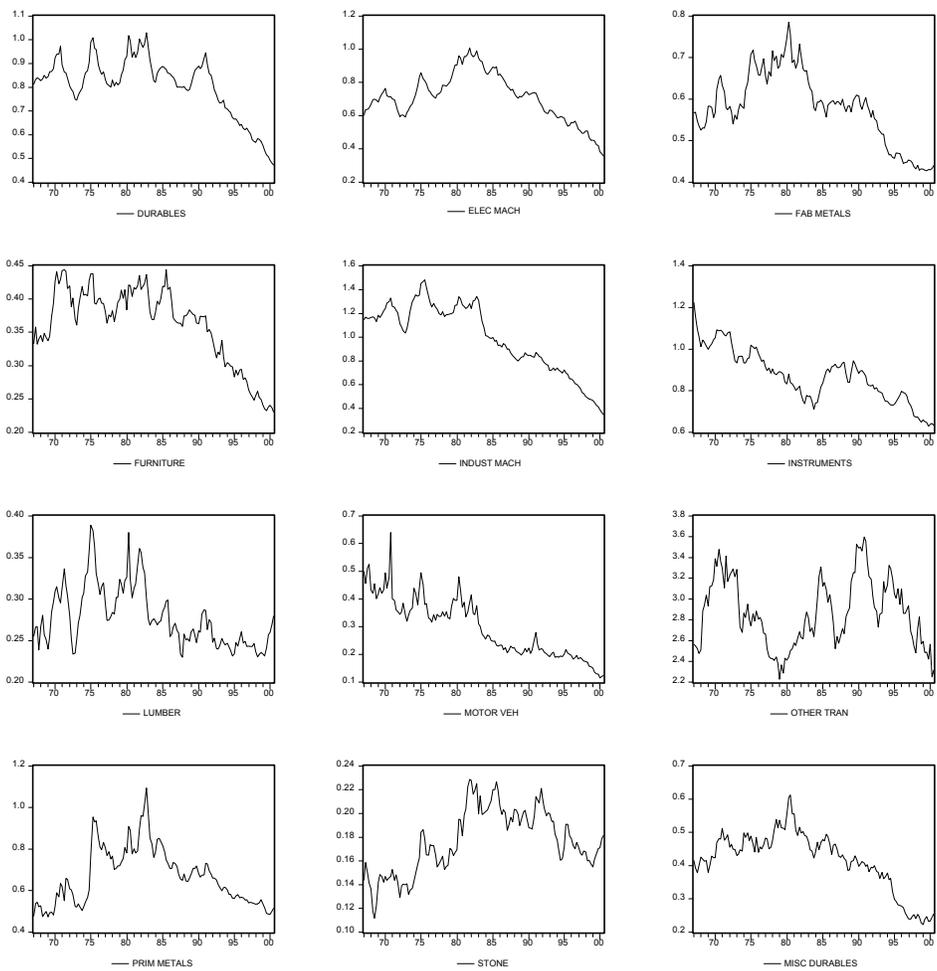


Figure 6: Time Structure of Decisions and Information

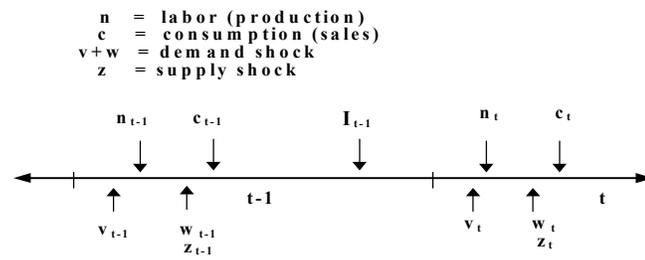


Figure 7: The Impact of Information on Production Decisions

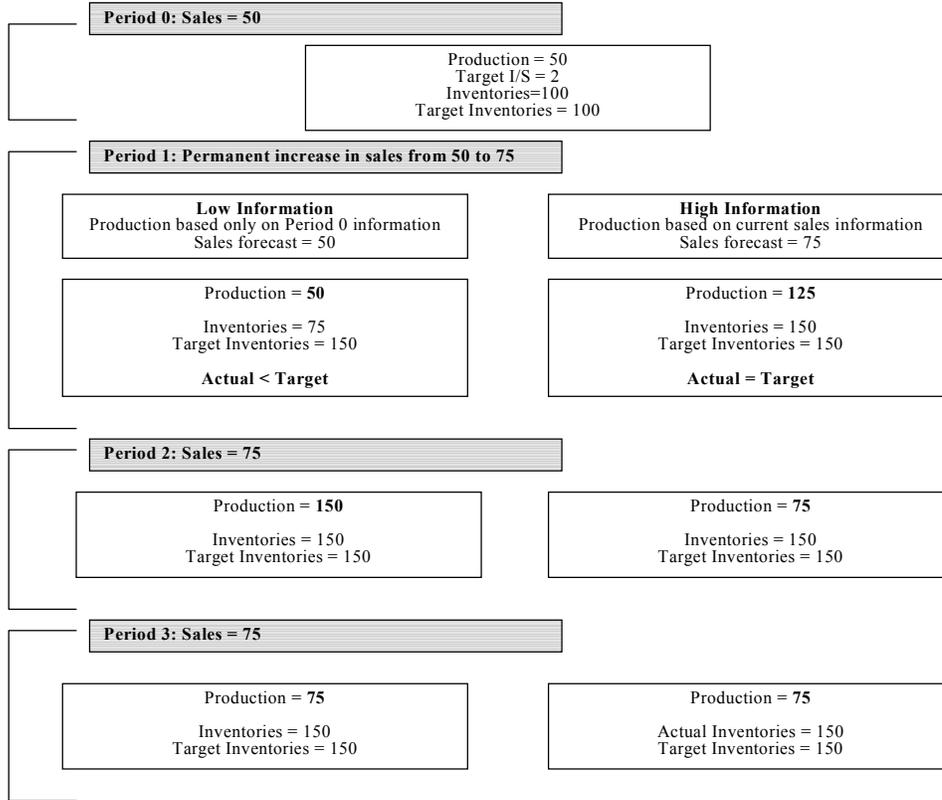


Figure 8: The Impact of Information on Volatility

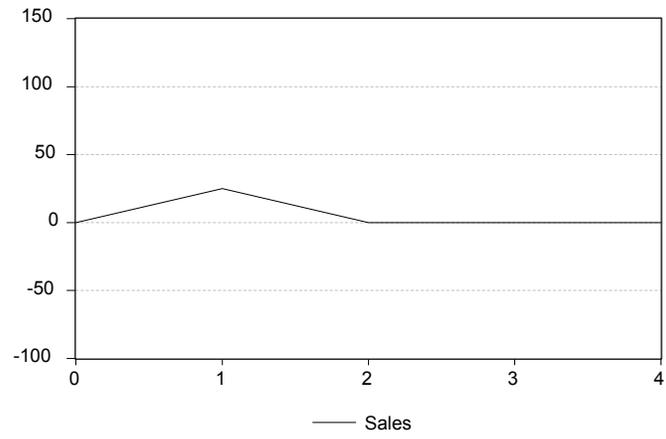
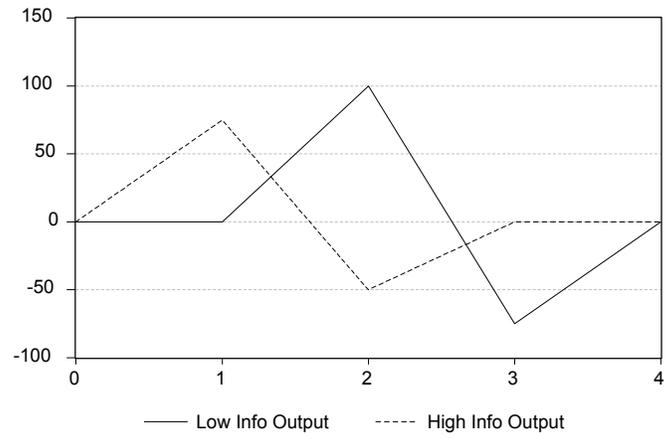


Figure 9: Equilibrium Responses to Demand Shocks: Contemporaneous Information

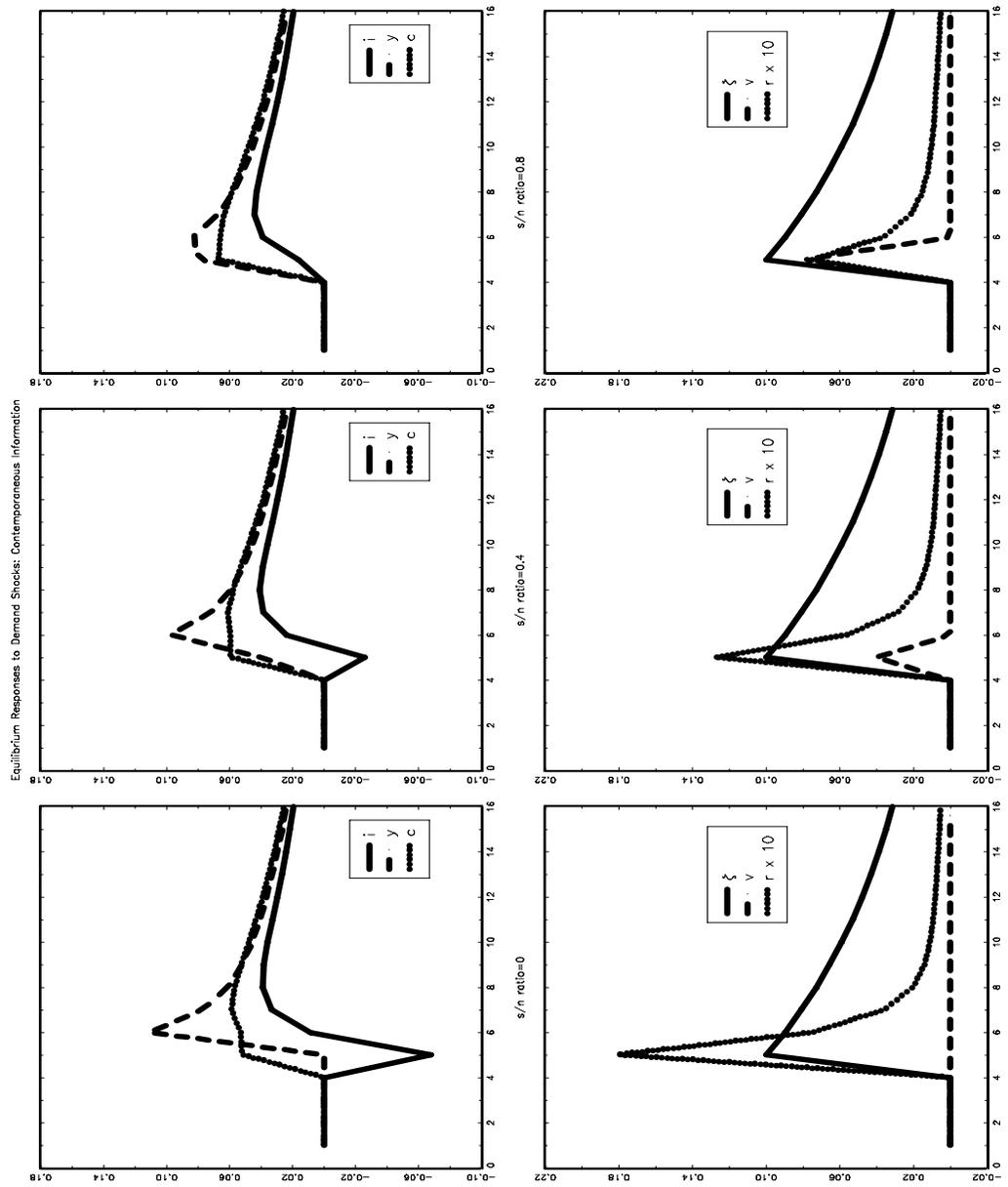
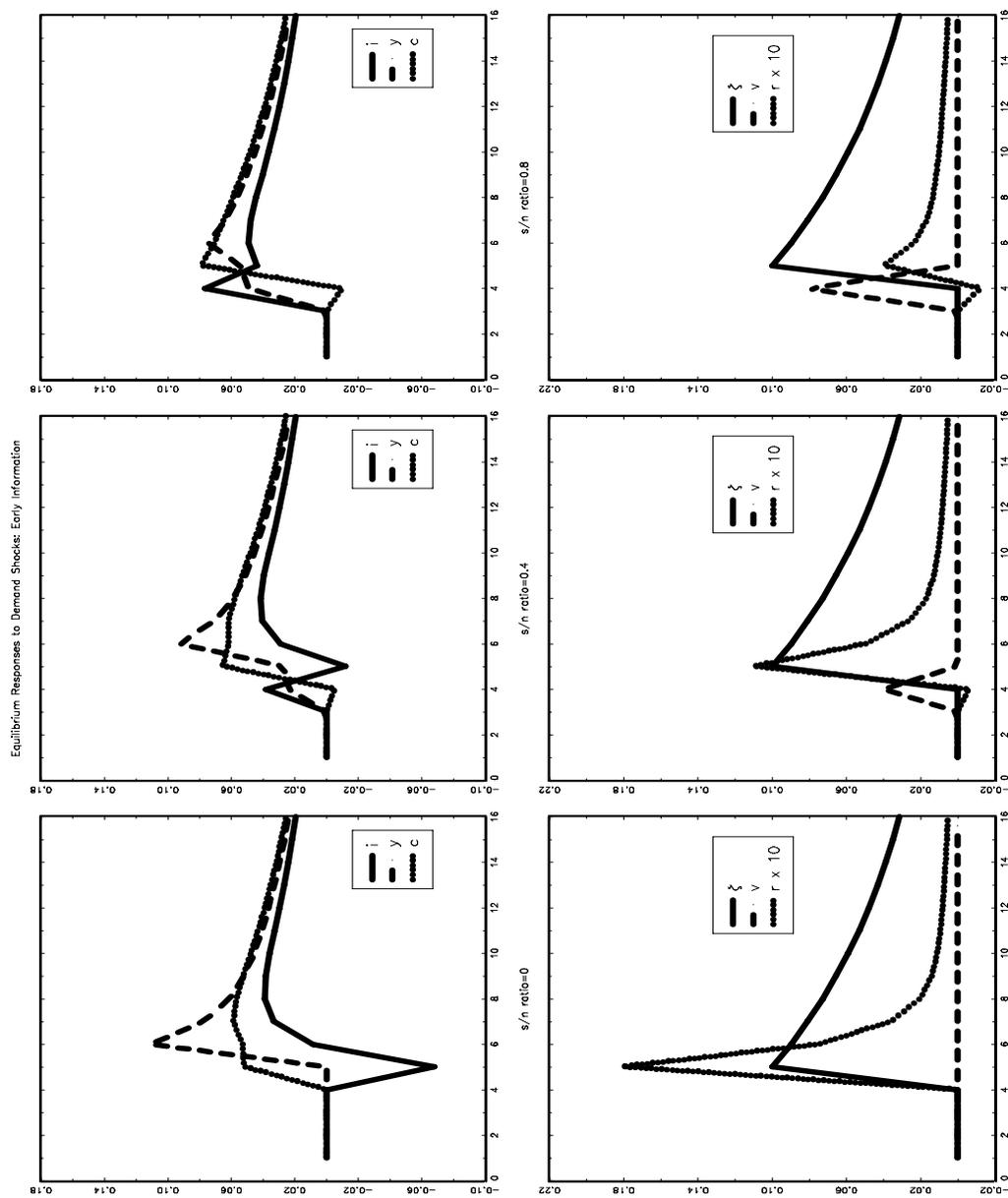


Figure 10: Equilibrium Responses to Demand Shocks: Early Information



Appendix

Kalman Filter Estimates of I/S Target

In order to decompose the inventory-to-sales ratio for the durable goods sector into its permanent and transitory components we estimate the following model:

$$y_t = n_t + x_t$$

$$n_t = g_{t-1} + n_{t-1} + v_t \quad v_t \sim iid, N(0, \sigma_v^2)$$

$$g_t = g_{t-1} + w_t \quad w_t \sim iid, N(0, \sigma_w^2)$$

$$x_t = \phi_1 x_{t-1} + \phi_2 x_{t-2} + e_t \quad e_t \sim iid, N(0, \sigma_e^2)$$

y_t is the inventory to sales ratio, n_t is the permanent component and x_t is the

transitory component.

To address the question of whether σ_e^2 has fallen, we split the sample in 1984:1 (following MPQ) and estimating:

$$y_t = n_t + x_t$$

$$n_t = g_{t-1} + n_{t-1} + v_t \quad v_t \sim iid, N(0, \sigma_v^2)$$

$$g_t = g_{t-1} + w_t \quad w_t \sim iid, N(0, \sigma_w^2)$$

$$x_t = \phi_1 x_{t-1} + \phi_2 x_{t-2} + e_t \quad e_t \sim iid, N(0, \sigma_{e,t}^2)$$

$$\sigma_{e,t}^2 = \sigma_{e,1}^2(1 - I_t) + \sigma_{e,2}^2 I_t$$

Where $I_t = 1$ if $t > 1984.1$ and 0 otherwise.

The estimated values are:

$$\sigma_v^2 = 0.000010 \quad (0.000831)$$

$$\sigma_w^2 = 0.000253 \quad (0.000093)$$

$$\sigma_{e,1}^2 = 0.018434 \quad (0.001151)$$

$$\sigma_{e,2}^2 = 0.011650 \quad (0.001036)$$

$$\phi_1 = 0.766974 \quad (.074982)$$

$$\phi_2 = 0.058569 \quad (0.073654)$$

We reject the null hypothesis of $\sigma_{e,1}^2 = \sigma_{e,2}^2$ with a p-value of 0.000.

An alternative specification in which we use the logs of the I/S ratio yields similar results.