# Inventory Dynamics and Business Cycles: What Has Changed?†

Jonathan McCarthy
Federal Reserve Bank of New York
33 Liberty Street
New York, NY 10045
Email: jonathan.mccarthy@ny.frb.org

Egon Zakrajšek
Federal Reserve Board
20th Street & Constitution Avenue, NW
Washington D.C., 20551
Email: egon.zakrajsek@frb.gov

December 18, 2002

**Abstract**

By historical standards, the U.S. economy has experienced a period of remarkable stability since the mid-1980s. One explanation attributes the diminished variability of economic activity to information-technology led improvements in inventory management. Our results, however, indicate that the changes in inventory dynamics since the mid-1980s played a reinforcing—rather than a leading—role in the volatility reduction. A decomposition of the reduction in the volatility of manufacturing output shows that it almost entirely reflects a decline in the variance of the growth contribution of shipments. And although the volatility of total inventory investment has fallen, the decline occurred well before the mid-1980s and was driven by the reduced variability of

†We thank Doug Elmendorf, Mark Gertler, Kenneth Kuttner, Andrew Levin, Dan Sichel, Eric Swanson, Stacey Tevlin, Jonathan Wright, and participants of the New York Fed Domestic Research Brown Bag seminar and the Federal Reserve Board macro workshop for helpful comments. Amanda Cox provided outstanding research assistance. The views expressed in this paper are solely the responsibility of the authors and should not be interpreted as reflecting the views of the Board of Governors of the Federal Reserve System, the Federal Reserve Bank of New York, or of any other person associated with the Federal Reserve System.

materials and supplies. Our analysis does show that since the mid-1980s inventory dynamics have played a role in stabilizing manufacturing production: Inventory "imbalances" tend to correct more rapidly, and the quicker response of inventories to aggregate shocks—at all stages of fabrication—buffers production from fluctuations in sales to a greater extent. But more extensive production smoothing and faster dissolution of inventory imbalances appear to be a consequence of changes in the way industry-level sales and aggregate economic activity respond to shocks, rather than a cause of changes in macroeconomic behavior.

*JEL Classification:* E32, E22, D24
*Keywords:* inventories, inventory management, business cycles, GDP volatility

# 1 Introduction

The economic stability of the 1983–2000 period stands out in marked contrast to the frequent and relatively severe cyclical fluctuations that characterized the American economy through much of the twentieth century. Between 1983 and 2000, the U.S. experienced two of the longest expansions and one of the mildest and shortest recessions on record. While the abrupt economic slowdown in 2001 and the wobbly recovery in 2002 has shown that the business cycle is far from dead, the striking decrease in the volatility of real aggregate output since the mid-1980s continues to intrigue economists, who are still trying to uncover its underlying source.[1]

Economists have advanced a number of explanations for the decline in the volatility of aggregate output; see Stock and Watson (2002) for a comprehensive review. Among the leading hypotheses is that a more transparent and credible monetary policy since the "Volcker deflation" of the early 1980s has resulted in a more stable economic environment. A second, "good luck," theory argues that exogenous shocks (e.g., productivity and commodity price shocks) have been milder over the past twenty years. A third hypothesis, which has received a great deal of attention, points to the widespread adoption of better business practices—in particular, inventory manage-

[1] McConnell and Perez-Quiros (2000) provided the first rigorous evidence of a decline in real GDP volatility, which their statistical techniques placed in the first quarter of 1984. Subsequently, a number of studies employing different statistical methods confirmed that real GDP has become more stable since the mid-1980s; see, for example, Kim, Nelson, and Piger (2001), Ahmed, Levin, and Wilson (2001), Sensier and van Dijk (2001), Blanchard and Simon (2001), and Stock and Watson (2002). Unlike McConnell and Perez-Quiros (2000), however, these studies found that the decline in GDP volatility is emblematic of reduced volatility in many economic series, both real and nominal, over the past two decades.

ment techniques—spurred by technological advances of the past two decades.

In this paper, we focus principally on the better business practices hypothesis, or what we call the inventory conjecture. Proponents of this view argue that while the integrated physical distribution management has been around since the 1960s, advances in information technology over the past two decades have only just recently made widespread implementation of this concept possible.[2] The ready availability of accurate cost and financial data has made it possible for decision makers to evaluate the cost tradeoffs inherent in the integrated distribution management concept and, as a result, to implement policies more effectively tracking the complex array of tasks and activities within the production process as well as to better coordinate the supply chain.

As a result, firms' better control of production and delivery processes allows them to identify and resolve inventory imbalances more rapidly. Because enterprises now operate on the basis of essentially the same information set, economic decisions of firms within and across industries may have become more synchronized. In the aggregate, synchronous efforts to correct emerging inventory imbalances may induce a steeper initial contraction in economic activity, but because these imbalances are more readily contained, they are less persistent and inventory runoffs—and consequently business cycles—thus should be less severe.

Although a persuasive story, economists have so far uncovered only indirect support for these arguments. McConnell and Perez-Quiros (2000) (MPQ hereafter) trace the GDP volatility reduction to a narrow source—a structural break in the volatility of durable goods output. Because they do not find a similar decline in the variability of final sales of durable goods, MPQ argue that a more stable economy since the mid-1980s stems from a reduction in the volatility of inventory investment in that sector. Moreover, they argue, the timing of the break in the volatility of durable goods output occurs after the widespread adoption of just-in-time (JIT) techniques and computerized production and supply-chain management by U.S. manufacturers during the late 1970s and early 1980s.[3] The effects of these innovations are evident

[2]Integrated physical distribution management is a total system approach to the management of interrelated activities such as transportation, warehousing, order processing, inventory/production scheduling, and consumer service. According to the survey by Lambert and Mentzer (1978) of a sample of firms in the late 1970s, the lack of necessary cost data—in particular, inventory carrying costs at different stages of production—has seriously hampered a full, successful implementation of the integrated distribution management system.

[3]Pioneered by the Japanese, JIT management of production allows firms to keep a minimum of

in the decline in the aggregate inventory-sales ratio, as firms are able to meet production and sales with leaner stocks, and in a significant reduction in the time between ordering and receiving parts and other production materials (see McConnell, Mosser, and Perez-Quiros (1999)).

Earlier attempts to more directly assess the effects of changes in inventory control methods on the business cycle by Morgan (1991), Bechter and Stanley (1992), Little (1992), Allen (1995), and Filardo (1995) have reached mixed conclusions. These authors agree that the adoption of new inventory management techniques has resulted in a lower ratio of inventories to sales, but the impact of these innovations on cyclical fluctuations, at least through the mid-1990s, is ambiguous.

More recently, Kahn, McConnell, and Perez-Quiros (2001) developed a theoretical model incorporating both inventories and information technology. In the model, advances in information technology improve information about final demand and thus lead to a lower ratio of inventories to sales and diminished output variability. Their simulation results, however, suggest that the quantitative effects of better information on the variability of inventory investment and, consequently, output are modest. Following a different tack, Feroli (2002) calibrates a variant of the neoclassical growth model in which inventories enter the production function along with labor, nonresidential structures, and equipment and software (E&S). The key finding is that the sustained fall of E&S prices, relative to the price of inventories, has caused firms to substitute E&S for inventory stocks, inducing a decline in the aggregate inventory-sales ratio.[4] The technical substitution of capital equipment for inventory stocks, however, has a negligible effect on the volatility of output.

In this paper, we take a detailed look at the inventory conjecture with the advantage of disaggregated (by industry and stage of fabrication), high-frequency data. Our empirical strategy consists of two parts. To determine more accurately the changes in the volatility of manufacturing activity, as well as to compare the timing of these changes with the decline in the variability of aggregate output, we first examine the

inventories of work-in-progress, raw materials, parts, and other supplies, thereby lowering inventory financing costs. Because JIT delivery methods respond mostly to the current conditions on the factory's floor, they work best when demand is predictable. JIT practices, however, can be combined with the computer-driven systems that initiate production and place orders in anticipation of future demand. Because businesses have to purchase the necessary computer systems and train workers to use them, this technology is expensive relative to JIT; see Little (1992) for additional details.

[4]As noted by Feroli (2002), this explanation is consistent with the inventory conjecture, which holds that the reduction in average inventory holdings over the past two decades is a direct result of firms utilizing cheaper information processing equipment and software.

evolution of the volatility of production, shipments, and inventories at the broad sectoral level. In the second part, we assess whether changes in industry-level inventory adjustment since the mid-1980s have stabilized production to a greater extent than previously, as suggested by the inventory conjecture.

Our simple decomposition of the unconditional variance of the growth rate of manufacturing output indicates that the observed decline in production volatility in that sector since the mid-1980s stems overwhelmingly from a reduction in the volatility of shipments rather than the volatility of finished goods inventory investment. We reach similar conclusions when testing for structural breaks in the conditional volatility of output and shipments. In both the durable and nondurable goods sectors, the estimated break dates in the conditional mean and variance of the growth rate of output nearly match those of the growth rate of shipments.

Next, we parse the variance of total inventory investment and find that it has been trending lower since the mid-1970s, driven largely by a substantial decrease in the volatility of its materials and supplies component. The timing of the decline in the variance of inventory investment in materials and supplies in both durable and nondurable goods sectors is consistent with the adoption of JIT and other inventory management innovations in response to the oil price shocks of the 1970s. However, there appears to be little systematic reduction in the unconditional variance of inventory investment at other stages of fabrication.

In the second part of the paper, we employ two empirical models to study the changes in the inventory adjustment since the mid-1980s. The first model, a vector autoregression, links industry shipments, relative prices, and inventories at different stages of production to a model typically used to identify the effects of monetary policy and other shocks on aggregate economic activity. In addition, we estimate industry-level inventory adjustment speeds at different stages of fabrication, using a version of the accelerator model with time-varying targets. We find that industry-level responses of inventories to monetary policy and supply shocks since the mid-1980s are consistent with firms buffering production from sales fluctuations to a greater extent than in the earlier period. Our estimates of adjustment speeds also indicate a significantly faster dissipation of inventory imbalances since the mid-1980s, especially for finished goods and work-in-progress stocks.

The prevalence of production smoothing and faster inventory adjustment in the later period, however, appears to be driven largely by changes in the way aggregate economic activity and industry shipments respond to aggregate shocks. We thus interpret our results as suggesting that changes in the macroeconomic environment—such as a shift to a more transparent monetary policy, deregulation of financial and product markets, and trade liberalization—were likely the key factors in the moderation of output volatility. Improvements in inventory control methods, however, appear to have amplified the reduction in output volatility.

# 2 Data

Throughout our analysis, we use monthly, industry-level (2-digit SIC) data for the manufacturing sector provided by the Bureau of Economic Analysis (BEA).[5] Our key variables for the twenty manufacturing industries—sales, materials and supplies inventories, work-in-progress inventories, and finished goods inventories—are seasonally adjusted and reported in millions of chain-weighted 1996 dollars. Inventory stocks are measured as of the end-of-period, and sales are defined as the value of shipments. The sample covers the period from January 1967 through December 2000, yielding a balanced panel of 408 monthly observations per industry, for a total of 8,160 industry/month observations.

Although the manufacturing sector accounts for a relatively small (and declining) share of aggregate economic output (26.5 percent of GDP in 1967 and 15.9 percent in 2000), its share of goods production is more substantial. Manufacturing firms accounted for more than 80 percent of durable goods GDP in the late 1960s, and even though this share has fallen over the years, they still accounted for more than 50 percent of durable goods GDP in 2000. In the nondurable goods sector, by contrast, the manufacturing share of GDP has remained fairly steady at about 35 percent over this period.

At the beginning of our sample period, U.S. manufacturers also held more than 50 percent of aggregate inventory stocks, but this share has fallen to about 35 percent in 2000. By sector, the manufacturing share of durable goods inventories has declined from 60 percent in the late 1960s to about 40 percent by the end of 2000; for non-

[5]In spring 2001, the BEA and the Census Bureau, the BEA's source of the raw book-value of inventories used to calculate real inventory stocks, replaced the SIC system with the North American Industrial Classification System (NAICS). At the time of this paper, NAICS-classified data were available only starting in the early 1990s. For this reason, as well as to make the paper comparable to earlier studies, we use industry-level data aggregated according to the SIC system. The twenty manufacturing industries, along with their respective 2-digit SIC codes, are listed in the Appendix.

durable goods, the manufacturing share has decreased from 40 percent to about 25 percent over the same period. Despite the diminished role of manufacturing firms in overall economic activity, their still-sizable presence in goods production, along with the fact that this sector was an early adopter of inventory and production control innovations, warrants our narrow focus.

# 3 Evolution of Volatility

In this section, we establish some facts about the variability of manufacturing production, sales, and inventories at the sectoral level. This provides a more direct comparison to the previous research documenting the decline in the volatility of similar, though typically broader, components of GDP. We begin by parsing out changes in the variance of sectoral output to changes in the variance of sales and inventory investment as well as to changes in their covariance. We then turn to the evolution of volatility of total inventory investment and of inventory investment at each stage of fabrication.

## 3.1 Methodology

Because our data are chain-weighted, the components of an aggregate are not additive (see Whelan (2000)). The growth contributions of components, however, do add up to the growth rate of the chain-weighted aggregate. In addition, because the growth contribution of a component is approximately equal to its share of the nominal aggregate times the component's growth rate, working with growth contributions adjusts for the fact that a very volatile component may have little effect on the overall volatility if it accounts for a small share of the aggregate. Accordingly, we decompose the growth rate of output and total inventories into the growth contributions of their respective components. In particular, we write the growth rate of a generic aggregate $X_t$ in period $t$, denoted by $\%\Delta X_t$, as

$$\%\Delta X_t = \sum_j g_t^j, \tag{3.1.1}$$

where $g_t^j$ is the growth contribution of component $j$ in period $t$.

As in Blanchard and Simon (2001), our measure of the time-varying volatility of the growth contribution $g_t^j$ is a rolling unconditional sample standard deviation. We use a three-year (36-month) window to compute these standard deviations, with rates of change expressed at a monthly basis. Because the monthly disaggregated data are volatile, we employ a robust estimator of scale proposed by Rousseeuw and Croux (1993a) to mitigate the effect of outliers.[6] The comovements between growth contributions over time are measured by rolling correlations, again computed over a 36-month window. To minimize the effect of outliers, we report 5-percent trimmed correlations, computed using the standardized sums and differences method (see Huber (1981)).

## 3.2 Volatility of Output

Our starting point is the standard NIPA accounting identity

$$Q_{it} \equiv S_{it} + \Delta H_{it}, \tag{3.2.1}$$

where $Q_{it}$ denotes real output or production of sector (industry) $i$ in period $t$, $S_{it}$ are real sales, and $H_{it}$ are real finished goods inventory stocks at the end of period $t$.[7] Using (3.2.1), we decompose the growth rate of output into the growth contribution of sales $g_{it}^S$ and the growth contribution of finished goods inventory investment $g_{it}^{\Delta H}$:

$$\%\Delta Q_{it} = g_{it}^S + g_{it}^{\Delta H}.$$

The growth contributions are calculated in a manner consistent with chain aggregation used in the NIPA and thus are well-defined for both positive and negative values

[6] In particular, we use the $Q_n$ estimator with a small-sample correction factor derived in Rousseeuw and Croux (1993b). This estimator has a 50 percent breakdown point, is suitable for asymmetric distributions, and attains very high efficiency for Gaussian distributions. In addition, we examined the evolution of volatility of our key series using a GARCH model. The contours in the conditional variance of output, sales, and inventory investment from a GARCH specification match up closely with those of the unconditional volatility reported in the paper.

[7] Although we define output using identity (3.2.1), we construct real output by calculating a proper chain-aggregated output index; see Whelan (2000) for details. An additional issue concerning construction of an output measure is whether to include work-in-progress inventories in the inventory investment term $\Delta H_{it}$. According to Blinder (1986), including work-in-progress inventories may provide a more accurate economic measure of output, though restricting inventory investment to finished goods is more standard in empirical work on inventory dynamics. We performed our analysis using both measures of output, and our results were virtually identical, as the correlation between the growth rates of the output measures is 0.94 for the durable goods and 0.98 for the nondurable goods sector.

of $\Delta H_{it}$.

The variance of the growth rate of real output for sector $i$ is then given by

$$\mathrm{Var}(\%\Delta Q_{it}) = \mathrm{Var}(g_{it}^{S}) + \mathrm{Var}(g_{it}^{\Delta H}) + 2 \times \mathrm{Cov}(g_{it}^{S}, g_{it}^{\Delta H}). \tag{3.2.2}$$

The paths of the standard deviations corresponding to the variance terms in (3.2.2) are presented in Figure 1. To provide a reference for possible volatility breaks, thin vertical lines labeled 1984:Q1 and 1986:Q3 mark the break dates in the volatility of durable and nondurable goods GDP, respectively, as estimated by Kim, Nelson, and Piger (2001) (KNP hereafter).[8] Shaded vertical bars denote NBER-dated recessions.

The volatility of output growth—the solid line—is generally lower in both sectors after the KNP break dates. Neither sector, however, appears to have experienced a marked decline in output volatility around their respective break dates. Rather, there has been a general trend toward less variable output growth in both sectors since the early 1980s. The trend decline in the durable goods sector (upper panel), however, was interrupted by a substantial runup in volatility in the late 1980s and early 1990s, before it dropped sharply during the mid-1990s. In the nondurable goods sector (lower panel), the standard deviation of output growth also started to decrease around 1980, moving back into the range that prevailed at the beginning of our sample. After further decreases in the latter half of the 1980s, output growth volatility generally has remained at a historically low level.[9]

In both sectors, the evolution of volatility of the sales growth contribution (dotted line) is strikingly similar to that of output growth volatility. The variability of the growth contribution of inventory investment in finished goods (dashed line), by contrast, is small. Moreover, it has remained in a narrow range throughout our sample period, and its movements are not well correlated with the swings in the volatility of

[8] Ahmed, Levin, and Wilson (2001) and Stock and Watson (2002) find similar dates using different methods.

[9] Using the Federal Reserve Board's index of industrial production—an alternative measure of manufacturing output—Stock and Watson (2002) find evidence of a volatility break in the growth rate of manufacturing output in the mid-1980s, driven by a volatility reduction in its durable goods component. They do not, however, find a statistically significant structural break in the volatility of nondurable goods output. These differences in volatility patterns likely reflect the different time-series properties of the two output measures, which, in principle, measure the same concept; see Miron and Zeldes (1989) for an earlier analysis. Our interpretation of their conclusions is that neither series is universally "better" than the other. We use the output measure based on the BEA's accounting identity because it allows us to examine systematically the effect of the different components and their interaction on output fluctuations.

output growth.

According to (3.2.2), however, inventory investment could have still contributed to a lower variance of output growth through changes in the sign or magnitude of the covariance between growth contributions of inventory investment and sales. The evolution of these correlations for the two sectors is shown in Figure 2.

The path of this correlation in the durable goods sector (upper panel) indicates that this interaction did not systematically contribute to the decline in output growth volatility in that sector. The movement of this correlation around the break date in 1984:Q1, and indeed over the last three decades, shows no clear pattern, and the magnitude of the correlation is generally modest. This finding, combined with the fact that the volatility of finished goods inventory investment shows little systematic decline, suggests that any changes in the management of finished goods stocks have not had much effect on output variability.

In the nondurable goods sector (lower panel), by contrast, the correlation between the growth contributions of sales and of inventory investment started to drift lower in the early 1980s. After being largely uncorrelated in the 1970s, the correlation between the two growth contributions declined to about -0.6 by the end of the 1990s.[10] The negative correlation suggests that production smoothing may have become more prevalent in the nondurable goods sector, perhaps as a result of the adoption of new inventory management techniques. Accordingly, inventory movements in response to fluctuations in sales have stabilized the growth of nondurable goods output over the past two decades, although the driving force of the volatility reduction over this period is still the decline in the volatility of sales.

## 3.3 Volatility of Inventories

According to the NIPA, it is total inventory investment rather than finished goods inventory investment that enters into the measurement of GDP. In manufacturing, total inventories ($I_{it}$) consist of inventories of materials and supplies ($M_{it}$), work-in-progress ($W_{it}$), and finished goods ($H_{it}$). Using (3.1.1), the growth of total inventories, $\%\Delta I_{it}$, can then be written as

$$\%\Delta I_{it} = g_{it}^{M} + g_{it}^{W} + g_{it}^{H}, \tag{3.3.1}$$

[10] Blanchard and Simon (2001) report a similar change in the covariance between inventories and sales using data for the broader nonfarm business sector.

where $g_{it}^M$ is the growth contribution of materials and supplies, $g_{it}^W$ is the growth contribution of work-in-progress inventories, and $g_{it}^H$ is the growth contribution of finished goods inventories. We can then parse the variance of $\%\Delta I_{it}$ into the variances of its growth contributions and the covariances between growth contributions at different stages of fabrication.

The results of this exercise are summarized in Figures 3–5. The top panel of Figure 3a shows the evolution of the standard deviation of the growth rate of total inventories in the durable goods sector, while the bottom panel depicts the paths of the volatilities of growth contributions by stage of production. The same information for the nondurable goods sector is presented in Figure 3b. To gauge the relative importance of inventories at different stages of fabrication, we plot a rolling 36-month average share of each type of inventory in Figure 4. Comovements between growth contributions in (3.3.1) are shown in Figure 5.

As seen in the top panels of Figures 3a and 3b, the volatility of the growth rate of total inventories in both the durable and nondurable goods sectors spiked in the aftermath of the first oil shock in 1973, the economic turmoil of the 1980-83 period, and the 1990-91 recession. These jumps in volatility are not surprising, given the well-documented role of inventory investment during cyclical retrenchments; see, for example, Ramey and West (1999). Most striking in both panels, however, is the inverted V-pattern of the standard deviation of total inventory investment straddling KNP's estimated dates of volatility reduction, a pattern that obscures the reduction in inventory investment volatility that began in the late 1970s.

In particular, the standard deviation of total inventory growth declined in the late 1970s to very low levels in both sectors, with an especially pronounced decrease among producers of durable goods. It then shot up in the early 1980s, reaching the highest levels for our sample period around the KNP volatility break dates. Over the second half of the 1980s, variability of total inventory growth dropped back to the range observed at the end of the previous decade. Volatility in both sectors increased again around the 1990-91 recession, before dropping to historically low levels for the remainder of the 1990s.

As shown by the dashed lines in the bottom panels of Figures 3a and 3b, the decrease in the standard deviation of total inventory growth during the late 1970s coincides with a decline in the volatility of the growth contribution of materials and supplies. The reduction in the volatility of materials and supplies in both sectors began in earnest in the mid-1970s, around the time when U.S. manufacturers started to adopt JIT methods to reduce lead times and to better manage supply channels in the wake of the first oil crisis. At the same time, there is a similar, though less pronounced, reduction in the volatility of the growth contribution of finished goods inventories in the durable goods sector (the solid line in the bottom panel of Figure 3a). The same component in the nondurable goods sector (Figure 3b), by contrast, does not start to edge lower until the mid-1980s. The volatility of the growth contribution of work-in-progress inventories shows no discernible trend in either sector.

These patterns suggest that firms' efforts during the late 1970s to stabilize inventory fluctuations were largely concentrated on their holdings of materials and supplies. Still, because we are working with growth contributions, it is possible that changes in the composition of inventories have masked a decline in the volatility of other inventory components. As shown in Figure 4, however, the shares of inventories at different stages of fabrication have remained fairly constant over most of our sample period. The largest compositional shift occurred in the early 1990s among durable good producers (top panel), who over the course of the decade significantly reduced the portion of inventories held as work-in-progress.[11]

The last set of factors that could account for the movements in the volatility of total inventory investment are the correlations between the growth contributions at different stages of fabrication plotted in Figure 5. Most notably, in the durable goods sector (top panel), the correlations between the growth contributions moved largely in tandem during most of the 1980s, which contributed to the inverted V-pattern of inventory investment volatility discussed earlier. In addition, the negative comovement of these factors in the late 1990s helped damp an increase in the volatility of total inventory investment stemming from a temporary runup in the standard deviation of the growth contribution of finished goods inventories (see top panel of Figure 3a). In the nondurable goods sector (bottom panel), by contrast, these correlation show little systematic pattern throughout the sample period.

To summarize, we draw three conclusions from the preceeding analysis:

1. The variability of output in U.S. manufacturing has generally been lower since

[11] Although the exact timing differs across durable goods industries, the fraction of inventories designated as work-in-progress generally declined after the 1990–91 recession. The reductions are especially notable in the large industries, SICs 35–38.

the mid-1980s. In the nondurable goods sector, the volatility of output started to trend lower as early as the mid-1970s.

2. The reduction in output volatility in both production sectors has occurred largely because of a concurrent decline in the volatility of sales.

3. The standard deviation of the growth rate of total inventories has been trending lower since the mid-1970s, driven primarily by a reduction in the volatility of the materials and supplies inventories. However, a substantial runup in the volatility of inventory investment interrupted the decline during the early 1980s.

# 4 Structural Breaks

Our focus, thus far, has been the time-varying volatility of output, sales, and inventories, as measured by unconditional standard deviations. In this section, we complement our previous analysis by testing for the presence of structural breaks in the conditional variances of the univariate processes of these variables. Our aim is to disentangle changes in dynamics from the changes in the volatility of innovations as well as to provide a more direct comparison with the volatility break dates estimated by other researchers for typically broader components of aggregate output.

Our methodology follows that of Stock and Watson (2002). We assume that the log-difference of each variable follows a univariate AR($p$) process:

$$y_t = \mu_t + \phi_{1t} y_{t-1} + \phi_{2t} y_{t-2} + \cdots + \phi_{pt} y_{t-p} + u_t = \mu_t + \phi_t(L) y_{t-1} + u_t,$$

with a possible one-time change at an unknown date $\tau_1$ in the parameters determining the conditional mean of $y_t$,

$$\mu_t + \phi_t(L) = \begin{cases} \mu_1 + \phi_1(L) & \text{if} \quad t \leq \tau_1 \\ \mu_2 + \phi_2(L) & \text{if} \quad t > \tau_1; \end{cases}$$

and with a possible one-time change at an unknown date $\tau_2$ in the innovation variance of $u_t$,

$$\text{Var}(u_t) = \begin{cases} \sigma_1^2 & \text{if} \quad t \leq \tau_2 \\ \sigma_2^2 & \text{if} \quad t > \tau_2. \end{cases}$$

The test consists of two steps. We first look for a structural break in the conditional mean parameters $\mu_t$ and $\phi_{1t}, \phi_{2t}, \ldots, \phi_{pt}$, using a heteroscedasticity-robust sup-Wald test with 15 percent trimming (see Andrews (1993)). Using the approximation for asymptotic $p$-values of the sup-Wald statistic from Hansen (1997), we allow the conditional mean parameters to switch at date $\hat{\tau}_1$ if the $p$-value of the test statistic is 10 percent or less; otherwise, we impose parameter stability over the entire sample period. Conditional on this outcome, we then use the same test to look for a break in the mean of the absolute value of the residuals from step one, which is equivalent to testing for a break in the variance of the error term $u_t$. To gauge the precision of our estimates, we computed the 95 percent confidence intervals for the statistically significant break dates—at a 10 percent level—according to Bai (1997).[12]

Table 1 contains the estimated break dates in the conditional mean and variance of an AR(3) process for the growth rate of output, sales, total inventories, and inventories at each stage of fabrication.[13] In the durable goods sector (upper panel), we find statistically significant breaks in the conditional mean parameters for both the growth rate of output and sales in the mid-1980s, around the common estimates of a break in the volatility of durable goods GDP. There is also strong evidence of a break in the conditional mean of the process for finished goods inventories in the mid-1990s, coinciding with the runup in the unconditional standard deviation of the growth contribution shown in the bottom panel of Figure 3a.

Turning to the conditional variances, we find a common break date—March 1992—in the volatility of sales and output growth. These point estimates fall well after typical estimates of a break in the conditional volatility of durable goods GDP, although the mid-1980s are covered by the 95 percent confidence intervals. The volatility break dates in early 1992 correspond most closely to the concomitant decline in the unconditional volatilities of these variables shown in the top panel of Figure 1.

Our estimate of the break date in the conditional variance of total inventory investment—October 1985—lies close to the volatility break date in the growth rate of durable goods GDP, though it is subject to considerable uncertainty. Although the timing differs slightly, the break in the conditional variance of total inventory investment appears to be a result of a break in the volatility of materials and supplies—no significant breaks are evident in the volatility of inventory investment at the other

[12]The confidence interval is asymmetric in the case of a break in the conditional mean parameters and symmetric in the case of a break in the conditional variance; see Bai (1997) for further details.

[13]Our choice of a third-order autoregressive process was based on the Akaike Information Criterion. Using an AR(6) specification yielded almost identical results.

stages of fabrication. The break date in the conditional variance of inventory investment in materials and supplies occurs after the substantial reduction in the unconditional volatility during the second half of the 1970s. It appears, then, that the economic turmoil associated with the second oil shock and the Federal Reserve's disinflationary policy under Chairman Volcker interrupted the decline of materials volatility to such an extent that our structural break test does not pick up a volatility reduction until the mid-1980s.[14]

In the nondurable goods sector (lower panel), we find evidence of structural breaks in the conditional mean of all variables except work-in-progress inventories. The break in the growth rate of output and sales is estimated to have occurred at the same time—at the end of 1990—although the confidence intervals are quite wide. The break dates in the conditional means of total inventory investment and investment in finished goods and materials and supplies are scattered over the past three decades and generally predate significant shifts in the unconditional volatilities shown in the bottom panel of Figure 3b, in particular for materials and supplies.

With the exception of finished goods inventory investment, the estimated break dates in the conditional variances for the variables in the nondurable goods sector lie near the estimated volatility break date for nondurable goods GDP as reported by KNP. Breaks in the conditional variance of output and sales growth occur fairly close together during the 1985–88 period, although the confidence intervals extend into the early 1980s, the beginning of the decline in the unconditional volatilities depicted in the bottom panel of Figure 1.

For inventory investment other than that in finished goods, the break dates in the nondurable goods sector appear to reflect the subsidence of a runup in inventory investment volatility that occurred over the first half of the 1980s, a period of exceptional turmoil in U.S. manufacturing. The break in the conditional variance of inventory investment in finished goods, by contrast, is estimated to have occurred much later—February 1993. The later date for the break in the volatility of finished goods inventory investment is also evident in the path of the unconditional standard deviation shown in the bottom panel of Figure 3b.

To summarize, the structural break analysis confirms the patterns of volatility described earlier. In both production sectors, breaks in the conditional variance

[14] In this context, a structural break test that allows for multiple change points may be more appropriate. Indeed, such a test is employed by Ahmed, Levin, and Wilson (2001), who find evidence of multiple break points in a number of macroeconomic series.

of output and sales occur at about the same time and mark the notable declines in the unconditional volatilities, providing further evidence that the reduction in the volatility of manufacturing production is largely a result of the decline in the volatility of sales. Relatedly, our point estimates of breaks in manufacturing production and sales match up better with the breaks in the conditional variance of aggregate final sales—rather than GDP—reported by Stock and Watson (2002).[15]

Lastly, changes in the volatility of inventory investment are driven to a large extent by breaks in the volatility of inventory investment in materials and supplies. However, the unusually large aggregate shocks of the late 1970s and early 1980s obscured the substantial reduction in the unconditional volatility of materials and supplies stemming from the adoption of JIT and other inventory management innovations over the second half of the 1970s. As a result, our estimates of the breaks in the conditional variance of inventory investment at different stages of fabrications generally occur in the late 1980s or early 1990s.

# 5 Inventory Adjustment

In the remainder of the paper, we focus on the possible changes in the nature of inventory adjustment in recent years. To that purpose, we first use a vector autoregression (VAR) model to examine changes in the adjustment of inventory imbalances following aggregate shocks. This multivariate framework allows us to identify some important linkages implicit in the inventory management hypothesis and to track how responses of inventories at the industry level to common shocks may have changed over time. Secondly, we estimate industry-specific error-correction models for inventory investment at each stage of fabrication. This approach provides a more direct method with which to assess changes in the inventory adjustment process, because the error-correction parameter measures the speed with which inventories move toward their target level.

[15] Their point estimates of the break dates in the conditional variance of final sales in the durable and nondurable goods sectors are 1991:Q1 and 1986:Q2, respectively; the conditional volatility break dates for durable and nondurable goods GDP, by contrast, are 1983:Q4 and 1985:Q2, respectively. These estimates, however, are subject to considerable uncertainty.

## 5.1 Inventory Adjustment and Aggregate Shocks

We begin by examining changes in the industry-level impulse response functions following monetary policy and aggregate supply shocks. The key feature of our specification and identification scheme is that the VAR equations can be separated into two exogenous blocks—industry and aggregate.[16] The industry block interlinks the dynamics of industry sales, relative output price, and inventories given the behavior of the aggregate variables. The aggregate block is a version of the Bernanke and Gertler (1995) model used to identify the effects of monetary policy and other shocks on aggregate economic activity.

In assuming block-exogeneity, we impose the restriction that the industry-level variables do not enter into the aggregate block, whereas the aggregate variables enter into the industry block. In particular, the reduced form of the VAR for industry $i$ is given by

$$\begin{bmatrix} \mathbf{x}_{it} \\ \mathbf{y}_t \end{bmatrix} = \mathbf{A}_i(L) \begin{bmatrix} \mathbf{x}_{it-1} \\ \mathbf{y}_{t-1} \end{bmatrix} + \begin{bmatrix} \mathbf{e}_{it} \\ \mathbf{u}_t \end{bmatrix}; \quad i = 1, 2, \ldots, N, \tag{5.1.1}$$

where $\mathbf{x}_{it} = (s_{it}\, \bar{p}_{it}\, m_{it}\, h_{it})^\top$ is a vector of industry-specific variables consisting of (in logarithms) sales $s_{it}$, relative output price $\bar{p}_{it}$, materials and supplies inventories $m_{it}$, and the sum of work-in-progress and finished goods inventories $h_{it}$. The output price in industry $i$ is measured relative to the PCE price deflator, our aggregate price measure.

The aggregate block is described by the vector $\mathbf{y}_t = (e_t\, p_t\, p_t^c\, r_t)^\top$ comprising the logarithm of a measure of aggregate economic activity $e_t$, the logarithm of the aggregate price level $p_t$, the logarithm of a commodity price index $p_t^c$, and the effective Federal funds interest rate $r_t$. Because we use monthly data, GDP is not readily available as a measure of aggregate economic activity. As an alternative, we use private nonfarm payroll employment.[17] The commodity price index is the Journal of Commerce-Economic Cycle Research Institute Industrial Price Index.

Given our block-exogeneity assumption, the $(8 \times 8)$ industry-specific matrix poly-

[16] Barth and Ramey (2001) use a similar block-exogenous VAR in their study of the "cost channel" of monetary transmission mechanism.

[17] According to Warnock and Warnock (2000), volatility in aggregate employment has also fallen since the mid-1980s. To explore the robustness of our results to the choice of the aggregate activity variable, we also performed the VAR analysis using the index of industrial production and real personal consumption expenditures in place of private employment. The substantive conclusions were the same as those presented in the text.

nomial in the lag operator $L$ in (5.1.1) takes the following form:

$$\mathbf{A}_i(L) = \begin{bmatrix} \mathbf{A}_{i,11}(L) & \mathbf{A}_{i,12}(L) \\ \mathbf{0} & \mathbf{A}_{22}(L) \end{bmatrix}.$$

The $(4 \times 4)$ submatrix of zeros in the lower left corner encompasses the assumption that lagged values of the industry variables do not affect the dynamics of the aggregate variables.

To identify the structural shocks underlying the reduced-form VAR innovations, we place restrictions on the contemporaneous relationships between the variables. The first set of restrictions comes from the block exogeneity assumption—industry variables have no contemporaneous effect on the aggregate variables. The second is that the aggregate structural shocks are identified, as in Bernanke and Gertler (1995), by a recursive ordering of private employment, price level, commodity prices, and the Fed funds rate. The third is that aggregate variables affect some industry variables contemporaneously, which allows for a degree of strategic complementarity.[18] In particular, the level of aggregate employment may affect industry output and price; the aggregate price level may influence industry-level prices; and commodity prices may affect the inventory of materials and supplies. The fourth assumption is that industry sales and relative prices may affect inventories contemporaneously, but not vice versa. This assumption reflects the stickiness of price and production plans that underlie many New Keynesian models and seems reasonable given the monthly frequency of our data. The last assumption is that inventories at each stage of fabrication are determined contemporaneously.

Under these restrictions, the relationship between the VAR innovations and structural shocks can be written as:

$$\mathbf{A}_{i0} \begin{bmatrix} \mathbf{e}_{it} \\ \mathbf{u}_t \end{bmatrix} = \begin{bmatrix} \boldsymbol{\epsilon}_{it} \\ \boldsymbol{\nu}_t \end{bmatrix}; \quad \begin{bmatrix} \boldsymbol{\epsilon}_{it} \\ \boldsymbol{\nu}_t \end{bmatrix} \sim \mathrm{MVN}(\mathbf{0}, \boldsymbol{\Sigma}_i), \quad i = 1, 2, \ldots, N,$$

[18] See Cooper and John (1988) and Blanchard and Kiyotaki (1987) for macro models containing such complementarities.

where $\mathbf{\Sigma}_i$ is a diagonal covariance matrix of structural shocks, and

$$\mathbf{A}_{i0} = \begin{bmatrix} 1 & 0 & 0 & 0 & a_{i,15} & 0 & 0 & 0 \\ a_{i,21} & 1 & 0 & 0 & a_{i,25} & a_{i,26} & 0 & 0 \\ a_{i,31} & a_{i,32} & 1 & a_{i,34} & 0 & 0 & a_{i,37} & 0 \\ a_{i,41} & a_{i,42} & a_{i,43} & 1 & a_{i,45} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & a_{65} & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & a_{75} & a_{76} & 1 & 0 \\ 0 & 0 & 0 & 0 & a_{85} & a_{86} & a_{87} & 1 \end{bmatrix}.$$

One issue in estimating the VAR is whether or not to remove trends from the series. Changes in the inventory-sales ratios owing to the adoption of new management techniques have certainly altered the relationship between inventories and sales at low frequencies, which may obscure changes in inventory dynamics at business cycle or higher frequencies. Accordingly, we used a one-sided exponential smoother with a gain parameter of 0.25 to remove a stochastic trend from each of our series; see, for example, Gourieroux and Monfort (1997). An attractive feature of this detrending procedure is that it preserves high-frequency temporal patterns that may be distorted by two-sided filters such as the Hodrick-Prescott and Baxter-King band-pass filters.[19] Given the high dimensionality of our system, another issue is parameter parsimony. To conserve degrees of freedom, we impose an asymmetric lag structure on our model—seven lags on the variables in the aggregate block and four lags on the variables in the industry block.[20]

The block-exogeneity assumption implies that the reduced-form specification (5.1.1) can be estimated industry by industry. Although the model is not recursive, standard likelihood techniques can then be used to estimate the structural parameters in $\mathbf{A}_{i,0}$ and $\mathbf{\Sigma}_i$ for each industry (see Hamilton (1994), p. 330–33). Because of the volatility of the Fed funds rate associated with the Volcker monetarist experiment, we exclude

[19] As a robustness check, we tried several other values for the gain parameter in the typical range between 0.15 and 0.30, with negligible effects on our result. We also estimated the VAR in log levels. At shorter horizons, the focus of our analysis, the pattern of impulse responses for employment, sales, and inventories was substantively similar to those we present in the paper.

[20] As suggested by Kilian (2001) and Ivanov and Kilian (2001), we determined the lag structure using the Akaike Information Criterion, allowing for some additional lags to preclude underfitting. We examined a number of symmetric and asymmetric lag structures, and the substantive conclusions are very similar to those presented in the paper.

the 1979–83 period from the estimation. In addition, omitting the period associated with exceptional volatility and restructuring in the manufacturing sector should enhance our ability to detect differences in inventory dynamics across the subsamples. We thus estimate the structural parameters over two periods—1967:I–1978:XII and 1984:I–2000:XII—and compute the orthogonalized impulse responses. Using the industry-specific average shares of sales and inventories within each sample period, we then aggregate industry responses to the sectoral level.

### 5.1.1 Responses to Monetary Policy Shocks

In this section, we examine the responses to a 50-basis-point shock in the Fed funds rate equation, commonly identified as a contractionary monetary policy shock. Figure 6a depicts impulse responses for the aggregate block. Figures 6b and 6c contain impulse responses for the durable and nondurable goods sectors, respectively; in addition to the impulse responses of the four variables in the industry block, the two figures also depict the response of the log inventory-sales ratio for both materials and supplies and finished goods stocks, constructed as the difference between the responses of the log-level of inventories and the log-level of sales.

**Aggregate block:** According to Figure 6a, the behavior of the employment in the early period (1967:I–1978:XII) displays the familiar response of aggregate economic activity to an unanticipated monetary policy tightening, as discussed, for example, by Bernanke and Gertler (1995). Employment, relative to trend, does not begin to decline until about six months after the policy tightening, but the response is persistent thereafter, with private employment running below trend up to 36 months after the initial shock. The response of employment in the later period (1984:I–2000:XII), by contrast, is quite different. Employment falls below trend much more quickly, with the trough occurring six to nine months after the unanticipated monetary policy tightening. Moreover, the response is considerably less persistent, dying out within two years after the shock. These differences in the employment responses will have a substantial effect on the dynamics of industry-level sales and inventories, even though the response of the Fed funds rate, at shorter horizons, is quite similar across the two periods.

**Industry block:** In the durable goods sector, there is a noticeable difference in the responses of sales between the two periods (Figure 6b). The response of sales in the earlier period, like that of aggregate employment, is one typically expected after a contractionary monetary policy shock. After increasing relative to trend over the first three months, durable goods sales decline sharply and then oscillate below trend for more than two years. The response of sales in the post-1983 period, again much like that of the aggregate activity, is quicker, larger, but less persistent. Durable goods sales rise slightly for the first few months after the shock, then slump, bottoming out about six months after the shock—roughly at the same time as the trough of the employment response; they then recover smartly and are back to baseline within about one year after the shock. In both sample periods, the initial increase in sales is consistent with the behavior of relative prices, which decline immediately after the policy tightening.

The differences in the responses of aggregate employment and sectoral sales between the two periods are associated with significant differences in the dynamics of inventories at each stage of fabrication. Compared with the later period, the response of inventories at both stages is significantly smaller in the pre-1979 period, despite the sizable response of sales to a monetary policy tightening during that period. In the case of finished goods inventories, this pattern suggests a minor role for inventories as a buffer against fluctuations in demand, implying larger swings in production in the pre-1979 period.[21] In the later period, by contrast, the response of inventories at both stages of fabrication is large and positive at shorter horizons. Given the response of sales, the response of finished goods inventories is consistent with production smoothing, which would attenuate the volatility of output growth in the aftermath of an unexpected policy tightening.

The differences in the responses of inventories conditional on sales are clearly seen in the dynamics of the two inventory-sales ratios. In the pre-1979 period, the responses of the ratios are primarily driven by the dynamics of sales, as inventories at all stages of fabrication react little to a monetary policy shock. In the post-1983 period, however, the responses of the ratios largely reflect the accumulation of inventories in the face of slowing demand, a pattern that helps to stabilize production and results in less volatile output growth.

[21] This finding is consistent with the empirical literature on inventories, which generally has found that output is more variable than sales; see, for example, Ramey and West (1999).

Compared with the durable goods sector, the magnitude of responses in the nondurable goods sector, with the exception of relative prices, is smaller (Figure 6c). In the pre-1979 period, sales, relative to trend, decline immediately after a monetary policy tightening, rebound after a few months, and then start to fall, reaching the trough about two years after the initial policy shock. In the later period, by contrast, the response of sales is considerably less persistent: Sales fall below trend about three months after the policy tightening, reach the trough within six months, and are back to trend in about a year. The more persistent swings in sales in the pre-1979 period are also reflected in the behavior of the relative prices, which are more volatile than those in the latter period.

The response of materials and supplies to a policy tightening in the nondurable goods sector is relatively small in both periods, a sharp contrast to the dynamics in the durable goods sector. One notable difference is that materials and supplies inventories track sales much more closely during the post-1983 period than in the pre-1979 period.[22] Nonetheless, because of the small reaction of materials and supplies to monetary policy shock, the movements in the inventory-sales ratio in both periods largely reflect the dynamics of sales. For finished goods inventories, the differences in responses between the two periods are similar to those in the durable goods sector. The response in the earlier period is very small, while the response in the later period is immediate, positive, and large, a pattern that is consistent with production smoothing given the dynamics of sales in this period.

In general, the dynamics of inventories in both sectors following a contractionary monetary policy shock suggest that inventories in the post-1983 period have been used with greater success to shield production from a decline in sales. This behavior is evident across stages of fabrication in the durable goods sector, a segment of the U.S. economy that, by many measures, experienced the greatest reduction in the volatility of output since the mid-1980s. Countercyclical finished goods inventory investment in the nondurable goods sector since the mid-1980s is also consistent with greater production smoothing. In both sectors, however, much of the change in the behavior of inventories between the two periods reflects changes in the response of industry-level sales and aggregate employment to an unanticipated monetary policy tightening.

[22]Indeed, over the horizon shown, the correlation between the response of sales and the response of materials and supplies inventories is 0.33 in the post-1983 period, compared with -0.01 in the earlier period, a pattern consistent with the adoption of JIT management practices, which reacts more promptly to current economic conditions.

Both display a swifter, though considerably less persistent, reaction to monetary policy shocks, resulting in a smoother and shorter-lived inventory adjustment.

### 5.1.2 Responses to Commodity Price Shocks

We now examine the responses to a commodity price shock, which can be thought of as a negative supply shock. In the aggregate block, a positive commodity price shock exerts upward pressure on the aggregate price level, inducing a rise in the Fed funds rate to stave off inflation. In the industry block, this shock has a direct effect on the holdings of materials and supplies. The responses to this shock, standardized to 1 percent in each period, are presented in Figures 7a–7c.

**Aggregate block:** In the earlier period, employment responds sluggishly to the negative supply shock; it rises for the first six months, then falls over the rest of the year. A persistent trough lasting almost a year follows the decline. The negative gap then gradually dissipates, and employment returns to trend after about three years. In the later period, by contrast, the employment swings are much smaller as well as less persistent; indeed, employment returns to trend within two years after the shock. As expected, the aggregate price level increases in both periods following a negative supply shock, but the response in the later period is noticeably smaller and less persistent. One reason for the more muted response of prices in the later period is that Fed policy appears to have become more aggressive in counteracting inflationary pressures associated with commodity price shocks—the immediate response of the Federal funds rate in the post-1983 period is almost twice as large as that of the earlier period.

**Industry block:** The differences between the two periods in the aggregate responses are reflected in the responses of sectoral sales and inventories (Figures 7b and 7c). Overall, the responses of durable and nondurable goods sales in the earlier period display larger and more persistent oscillations than the responses in the later period. In addition, sales in both sectors bottom out earlier and return to trend quicker in the post-1983 period, a pattern similar to that of the aggregate employment.

The differences in the responses of sales between the two periods lead to notable differences in the behavior of inventories, especially in the durable goods sector (Figure 7b). In the pre-1979 period, both the materials and supplies and finished goods inventories in the durable goods sector are liquidated in the immediate aftermath of a shock to commodity prices. At the same time sales rise, exacerbating the decline in the inventory-sales ratios at shorter horizons. About six months after the shock, when sales start to weaken, both ratios begin to increase, and the resulting inventory overhangs persist for nearly two years. The joint dynamics of sales and inventories are consistent with production smoothing, but because finished goods inventory movements relative to those of sales are small, the resulting production fluctuations are nearly as large as those of sales.

In the post-1983 period, by contrast, stocks of materials and supplies and finished goods accumulate rapidly following a commodity price shock. The inventory build-up in the durable goods sector peaks about six months after the shock, coinciding with the trough in sales. Over the next twelve months, as sales return to trend, inventory stocks are gradually depleted, and the inventory-sales ratio at each stage of fabrication declines. Inventory movements in the post-1983 period are considerably smoother than those in the earlier period, and inventories at all stages of fabrication are better able to absorb fluctuations in demand, resulting in a less variable output growth when compared with that of the pre-1979 period.

In general, we observe similar inventory dynamics in the nondurable goods sector (Figure 7c). One notable exception is the behavior of materials and supplies. In the pre-1979 period, stocks of materials and supplies exhibit large and persistent oscillations after a commodity price shock, while in the later period, the response of materials and supplies is much less pronounced. The dampened response of materials and supplies inventories in the post-1983 period is consistent with the adoption of business practices that utilize technological and financial innovations of the past two decades, and which allow firms to isolate their supply and production chains from unanticipated movements in commodity prices to a greater extent. Differences in the dynamics of finished goods inventories are similar to those in the durable goods sector. In particular, finished goods inventories buffer production from sales fluctuations in the nondurable goods sector more in the post-1983 period than in the earlier period.

## 5.2 Inventory Adjustment Speeds

In this section, we explicitly investigate if the speed with which inventories at different stages of fabrication revert to their target levels has increased in recent years.[23] To that purpose, we estimate an error-correction model that incorporates both the long- and short-term dynamics of inventory investment at different stages of fabrication. The model also incorporates time-varying target inventory-sales ratios, because, as pointed out by a number of economists, the decline in the ratio of inventories to sales since the early 1980s is one key feature of aggregate inventory behavior consistent with improvements in inventory practices. The error-correction specification offers a convenient framework for addressing a question of whether or not these improvements in inventory practices are also evident in a more rapid adjustment of inventory stocks to their target levels.

### 5.2.1 Empirical Model

For each industry, we consider the following system of error-correction equations:

$$
\begin{aligned}
\Delta\ln H_t &= \alpha_H + \lambda_H \left[ E\left( \ln\left[\frac{H}{S}\right]^*_t \,\middle|\, \mathfrak{I}_{t-1} \right) - \ln\left[\frac{H}{S}\right]_{t-1} \right] + \\
&\quad \sum_{j=1}^{6} \beta_{Hj}\Delta\ln H_{t-j} + \sum_{j=1}^{6} \gamma_{Hj}\Delta\ln S_{t-j} + u_{Ht}; \\
\Delta\ln W_t &= \alpha_W + \lambda_W \left[ E\left( \ln\left[\frac{W}{S}\right]^*_t \,\middle|\, \mathfrak{I}_{t-1} \right) - \ln\left[\frac{W}{S}\right]_{t-1} \right] + \\
&\quad \sum_{j=1}^{6} \beta_{Wj}\Delta\ln W_{t-j} + \sum_{j=1}^{6} \gamma_{Wj}\Delta\ln S_{t-j} + u_{Wt}; \\
\Delta\ln M_t &= \alpha_M + \lambda_M \left[ E\left( \ln\left[\frac{M}{S}\right]^*_t \,\middle|\, \mathfrak{I}_{t-1} \right) - \ln\left[\frac{M}{S}\right]_{t-1} \right] + \\
&\quad \sum_{j=1}^{6} \beta_{Mj}\Delta\ln M_{t-j} + \sum_{j=1}^{6} \gamma_{Mj}\Delta\ln S_{t-j} + u_{Mt},
\end{aligned}
\tag{5.2.1}
$$

where $H_t$ denotes the real stock of finished goods inventories, $W_t$ the real stock of work-in-progress inventories, $M_t$ the real stock of materials and supplies, and $S_t$ real sales in period $t$. The terms $\ln\left[\frac{H}{S}\right]^*_t$, $\ln\left[\frac{W}{S}\right]^*_t$, and $\ln\left[\frac{M}{S}\right]^*_t$ represent the time-

[23] This section owes a great deal to the internal work on inventory dynamics by our Federal Reserve Board colleagues Rochelle Edge, Doug Elmendorf, Stacey Tevlin, and Peter Tulip.

varying "target" (log) inventory-sales ratio for finished goods, work-in-progress, and materials and supplies inventories, respectively, and $E(\cdot \mid \mathfrak{I}_{t-1})$ is the expectation operator conditional on the information set $\mathfrak{I}_{t-1}$, containing all the information dated $t-1$ and earlier. The vector of random disturbances $\mathbf{u}_t = (u_{Ht}\, u_{Wt}\, u_{Mt})^\top$ is assumed to be serially uncorrelated with a mean of zero and an unrestricted covariance matrix.

Although (5.2.1) is not derived explicitly from an optimization problem, it can be thought of as a version of the flexible accelerator model introduced by Lovell (1961), extended to allow inventory adjustment to differ by the stage of fabrication.[24] In that model, firms are assumed to balance the cost of straying from the inventory-sales ratios that are optimal in the absence of adjustment costs—the target ratios—against the cost of changing production. This assumption is consistent with the production smoothing dynamics evident in the impulse responses discussed in the previous section. As indicated by the expectation operators, this tradeoff is based not only on current inventory stocks, sales, and output, but also on the expected future paths of these variables. Lagged inventory investment affects current investment because past decisions are correlated with lagged output and altering production is costly. Past growth rates of sales enter the specification because they helps firms predict current and future sales and thus desired inventories. The parameters of interest, $\lambda_H$, $\lambda_W$, and $\lambda_M$, measure the speed of inventory stock adjustment to its target.

To make the model operational, we must specify the unobserved target inventory-sales ratios at each stage of fabrication. As discussed by Ramey and West (1999), for example, the target ratios are likely to depend on a number of factors, the most important being inventory holding costs, stockout costs, expected relative price changes, and properties of the exogenous shocks. While a complete structural model of inventory investment is beyond the scope of this paper, our focus—namely, changes in the rate of inventory adjustment over time—warrants the use of time-series filtering techniques to infer the target ratios. Specifically, the target inventory-sales ratios are

[24] As discussed by Ramey and West (1999), the error-correction equation underlying a flexible accelerator model can be derived from a standard linear-quadratic framework. By allowing dynamics to differ by stage of fabrication, the specification (5.2.1) has much in common with the model developed by Humphreys, Maccini, and Schuh (2001). We sacrifice some of their theoretical rigor in order to obtain an empirical model that can more easily encompass some of the low-frequency behavior of inventory-sales ratios.

estimated by a symmetric centered moving average filter:

$$\ln\left[\frac{z}{S}\right]_t^* = \sum_{i=-k}^{k} \theta_i \ln\left[\frac{z}{S}\right]_{t-i}; \quad z = H, W, M. \tag{5.2.2}$$

By appropriate choice of the moving average coefficients $\theta_i = \theta_{-i}$, $i = 1, 2, \ldots, k$, in (5.2.2), we can estimate the trend component of the inventory-sales ratio, which we then identify as the target ratio. In our specification, we use the Henderson moving average—a computationally tractable moving average with high series smoothing capabilities—to estimate the target inventory-sales ratios in (5.2.2).[25]

Given our assumptions, the estimation of (5.2.1) subject to (5.2.2) is straightforward. The terms dated $t, t+1, \ldots, t+k$ in the target ratios are replaced by their actual values, which transforms the serially uncorrelated disturbance vector $\mathbf{u}_t$ into a vector moving average process of order $k$. The induced moving average process is correlated with the explanatory variables in (5.2.1), necessitating the use of an instrumental variable estimation method. Because variables dated $t-k-1$ or earlier are in the information set $\mathfrak{I}_{t-1}$ and uncorrelated with the transformed error term, they are valid instruments for standard GMM estimation (see Hansen (1982)).

Our choice of the Henderson moving average window $k$ for each industry is six months, and, accordingly, we use the logarithms of $H_{t-7}, \ldots, H_{t-12}$, $W_{t-7}, \ldots, W_{t-12}$, $M_{t-7}, \ldots, M_{t-12}$, and $S_{t-7}, \ldots, S_{t-12}$ as instruments. For each industry, we estimate the system of equations (5.2.1) subject to (5.2.2) using GMM in a SUR framework to take into account the correlation of error terms across equations.[26] To make the results comparable to our previous analysis, we use the same two nonoverlapping sam-

[25] Coefficients of the Henderson moving average of order $2k+1$ are obtained by solving the following minimization problem:

$$\min_{\theta_i} \mathcal{Q} \equiv \sum_i (\Delta^3 \theta_i)^2$$

subject to

$$\sum_{i=-k}^{k} \theta_i = 1; \quad \sum_{i=-k}^{k} i\theta_i = 0; \quad \sum_{i=-k}^{k} i^2\theta_i = 0.$$

The quantity $\mathcal{Q}$ measures the smoothness of the coefficient distribution curve, which in turn is related to the smoothness of the transformed series. The moving average coefficients that minimize $\mathcal{Q}$ are symmetric, sum to 1, and preserve polynomials of degree 2, yielding a smooth estimate of the trend component; see Gourieroux and Monfort (1997) for a detailed exposition.

[26] In addition, we impose restrictions that $\sum_{j=1}^{6} \beta_{Hj} + \sum_{j=1}^{6} \gamma_{Hj} = 1$, $\sum_{j=1}^{6} \beta_{Wj} + \sum_{j=1}^{6} \gamma_{Wj} = 1$, and $\sum_{j=1}^{6} \beta_{Mj} + \sum_{j=1}^{6} \gamma_{Mj} = 1$, implying that in the steady state, sales and inventories at each stage of fabrication grow at a constant rate and that the inventory-sales ratios equal their targets.

ple periods—1967:I–1978:XII and 1984:I–2000:XII—to estimate the model. Table 2a contains the estimates for the speed of adjustment coefficients in the durable goods industries, while those in the nondurable goods industries are shown in Table 2b. Each table also contains $p$-values for the industry-specific Wald test of the stability of the speed of adjustment coefficients across the two periods.

### 5.2.2 Results

Tables 2a and 2b indicate that, in general, the error-correction specification (5.2.1)–(5.2.2) fits the data quite well in both sample periods. Inventory adjustment speeds for most industries are estimated with considerable precision and lie between zero and one, yielding economically plausible rates of trend reversion.[27] There are, however, some important differences between the two sectors as well as the two sample periods, which we discuss in turn.

For a majority of durable goods industries (Table 2a), the estimated adjustment speeds for finished goods and work-in-progress inventories are appreciably higher in the post-1983 period. Compared with the pre-1979 period, the weighted average of the estimates of the error-correction parameters for finished goods is almost 50 percent higher in the post-1983 period, implying a decline in the half-life of inventory deviations from 1.3 months to 0.7 months. In the case of work-in-progress inventories, the increase in adjustment speed is even more dramatic. For the sector as a whole, the error-correction parameter in the post-1983 period is three times as large as that in the earlier period, implying a decrease in the half-life of inventory deviations from about 5.0 months to 1.2 months. The faster adjustment of work-in-progress and finished goods stocks is consistent with the impulse responses presented in the previous section, which displayed considerably more rapid trend reversion of finished goods and work-in-progress inventory-sales ratios in the post-1983 period.

For materials and supplies, by contrast, the pattern of inventory adjustment speeds between the two periods is quite different. Although point estimates indicate a notable increase in the rate of trend reversion for a number of industries (SICs 24, 25, 33, and 39), these industries, with the exception of SIC 33 (Primary Metal Industries), account for a small share of inventory of materials and supplies in the durable goods sector. For the remaining industries, the estimates of the adjustment parameters

[27] Though not reported, Hansen's (1982) test of the over-identifying restrictions does not reject the orthogonality of the instruments in all cases.

are considerably smaller in the post-1983 period; indeed, for the largest industries in the sector (SICs 34–38), the estimates of the adjustment speeds for materials and supplies are economically slow and statistically not different from zero. As a result, the average inventory adjustment speed for the sector as a whole is about one-fifth lower in the post-1983 period.

At first glance, a slower adjustment speed for materials and supplies in the post-1983 period may seem at odds with the findings of the previous section, which showed a considerably quicker trend reversion of the inventory-sales ratio for materials and supplies in that period. However, because the objective of JIT inventory management is to keep materials and supplies inventories at a minimum and to gauge demand by waiting until the last possible moment to place an order, much of the adjustment of inventories to shocks is registered in the target. Consequently, a switch from forecast-based purchases implicit in the error-correction specification to just-in-time purchases is consistent with both a more rapid response of materials and supplies to shocks affecting sales as well as a slower dissipation of inventory imbalances.

Turning to the nondurable goods sector (Table 2b), the estimates of the inventory adjustment speeds across the different stages of fabrication generally indicate faster trend reversion in the post-1983 period. One notable exception is SIC 29 (Petroleum and Coal Products), an industry that experienced a statistically significant decline in all three coefficients between the two periods. As was the case in the durable goods sector, the largest increases in the estimated adjustment speeds are for finished goods and work-in-progress inventories, where the average coefficient rose 50 percent and 60 percent, respectively. This increase implies a reduction in the half-life of inventory deviations from 1.5 to 0.8 months for finished goods and a drop from 1.3 to 0.6 months for work-in-progress inventories. The increase in the rate of trend reversion for inventory of materials and supplies, by contrast, is more modest, with the average half-life of inventory imbalances decreasing from 1.3 to 1.0 months between the two sample periods.

## 5.3 Discussion

From the results of the previous two sections, we draw three principal conclusions:

1. In both the durable and nondurable goods sectors, inventory adjustment at all stages of fabrication has become more rapid since the mid-1980s.

2. The changes in the adjustment of finished goods and work-in-progress inventories since the mid-1980s are consistent with greater production smoothing by manufacturers, resulting in less variable output.

3. The changes in inventory adjustment appear largely to reflect changes in the aggregate economic environment.

Our first conclusion is supported by the finding that the responses of inventories and inventory-sales ratios to monetary policy and commodity price shocks in the post-1983 period are quicker and less persistent than those in the pre-1979 period. Moreover, finished goods and work-in-progress inventories adjust markedly faster to eliminate inventory imbalances in the post-1983 period. Adjustment speeds for materials and supplies, by contrast, appear not to have increased materially since the mid-1980s. However, the combination of a more rapid response of materials and supplies to aggregate shocks and a relatively low estimate of the adjustment speed likely reflects that, under JIT practices, much of the materials and supplies adjustment occurs through changes in the target level of inventories. These results are thus consistent with common conceptions that firms' improved control of production processes and delivery systems has led to the more rapid identification and resolution of inventory imbalances.

Several pieces of evidence support our second conclusion. First, according to our VAR model, the response of inventories has become more countercyclical relative to that of sales. Second, the error correction model—essentially a production-smoothing model—generally fits the data well for finished goods and work-in-progress inventories, and the estimated adjustment speeds for these two types of inventories have increased notably in the post-1983 period. Taken together, these results suggest that inventory behavior has contributed to lower output volatility since the mid-1980s.

While the first two conclusions support the inventory conjecture, our last point asserts that improved inventory management has likely played a supporting, rather than a primary, role in moderating the volatility of manufacturing output. We base this conclusion on two results from the VAR model: (1) the response of aggregate economic activity—private employment in our case—to the monetary policy and commodity price shocks; and (2) the response of the Fed funds rate, the monetary policy instrument, to commodity price shocks.

As discussed previously, the response of employment to monetary policy and commodity price shocks differs considerably between the two periods. In the post-1983 period, employment responded more immediately to the monetary policy shock, but it had a smaller response to the commodity price shock. Because the VAR model allows for complementarities, these differences in the employment response influence the differences in the responses of industry-level sales and inventories between the two periods. Accordingly, the differences in inventory dynamics between the two periods may be due to changes in the macroeconomic environment.

The significant difference in the response of the Fed funds rate to commodity price shocks suggests that one such change is a prompter response of monetary policy to incipient inflationary pressures in the post-1983 period. Compared with the earlier period, the response of the Fed funds rate to a commodity price shock is considerably larger, indicating that the Fed has done more to counteract inflationary shocks in the later period. Our evidence of a more aggressive monetary policy is also consistent with other recent studies that have estimated policy reaction functions; see, for example, Clarida, Galí, and Gertler (2000) and Boivin and Giannoni (2002).

Such shifts in the conduct of monetary policy are important because they may explain the changes in the response of aggregate employment and industry sales to identifiable shocks. If the Fed has become credibly more aggressive, then altering the stance of monetary policy signals changing inflationary pressures, which, ceteris paribus, should prompt quicker and more decisive responses by economic agents. In addition, a more aggressive monetary policy response to inflationary shocks should cause supply shocks to have a lesser effect on economic activity. Both features are evident in the responses of aggregate employment and industry-level sales and inventories to the monetary policy and commodity price shocks.

Given these changes in the responses of aggregate variables, it is then not clear that inventory management has played a primary role in lowering aggregate output volatility. Rather, the increase in the extent with which inventories buffer production from demand shocks may be a consequence of less variable sales, as evident in the response of shipments in the post-1983 period. If firms expect that their sales will experience less persistent fluctuations after a monetary policy shock, the benefits of maintaining stable production, in terms of lower adjustment costs, increase. The incentive to smooth production through inventories also increases, because the holding costs associated with additional stock accumulation are limited by the shorter period of "excess" inventories, an effect compounded by the generally lower interest rates since the mid-1980s. Therefore, the changes in inventory responses, rather than being a primary factor behind the decline in GDP volatility, instead may have been a consequence of changes in other features of the economy.

Nevertheless, our analysis does not deny that improved inventory management may have played an important complementary role in the volatility decline. If aggregate factors such as better monetary policy and smaller shocks have resulted in more predictable final sales, then businesses, faced with falling costs of information technology, will likely have a greater incentive to implement integrated physical distribution management of production and inventories, which in turn could lead to a further decline in volatility. It is unlikely, however, that these developments have eliminated the inventory cycle. In particular, when in 2001–02 aggregate uncertainty increased, sharp and sudden inventory liquidation, especially in the manufacturing sector, significantly exacerbated the economic contraction.

Overall, our analysis of the inventory adjustment process provides limited support for the inventory conjecture, a conclusion that falls between the two extremes on this question. While we do not assign as prominent a role for inventory management as do MPQ or Kahn, McConnell, and Perez-Quiros (2002), we have found convincing evidence indicating that inventory behavior has become more production-smoothing since the mid-1980s. But in the end, much of the change in inventory dynamics appears to be a consequence of changes in the aggregate environment, most notably the conduct of monetary policy.

# 6 Concluding Remarks

Our main goal in this paper was to examine if and how manufacturing inventory dynamics have changed since the mid-1980s, a period marked by a pronounced step-down in the volatility of aggregate economic activity. Our results indicate that although inventory behavior has changed in a manner consistent with the inventory conjecture, it is difficult to attribute most of the reduction in GDP volatility to changes in inventory management, for several reasons. First, the decline in manufacturing production volatility appears to be driven almost entirely by a reduction in the volatility of shipments. Second, a significant decline in the volatility of materials and supplies that started in the mid-1970s has moderated the variability of total inventory investment, but there is little evidence supporting similar reductions in the volatility of inventories at other stages of fabrications in the mid-1980s. Third, even though the responses of inventories to aggregate shocks and inventory adjustment speeds have changed in a manner consistent with inventories having a greater role in buffering sales fluctuations, these changes appear to reflect changes in the dynamics of aggregate variables and industry sales. Therefore, the changes in inventory behavior since the mid-1980s are more likely a consequence of changes in the macroeconomic environment and thus have had a complementary, rather than leading role, in the decline of aggregate output volatility.

These results, however, leave a number of issues for further analysis. For example, even though we found evidence of diminished volatility of inventory investment as well as faster adjustment to inventory imbalances (at least for finished goods and work-in-progress inventories), the responses of inventories to monetary policy and commodity price shocks since the mid-1980s are quite large. At the same time, the steady decline in the inventory-sales ratio evident in U.S. manufacturing typically has been presented as evidence of firms' enhanced ability to track inventories and sales in real time and thus keep inventories closer to desired levels. Although better inventory management does not preclude sharp initial responses of inventories to shocks, reconciling the large responses of inventories since the mid-1980s in the VAR model with these other features of the data will require a more structural analysis than that presented here.

Our analysis focused on the manufacturing sector, but our results have implications for inventories in the rest of the economy. Because of increased global competition, many companies have moved from "in-house" inventory management to vendor-managed inventory and have outsourced some manufacturing to other firms in an attempt to boost profit margins. Indeed, according to a number of industry reports, one of the best methods for controlling inventories is to outsource various segments of production to contract firms, which complete all the manufacturing steps and even carry the financial burden of the inventory until the finished product is delivered. This transformation of production and distribution has resulted in a much more complex supply chain system that integrates manufacturers, suppliers, and customers, and in which management of wholesale and retail trade inventories may be an important component of any changes in the transmission of aggregate shocks. Thus, understanding more about the role of trade inventories in the overall process of economic adjustment remains one important issue left for future research.

# References


Ahmed, S., A. Levin, and B. A. Wilson (2001): "Recent U.S. Macroeconomic Stability: Good Policy, Good Practices, or Good Luck?," Mimeo, Federal Reserve Board.

Allen, D. S. (1995): "Changes in Inventory Management and the Business Cycle," *Review, Federal Reserve Bank of St. Louis*, 4, 17–33.

Andrews, D. W. K. (1993): "Tests for Parameter Instability and Structural Change With Unknown Change Point," *Econometrica*, 61, 821–856.

Bai, J. (1997): "Estimation of a Change Point in Multiple Regression Models," *Review of Economics and Statistics*, 79, 551–563.

Barth III, M. J., and V. A. Ramey (2001): "The Cost Channel of Monetary Transmission," in *NBER Macroeconomics Annual*, ed. by B. S. Bernanke, and K. Rogoff, vol. 16. The MIT Press, Cambridge, MA.

Bechter, D. M., and S. Stanley (1992): "Evidence of Improved Inventory Control," *Federal Reserve Bank of Richmond Economic Review*, 1, 3–12.

Bernanke, B. S., and M. Gertler (1995): "Inside the Black Box: The Credit Channel of Monetary Policy Transmission," *Journal of Economic Perspectives*, 9, 27–48.

Blanchard, O. J., and N. Kiyotaki (1987): "Monopolistic Competition and the Effects of Aggregate Demand," *American Economic Review*, 77, 647–666.

Blanchard, O. J., and J. Simon (2001): "The Long and Large Decline in U.S. Output Volatility," *Brookings Papers on Economic Activity*, 1, 67–127.

Blinder, A. S. (1986): "Can the Production Smoothing Model of Inventories be Saved?," *Quarterly Journal of Economics*, 101, 431–454.

Boivin, J., and M. Giannoni (2002): "Has Monetary Policy Become Less Powerful?," Mimeo, Federal Reserve Bank of New York.

Clarida, R., J. Gali, and M. Gertler (2000): "Monetary Policy Rules and Macroeconomic Stability: Evidence and Some Theory," *Quarterly Journal of Economics*, 115, 147–180.

Cooper, R., and A. John (1988): "Coordinating Coordination Failures in Keynesian Models," *Quarterly Journal of Economics*, 103, 441–463.

Feroli, M. (2002): "An Equilibrium Model of Inventories with Investment-Specific Technical Change," Mimeo, Dept. of Economics, New York University.

Filardo, A. J. (1995): "Recent Evidence on the Muted Inventory Cycle," *Federal Reserve Bank of Kansas City Economic Review*, 2, 27–43.

Gourieroux, C., and A. Monfort (1997): *Time Series and Dynamic Models*. Cambridge University Press, Cambridge, UK.

Hamilton, J. D. (1994): *Time Series Analysis*. Princeton University Press, Princeton, NJ.

Hansen, B. E. (1997): "Approximate Asymptotic $P$-Values for Structural-Change Tests," *Journal of Business and Economic Statistics*, 15, 60–67.

Hansen, L. P. (1982): "Large Sample Properties of Generalized Method of Moment Estimators," *Econometrica*, 50, 1029–1054.

Huber, P. J. (1981): *Robust Statistics*. John Wiley, New York, NY.

Humphreys, B. J., L. J. Maccini, and S. Schuh (2001): "Input and Output Inventories," *Journal of Monetary Economics*, 47, 135–164.

Ivanov, V., and L. Kilian (2001): "A Practitioner's Guide to Lag-Order Selection for Vector Autoregressions," Mimeo, Dept. of Economics, University of Michigan.

Kahn, J. A., M. M. McConnell, and G. Perez Quiros (2001): "Inventories and the Information Revolution: Implications for Output Volatility," Mimeo, Federal Reserve Bank of New York.

——— (2002): "On the Causes of the Increased Stability of the U.S. Economy," *Economic Policy Review, Federal Reserve Bank of New York*, 8(1), 183–202.

Kilian, L. (2001): "Impulse Response Analysis in Vector Autoregressions with Unknown Lag Order," *Journal of Forecasting*, 20, 161–179.

Kim, C.-J., C. Nelson, and J. Piger (2001): "The Less Volatile U.S. Economy: A Bayesian Investigation of Timing, Breadth, and Potential Explanations," Mimeo, Federal Reserve Board.

Lambert, D. M., and J. T. Mentzer (1978): "Is Integrated Physical Distribution Management a Reality?," *Journal of Business Logistics*, 2, 18–33.

Little, J. S. (1992): "Changes in Inventory Management: Implications for the U.S. Recovery," *New England Economic Review*, November/December, 37–65., Federal Reserve Bank of Boston.

Lovell, M. (1961): "Manufacturers Inventories, Sales Expectations, and the Acceleration Principle," *Econometrica*, 39, 293–314.

McConnell, M. M., P. C. Mosser, and G. Perez Quiros (1999): "A Decomposition of the Increased Stability of GDP Growth," *Current Issues in Economics and Finance, Federal Reserve Bank of New York*, 5(13).

McConnell, M. M., and G. Perez Quiros (2000): "Output Fluctuations in the United States: What Has Changed Since the Early 1980s?," *American Economic Review*, 90, 1464–1476.

Miron, J. A., and S. P. Zeldes (1989): "Production, Sales, and the Change in Inventories: An Identity That Doesn't Add Up," *Journal of Monetary Economics*, 24, 31–51.

Morgan, D. P. (1991): "Will Just-In-Time Inventory Techniques Dampen Recessions?," *Federal Reserve Bank of Kansas City Economic Review*, 2, 21–33.

Newey, W. K., and K. D. West (1987): "A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix," *Econometrica*, 55, 703–708.

Ramey, V. A., and K. D. West (1999): "Inventories," in *Handbook of Macroeconomics*, ed. by J. B. Taylor, and M. Woodford, pp. 863–923. North-Holland, Elsevier, New York, NY.

Rousseeuw, P. J., and C. Croux (1993a): "Alternatives to Median Absolute Deviation," *Journal of the American Statistical Association*, 88, 1273–1283.

——— (1993b): "The Bias of $k$-Step M-estimators," *Statistics and Probability Letters*, 20, 411–420.

Sensier, M., and D. van Dijk (2001): "Short-Term Volatility versus Long-Term Growth: Evidence in U.S. Macroeconomic Time Series," University of Manchester, Centre for Growth and Business Cycle Research Discussion Paper No. 008, February.

Stock, J. H., and M. W. Watson (2002): "Has the Business Cycle Changed and Why?," Mimeo, Dept. of Economics, Princeton University.

Warnock, C. M. V., and F. E. Warnock (2000): "The Declining Volatility of U.S. Employment: Was Arthur Burns Right?," International Finance Discussion Papers, Federal Reserve Board.

Whelan, K. (2000): "A Guide to the Use of Chain-Aggregated NIPA Data," Finance and Economics Discussion Series Paper No. 35, Federal Reserve Board.

Table 1: Structural Breaks in Univariate AR(3) Processes

**Manufacturing Durable Goods Sector**

| | *Conditional Mean* | | *Conditional Variance* | |
|---|---|---|---|---|
| Variable[a] | Break Date | 95% Conf. Interval | Break Date | 95% Conf. Interval |
| $\Delta \ln Q$ | Dec83<br>(0.02) | Aug79 - Sep89 | Mar92<br>(<.01) | Nov83 - Jul00 |
| $\Delta \ln S$ | Feb85<br>(0.02) | Mar81 - Oct91 | Mar92<br>(<.01) | Feb85 - Apr99 |
| $\Delta \ln I$ | Jan93<br>(0.15) | - | Oct85<br>(0.03) | Aug75 - Dec95 |
| $\Delta \ln H$ | Sep94<br>(0.01) | Aug91 - May96 | Oct72<br>(0.15) | - |
| $\Delta \ln W$ | Jul92<br>(0.38) | - | Oct88<br>(0.51) | - |
| $\Delta \ln M$ | Jan93<br>(0.08) | Jun89 - Apr97 | Jan86<br>(<.01) | May83 - Sep88 |

**Manufacturing Nondurable Goods Sector**

| | *Conditional Mean* | | *Conditional Variance* | |
|---|---|---|---|---|
| Variable | Break Date | 95% Conf. Interval | Break Date | 95% Conf. Interval |
| $\Delta \ln Q$ | Dec90<br>(0.09) | Jun86 - Sep97 | Jun85<br>(<.01) | Apr82 - Aug88 |
| $\Delta \ln S$ | Dec90<br>(<.01) | Dec88 - Dec94 | Sep87<br>(<.01) | Jan83 - May92 |
| $\Delta \ln I$ | Jan85<br>(0.03) | Nov79 - Jun89 | Dec86<br>(<.01) | Jan82 - Nov91 |
| $\Delta \ln H$ | Jan94<br>(<.01) | Jul92 - Jul98 | Feb93<br>(<.01) | Jun89 - Oct96 |
| $\Delta \ln W$ | Feb87<br>(0.14) | - | Aug87<br>(0.03) | Oct76 - Jun98 |
| $\Delta \ln M$ | Mar75<br>(0.03) | Jun71 - Dec78 | Mar88<br>(<.01) | Feb83 - Apr93 |

Notes: Estimation period is June 1967 to December 2000 ($T = 403$). Break dates in the conditional mean and the conditional variance were estimated using a heteroscedasticity-robust Sup-Wald test (see Andrews (1993)), with 15% trimming. Approximate asymptotic $p$-values for the Sup-Wald test statistics were computed according to Hansen (1997) and are reported in parentheses. The asymmetric 95% confidence intervals surrounding break dates in the conditional means (for $p$-values less than .10) and the symmetric 95% confidence intervals surrounding break dates in the conditional variances (for $p$-values less than .10) were computed according to Bai (1997).

[a]All variables are in real (chain-weighted, 1996=100) terms. $Q$ = output; $S$ = sales; $I$ = total inventories; $H$ = finished goods inventories; $W$ = work-in-progress inventories; $M$ = materials & supplies inventories.

Table 2a: Inventory Adjustment Speeds

| | | Manufacturing Durable Goods Sector | | | | | |
|---|---|---|---|---|---|---|---|
| | | Sample: 1967:I–1978:XII | | | Sample: 1984:I–2000:XII | | |
| SIC | $\Pr > W^a$ | $\lambda_H$ | $\lambda_W$ | $\lambda_M$ | $\lambda_H$ | $\lambda_W$ | $\lambda_M$ |
| 24 | 0.87 | 0.55 | 0.61 | 0.34 | 0.63 | 0.64 | 0.45 |
| | | (0.12) | (0.15) | (0.13) | (0.12) | (0.13) | (0.10) |
| 25 | 0.20 | 0.66 | 0.50 | 0.43 | 0.96 | 0.76 | 0.82 |
| | | (0.10) | (0.12) | (0.10) | (0.22) | (0.21) | (0.20) |
| 32 | 0.02 | 0.62 | 0.52 | 0.35 | 0.21 | 0.51 | 0.06 |
| | | (0.13) | (0.17) | (0.09) | (0.11) | (0.17) | (0.15) |
| 33 | $< .01$ | 0.11 | 0.10 | -0.02 | 0.51 | 0.32 | 0.49 |
| | | (0.06) | (0.03) | (0.05) | (0.11) | (0.13) | (0.14) |
| 34 | 0.01 | 0.64 | 0.21 | 0.97 | 0.33 | 0.55 | 0.38 |
| | | (0.11) | (0.13) | (0.09) | (0.16) | (0.17) | (0.25) |
| 35 | 0.17 | 0.47 | 0.32 | 0.39 | 0.64 | 0.58 | 0.10 |
| | | (0.07) | (0.06) | 0.08 | (0.15) | (0.13) | (0.17) |
| 36 | 0.33 | 0.40 | 0.21 | 0.33 | 0.61 | 0.35 | 0.18 |
| | | (0.08) | (0.10) | (0.06) | (0.19) | (0.10) | (0.16) |
| 37 | 0.01 | 0.29 | 0.01 | 0.07 | 1.18 | 0.37 | 0.03 |
| | | (0.13) | (0.04) | (0.13) | (0.54) | (0.10) | (0.12) |
| 38 | 0.38 | 0.58 | 0.11 | 0.24 | 0.39 | 0.43 | 0.13 |
| | | (0.18) | (0.11) | (0.11) | (0.15) | (0.22) | (0.14) |
| 39 | 0.01 | 0.27 | 0.16 | 0.19 | 0.60 | 0.36 | 0.73 |
| | | (0.06) | (0.09) | (0.06) | (0.16) | (0.37) | (0.24) |
| | | *Weighted Average*[b] | | | *Weighted Average* | | |
| | | 0.42 | 0.13 | 0.32 | 0.60 | 0.43 | 0.25 |

Notes: The dependent variables in the 3-equation SUR system are the log-difference of finished goods inventories ($\Delta \ln H_t$), the log-difference of work-in-progress inventories ($\Delta \ln W_t$), and the log-difference of materials & supplies inventories ($\Delta \ln M_t$). All variables are in real (chain-weighted, 1996=100) terms. Entries in the table are the GMM estimates of the speed of adjustment parameters: $\lambda_H$ = speed of adjustment of finished goods inventories; $\lambda_W$ = speed of adjustment of work-in-progress inventories; and $\lambda_M$ = speed of adjustment of materials & supplies inventories. Heteroscedasticity- and autocorrelation-consistent asymptotic standard errors are reported parentheses and were computed according to Newey and West (1987) with the bandwidth parameter equal to six.

[a] $p$-value for the Wald test of null hypothesis that the speed of adjustment coefficients are equal across the two sample periods. The $W$-statistic is distributed as $\chi^2$ with 3 degrees of freedom.

[b] Average estimate of the speed of adjustment coefficient across durable goods industries, weighted by the corresponding industry-specific average shares of inventories over the sample period.

Table 2b: Inventory Adjustment Speeds

| | | **Manufacturing Nondurable Goods Sector**[a] | | | | | |
|---|---|---|---|---|---|---|---|
| | | Sample: 1967:I–1978:XII | | | Sample: 1984:I–2000:XII | | |
| SIC | $\Pr > W^b$ | $\lambda_H$ | $\lambda_W$ | $\lambda_M$ | $\lambda_H$ | $\lambda_W$ | $\lambda_M$ |
| 20 | 0.30 | 0.22 | 0.32 | 0.42 | 0.56 | 0.61 | 0.75 |
| | | (0.20) | (0.31) | (0.12) | (0.21) | (0.18) | (0.21) |
| 22 | $< .01$ | 0.49 | 0.18 | 0.33 | 0.41 | 1.28 | 0.72 |
| | | (0.09) | (0.11) | (0.10) | (0.14) | (0.21) | (0.18) |
| 23 | $< .01$ | 0.46 | 0.29 | 0.66 | 0.37 | 0.81 | 0.13 |
| | | (0.12) | (0.17) | (0.13) | (0.32) | (0.19) | (0.13) |
| 26 | 0.43 | 0.49 | 0.88 | 0.63 | 0.44 | 0.58 | 0.51 |
| | | (0.08) | (0.16) | (0.11) | (0.09) | (0.14) | (0.10) |
| 27 | $< .01$ | 0.36 | 0.71 | 0.41 | 1.17 | 1.12 | 0.64 |
| | | (0.12) | (0.20) | (0.10) | (0.18) | (0.20) | (0.17) |
| 28 | 0.46 | 0.54 | 0.37 | 0.38 | 0.72 | 0.35 | 0.44 |
| | | (0.03) | (0.15) | (0.12) | (0.11) | (0.15) | (0.12) |
| 29 | 0.01 | 0.30 | 0.83 | 0.64 | 0.14 | 0.48 | 0.15 |
| | | (0.15) | (0.08) | (0.13) | (0.12) | (0.16) | (0.12) |
| 30 | $< .01$ | 0.22 | 0.02 | -0.07 | 0.31 | 0.60 | 0.38 |
| | | (0.06) | (0.10) | (0.16) | (0.12) | (0.14) | (0.13) |
| 31 | 0.06 | 0.45 | 0.28 | 0.48 | 0.54 | 0.83 | 0.49 |
| | | (0.17) | (0.15) | (0.16) | (0.17) | (0.14) | (0.11) |
| | | *Weighted Average*[c] | | | *Weighted Average* | | |
| | | 0.37 | 0.41 | 0.42 | 0.56 | 0.68 | 0.51 |

Notes: The dependent variables in the 3-equation SUR system are the log-difference of finished goods inventories ($\Delta \ln H_t$), the log-difference of work-in-progress inventories ($\Delta \ln W_t$), and the log-difference of materials & supplies inventories ($\Delta \ln M_t$). All variables are in real (chain-weighted, 1996=100) terms. Entries in the table are the GMM estimates of the speed of adjustment parameters: $\lambda_H$ = speed of adjustment of finished goods inventories; $\lambda_W$ = speed of adjustment of work-in-progress inventories; and $\lambda_M$ = speed of adjustment of materials & supplies inventories. Heteroscedasticity- and autocorrelation-consistent asymptotic standard errors are reported parentheses and were computed according to Newey and West (1987) with the bandwidth parameter equal to six.

[a]SIC 21 (Tobacco & Related Products) is omitted from the analysis because of suspect data.

[b]$p$-value for the Wald test of null hypothesis that the speed of adjustment coefficients are equal across the two sample periods. The $W$-statistic is distributed as $\chi^2$ with 3 degrees of freedom.

[c]Average estimate of the speed of adjustment coefficient across durable goods industries, weighted by the corresponding industry-specific average shares of inventories over the sample period.

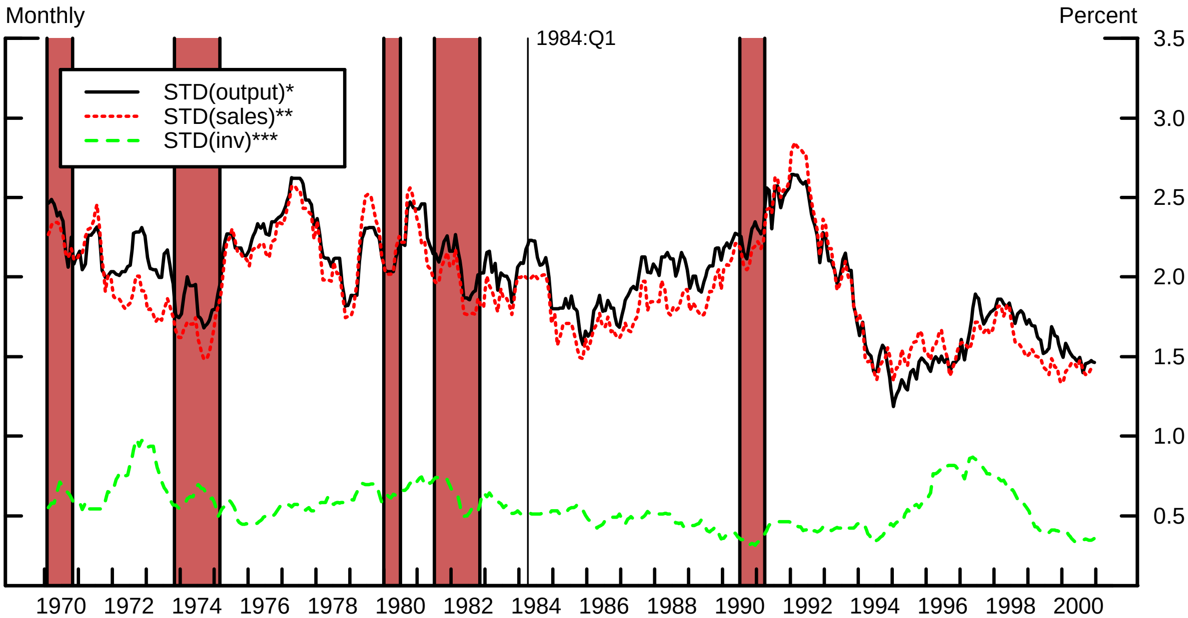
# Appendix

- **Manufacturing Durable Goods Sector**
  1. SIC 24: Lumber and Wood Products
  2. SIC 25: Furniture and Fixtures
  3. SIC 32: Stone, Clay, and Glass Products
  4. SIC 33: Primary Metal Industries
  5. SIC 34: Fabricated Metal Products
  6. SIC 35: Industrial Machinery and Equipment
  7. SIC 36: Electronic and Other Electric Equipment
  8. SIC 37: Transportation Equipment
  9. SIC 38: Instruments and Related Products
  10. SIC 39: Miscellaneous Durable Goods
- **Manufacturing Nondurable Goods Sector**
  1. SIC 20: Food and Kindred Products
  2. SIC 21: Tobacco and Related Products
  3. SIC 22: Textile Mill Products
  4. SIC 23: Apparel and Other Textile Products
  5. SIC 26: Paper and Allied Products
  6. SIC 27: Printing and Publishing
  7. SIC 28: Chemicals and Allied Products
  8. SIC 29: Petroleum and Coal Products
  9. SIC 30: Rubber and Miscellaneous Plastic Products
  10. SIC 31: Leather Products

Figure 1

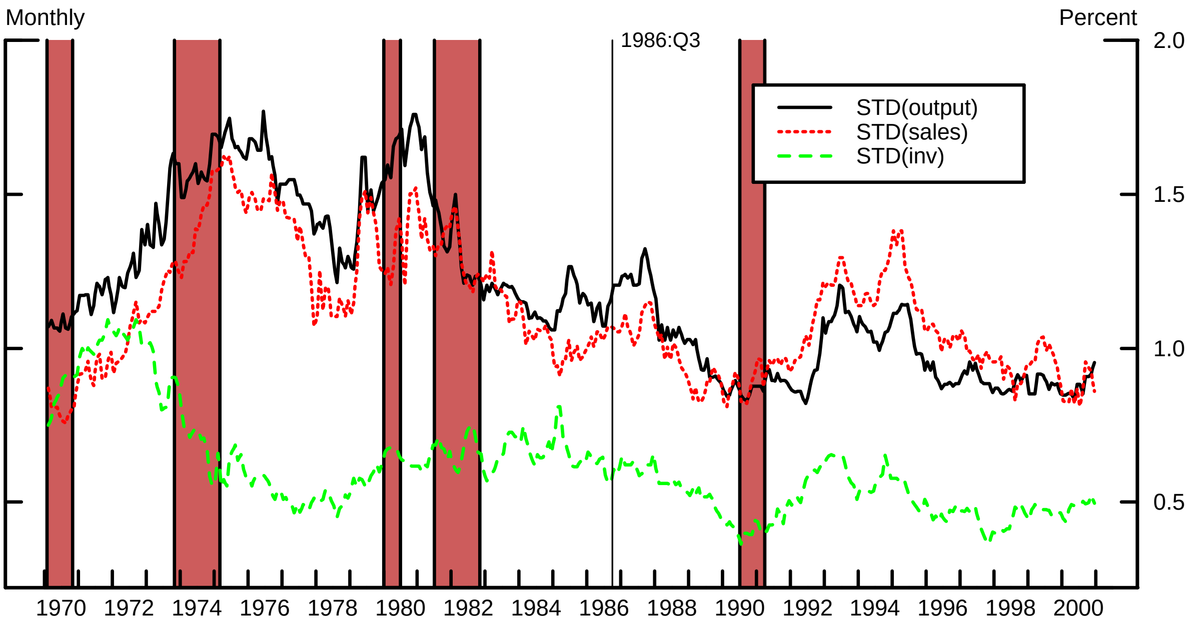
**Volatility of Output, Sales, and Inventory Investment**

Manufacturing Durable Goods Sector




Note: The vertical line at 1984:Q1 marks the estimated date of volatility reduction for durable goods GDP.

Manufacturing Nondurable Goods Sector



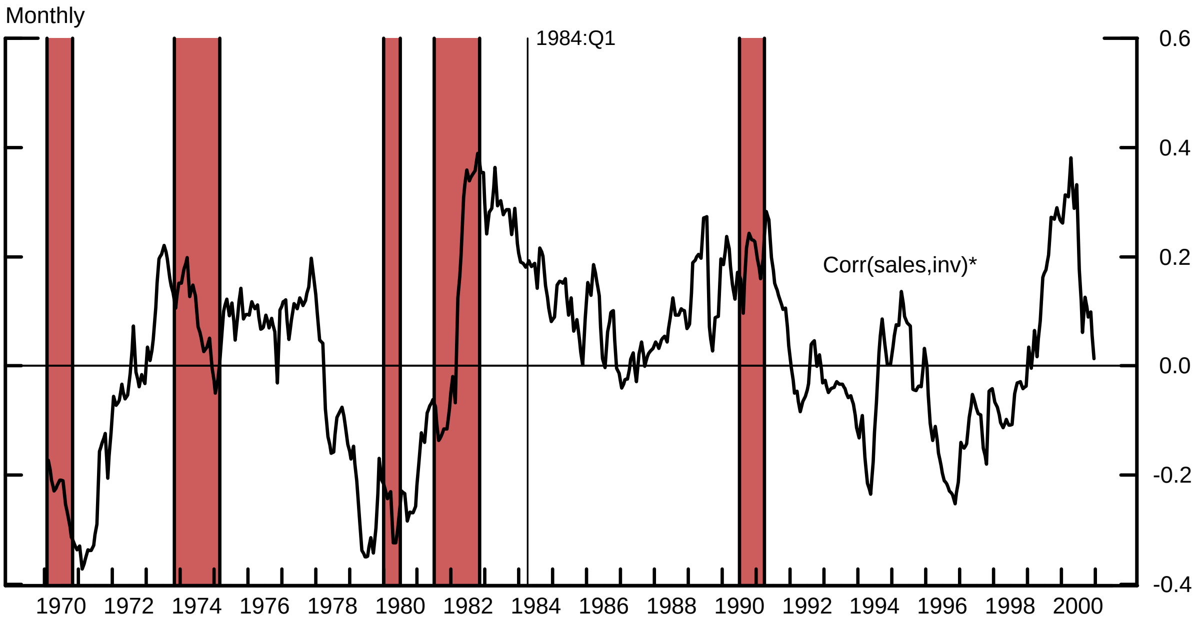

Note: The vertical line at 1986:Q3 marks the estimated date of volatility reduction for nondurable goods GDP.

* STD(output) denotes a rolling robust estimate of the standard deviation of the growth rate of output.
** STD(sales) denotes a rolling robust estimate of the standard deviation of the growth contribution of sales.
*** STD(inv) denotes a rolling robust estimate of the standard deviation of the growth contribution of inventory investment.

Figure 2

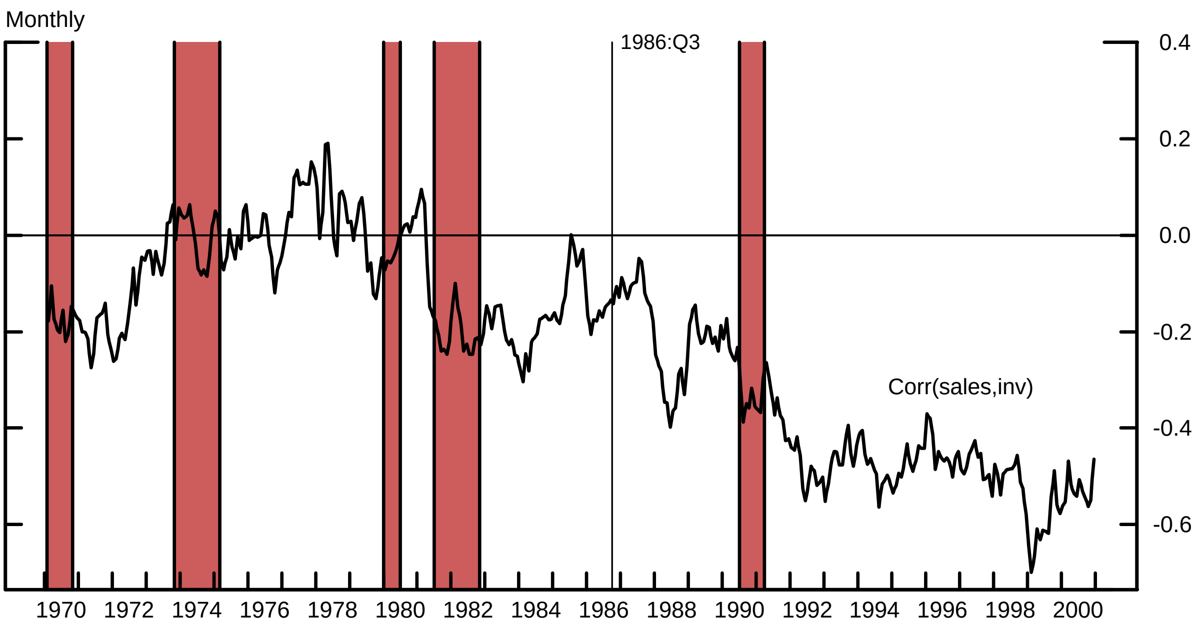
**Inventory Investment and Sales Correlations**

Manufacturing Durable Goods Sector




Note: The vertical line at 1984:Q1 marks the estimated date of volatility reduction for durable goods GDP.

Manufacturing Nondurable Goods Sector



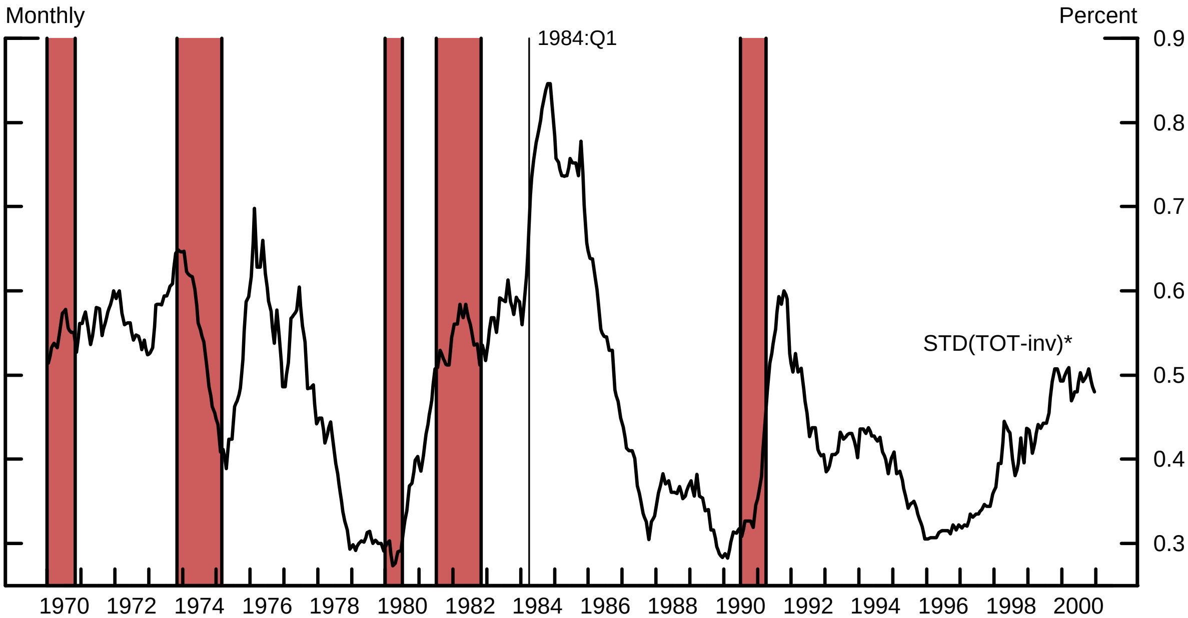

Note: The vertical line at 1986:Q3 marks the estimated date of volatility reduction for nondurable goods GDP.

* Corr(sales,inv) denotes a rolling 5-percent trimmed correlation between the growth contribution of sales and the growth contribution of inventory investment.

Figure 3a

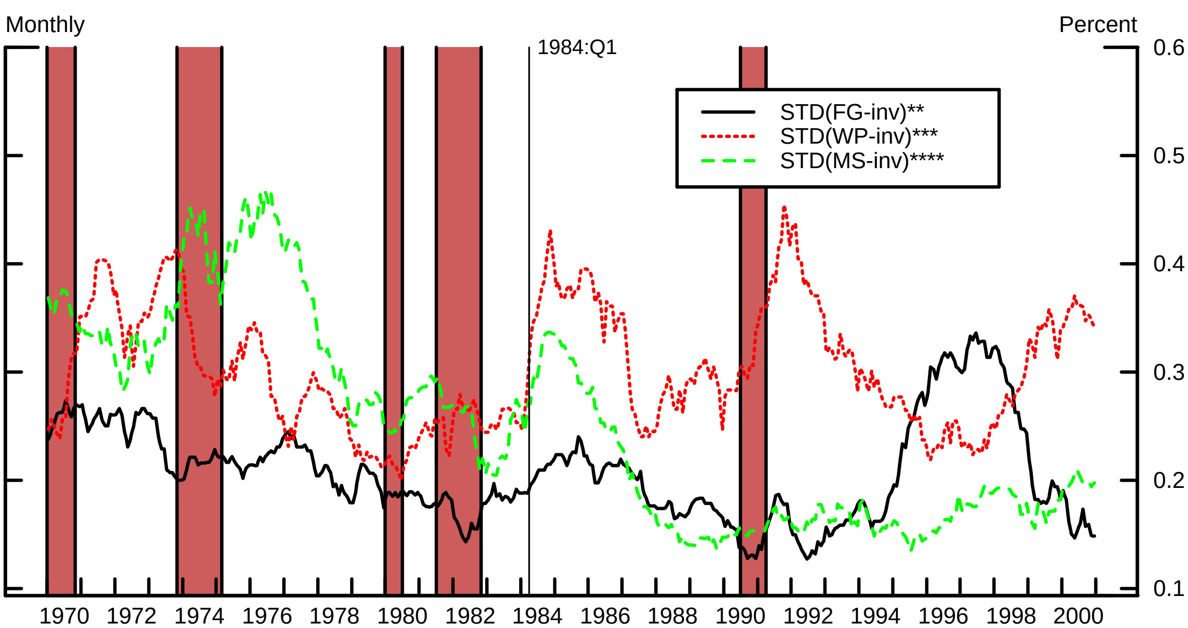
**Inventory Volatility in Manufacturing Durable Goods Sector**

Total Inventories




Note: The vertical line at 1984:Q1 marks the estimated date of volatility reduction for durable goods GDP.

Growth Contributions of Inventories By Stage of Production



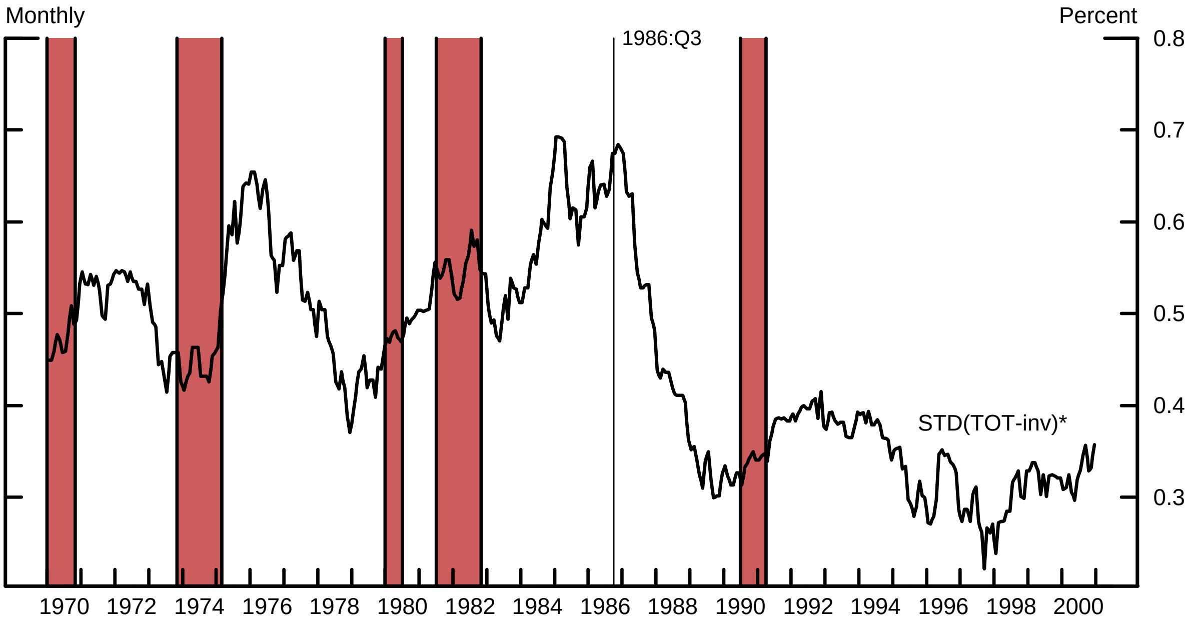

Note: The vertical line at 1984:Q1 marks the estimated date of volatility reduction for durable goods GDP.

* TOT-inv denotes the growth rate of total inventories.
** FG-inv denotes the growth contribution of finished goods inventories.
*** WP-inv denotes the growth contribution of work-in-progress inventories.
**** MS-inv denotes the growth contribution of materials and supplies inventories.
STD() denotes a rolling robust estimate of the standard deviation.

Figure 3b

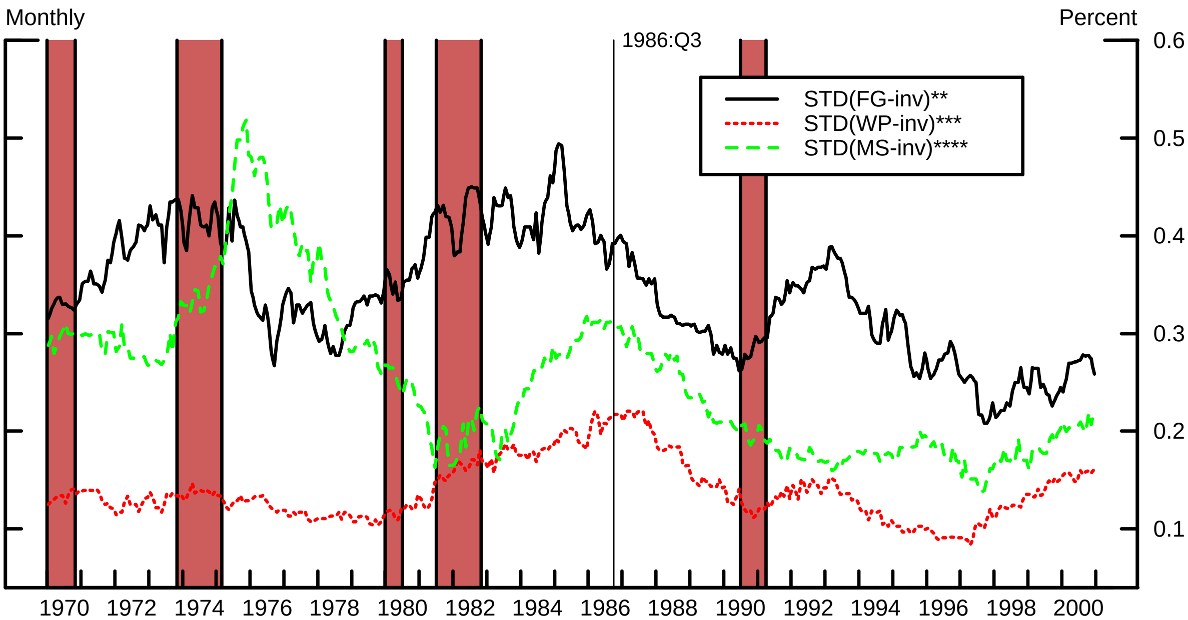
**Inventory Volatility in Manufacturing Nondurable Goods Sector**

Total Inventories




Note: The vertical line at 1986:Q3 marks the estimated date of volatility reduction for nondurable goods GDP.

Growth Contributions of Inventories By Stage of Production



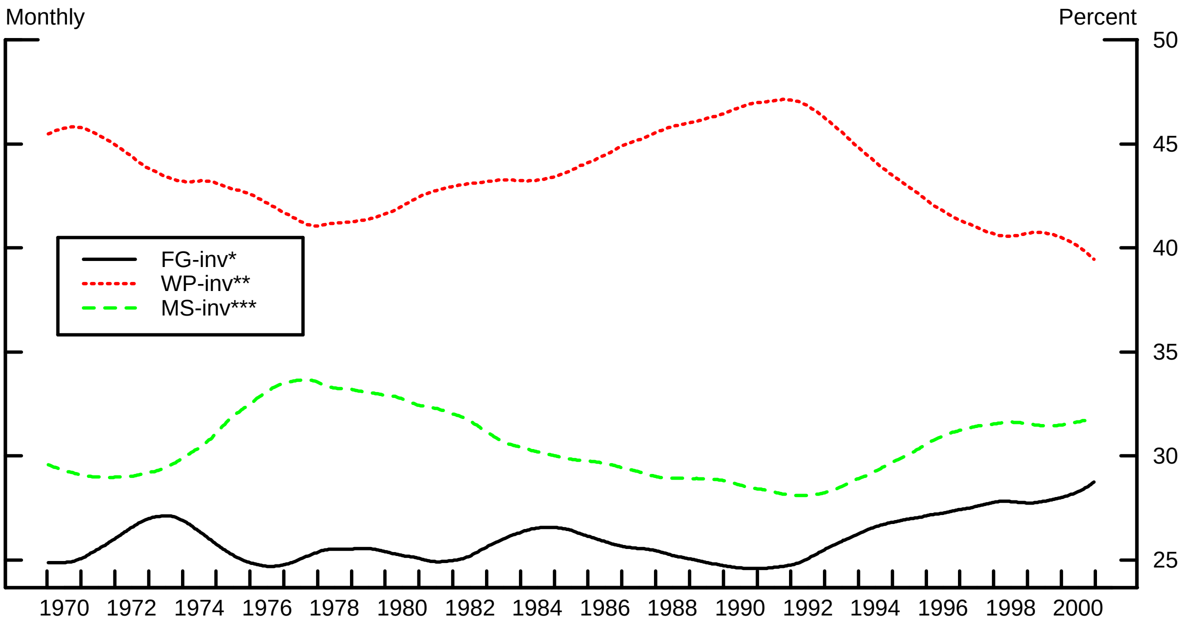

Note: The vertical line at 1986:Q3 marks the estimated date of volatility reduction for nondurable goods GDP.

* TOT-inv denotes the growth rate of total inventories.
** FG-inv denotes the growth contribution of finished goods inventories.
*** WP-inv denotes the growth contribution of work-in-progress inventories.
**** MS-inv denotes the growth contribution of materials and supplies inventories.
STD() denotes a rolling robust estimate of the standard deviation.

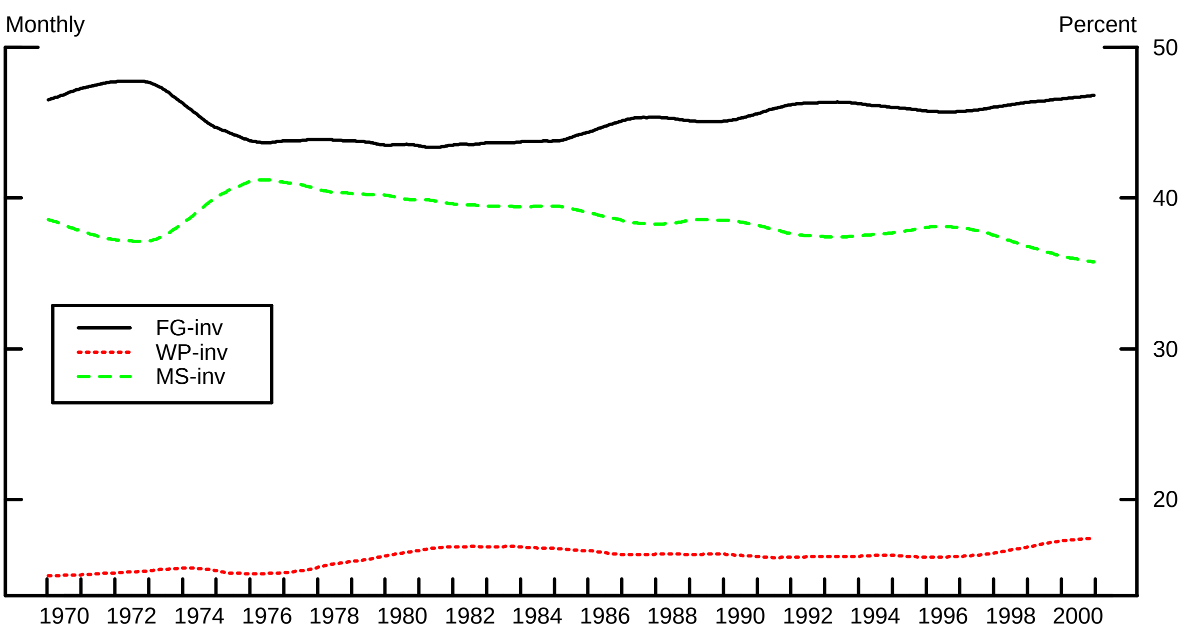
Figure 4

**Inventory Composition by Stage of Production**

Manufacturing Durable Goods Sector




Manufacturing Nondurable Goods Sector

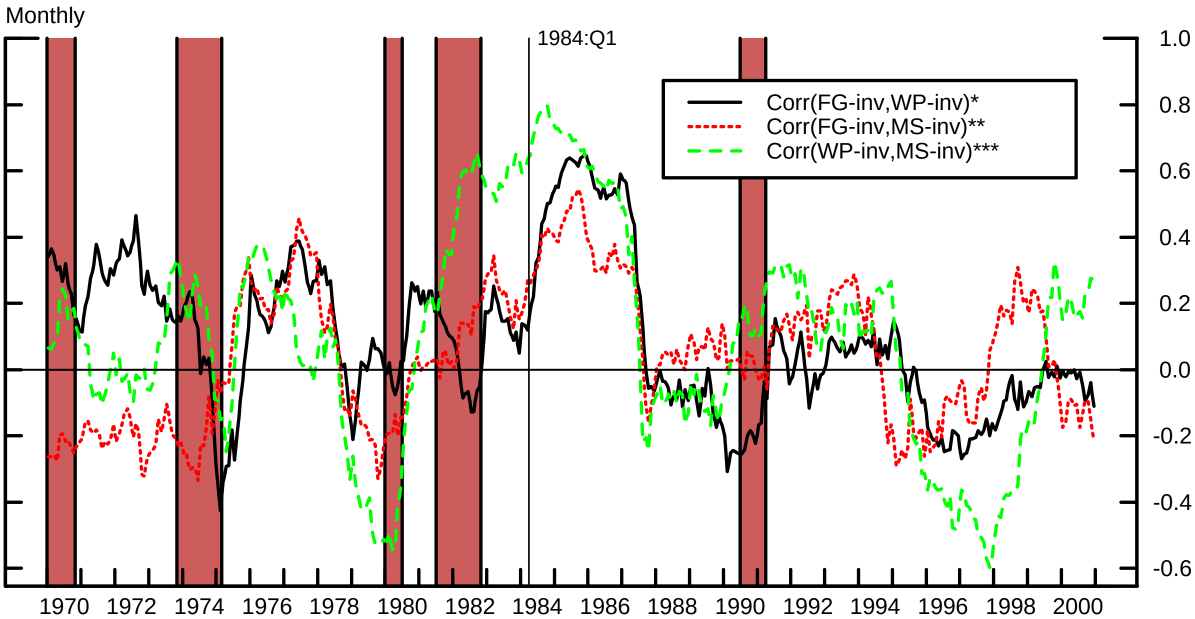



* FG-inv denotes a rolling average (nominal) share of finished goods inventories.
** WP-inv denotes the a rolling average (nominal) share of work-in-progress inventories.
*** MS-inv denotes a rolling average (nominal) share of materials and supplies inventories.

Figure 5

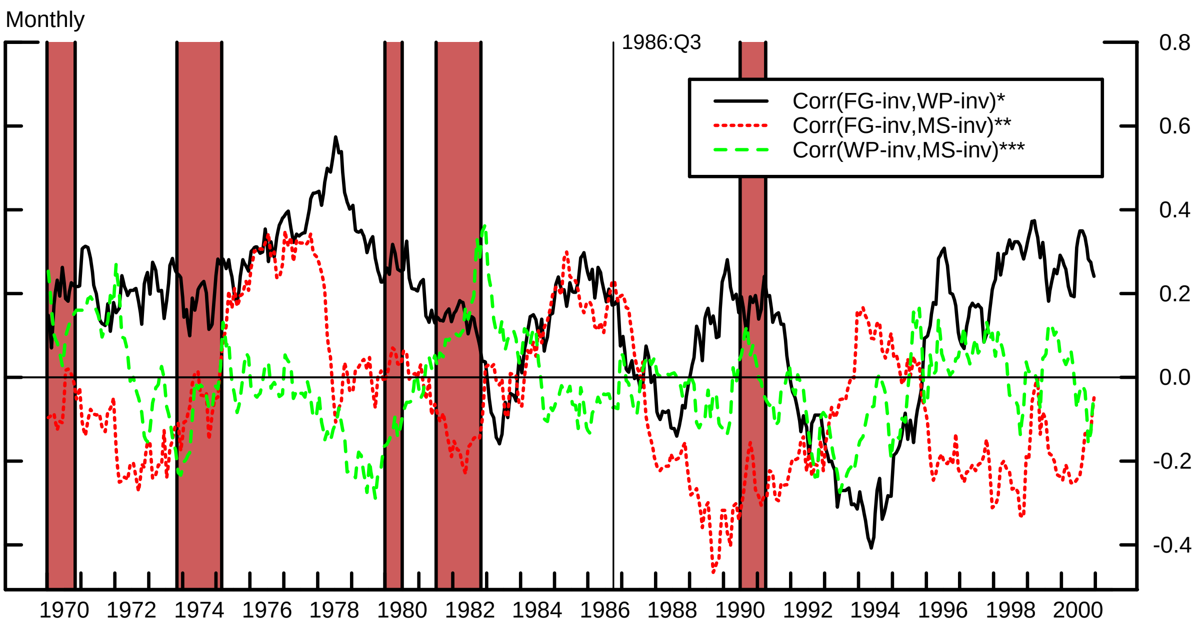
**Inventory Investment Correlations by Stage of Production**

Manufacturing Durable Goods Sector




Note: The vertical line at 1984:Q1 marks the estimated date of volatility reduction for durable goods GDP.

Manufacturing Nondurable Goods Sector




Note: The vertical line at 1986:Q3 marks the estimated date of volatility reduction for nondurable goods GDP.

* FG-inv denotes the growth contribution of finished goods inventories.
** WP-inv denotes the growth contribution of work-in-progress inventories.
*** MS-inv denotes the growth contribution of materials and supplies inventories.
Corr() denotes a rolling 5-percent trimmed correlation.

Figure 6a

**Impulse Responses to a 50 bps. Federal Funds Rate Shock**

Aggregate Block

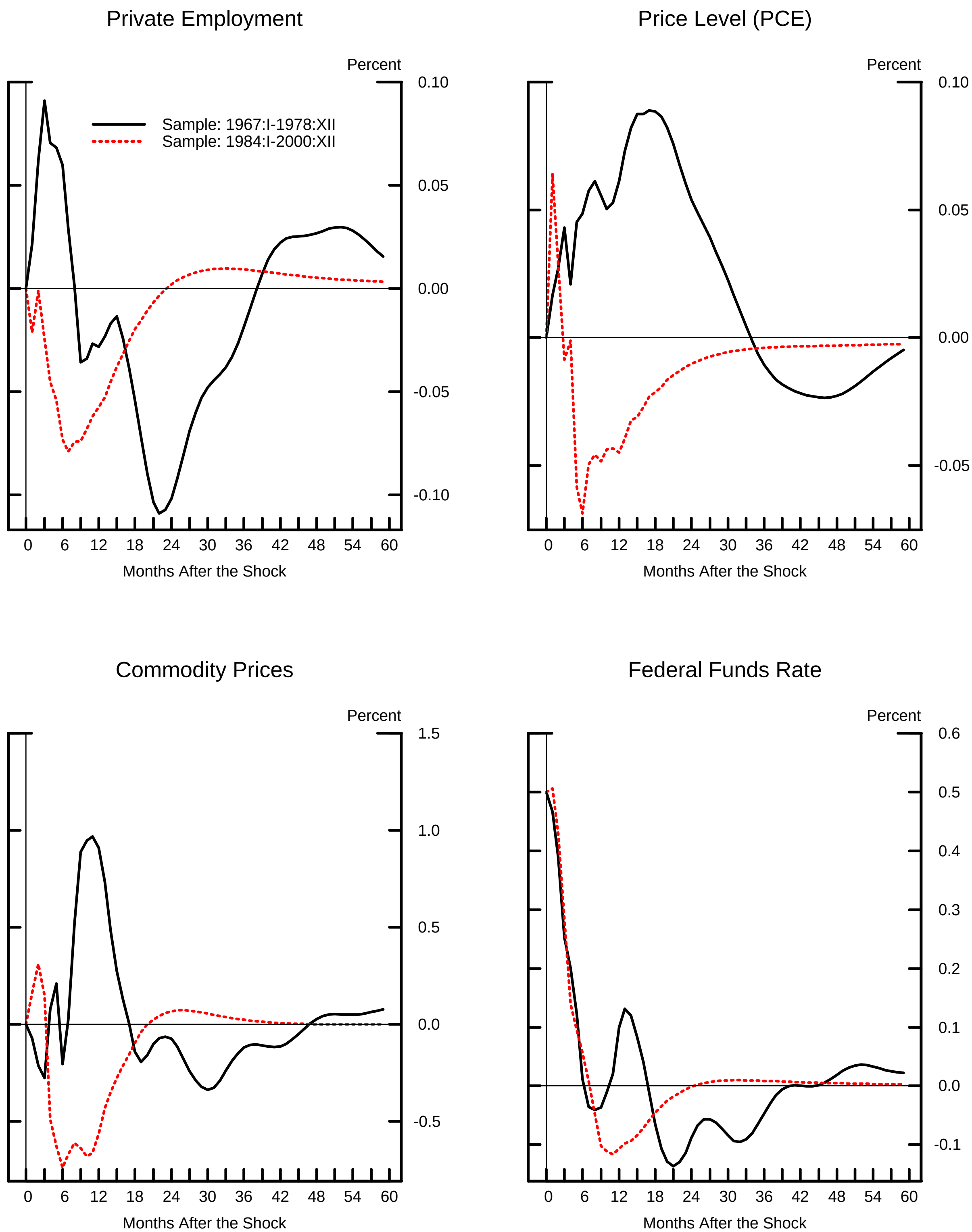
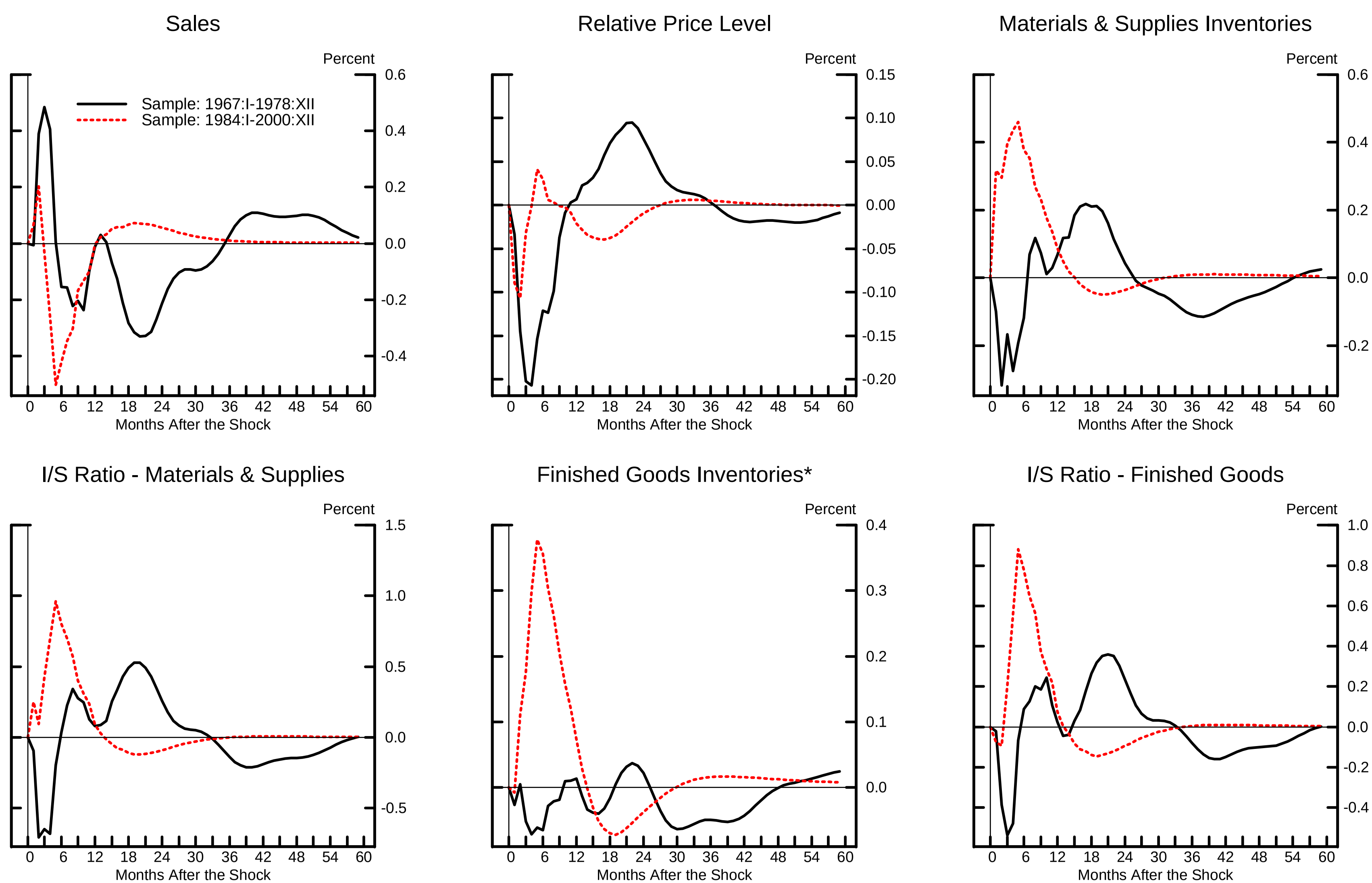


Figure 6b

**Impulse Responses to a 50 bps. Federal Funds Rate Shock**

Manufacturing Durable Goods Sector

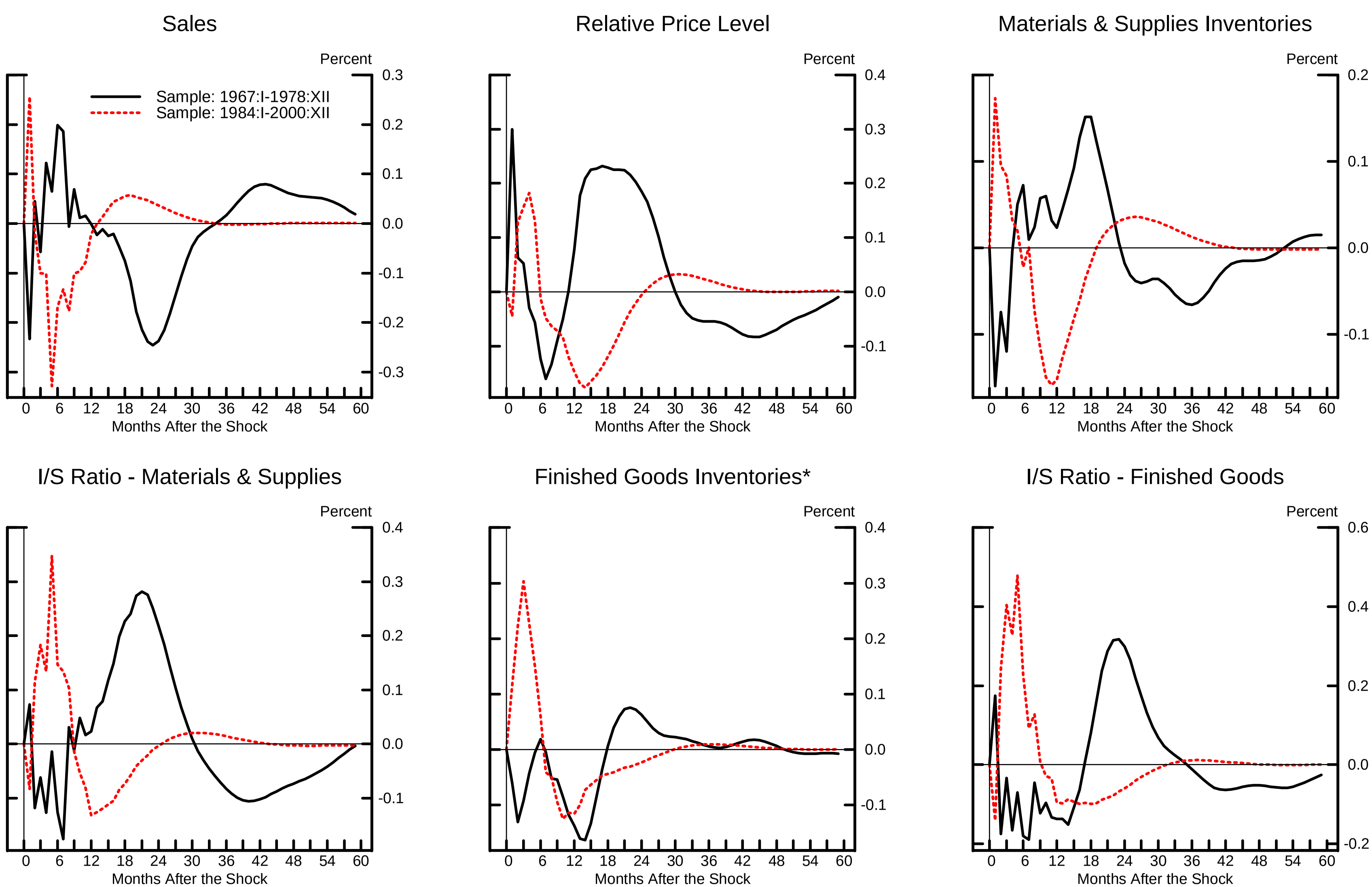



* Finished goods inventories include work-in-progress inventories.

Figure 6c

**Impulse Responses to a 50 bps. Federal Funds Rate Shock**

Manufacturing Nondurable Goods Sector




* Finished goods inventories include work-in-progress inventories.
Note: SIC 21 (Tobacco & Related Products is omitted from the analysis because of suspect data.

Figure 7a

**Impulse Responses to a 1% Commodity Price Shock**
Aggregate Block

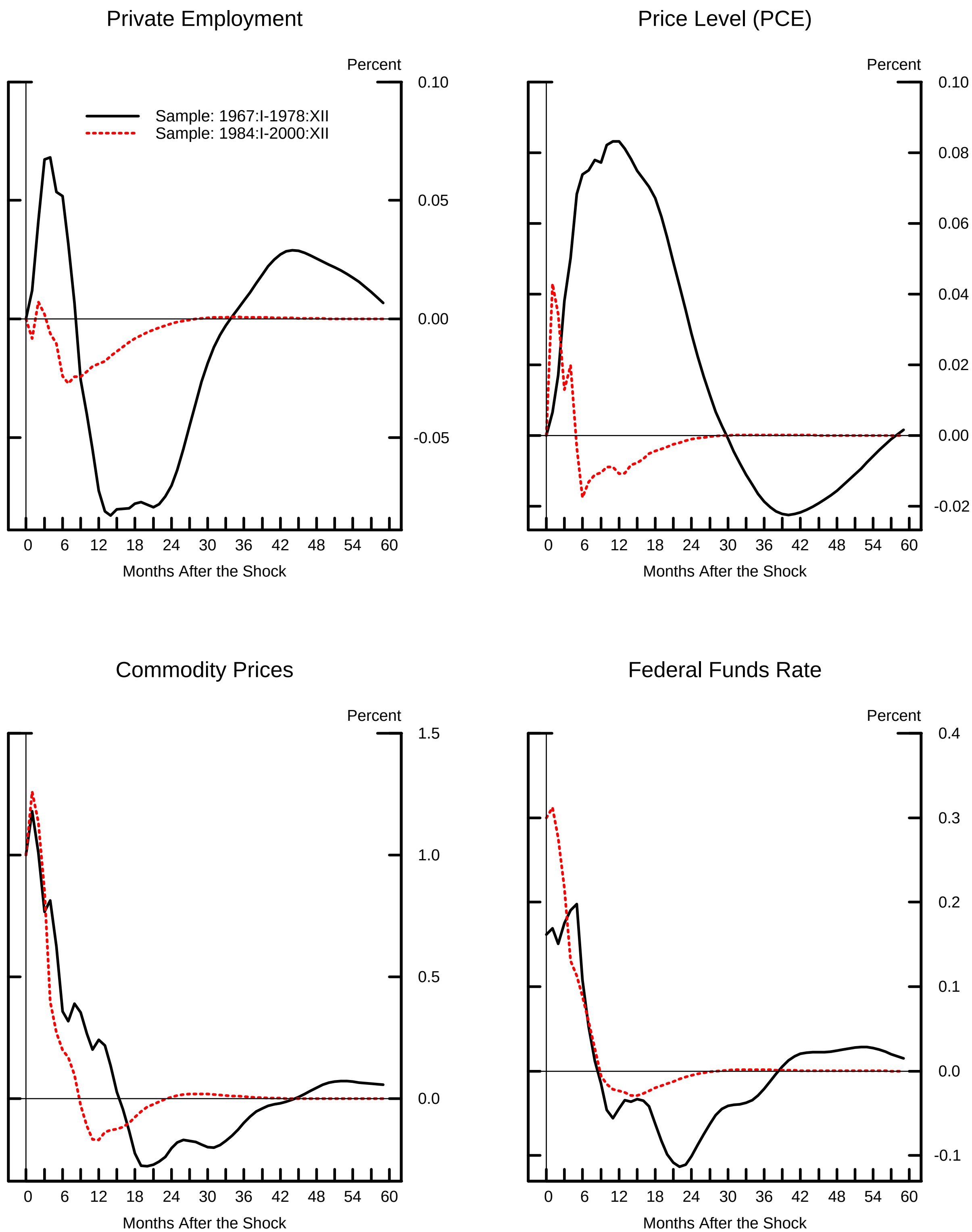
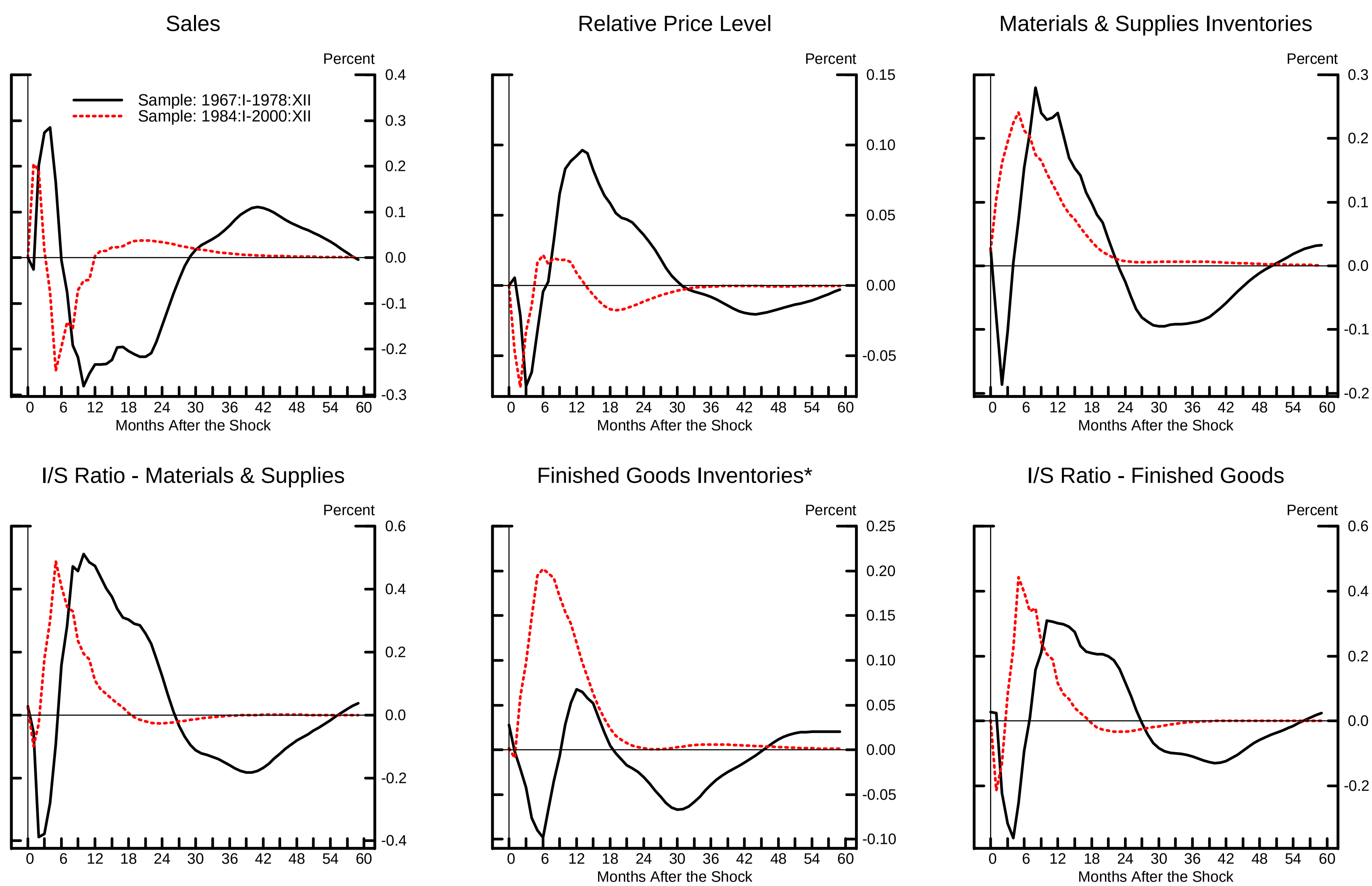


Figure 7b

**Impulse Responses to a 1% Commodity Price Shock**

Manufacturing Durable Goods Sector

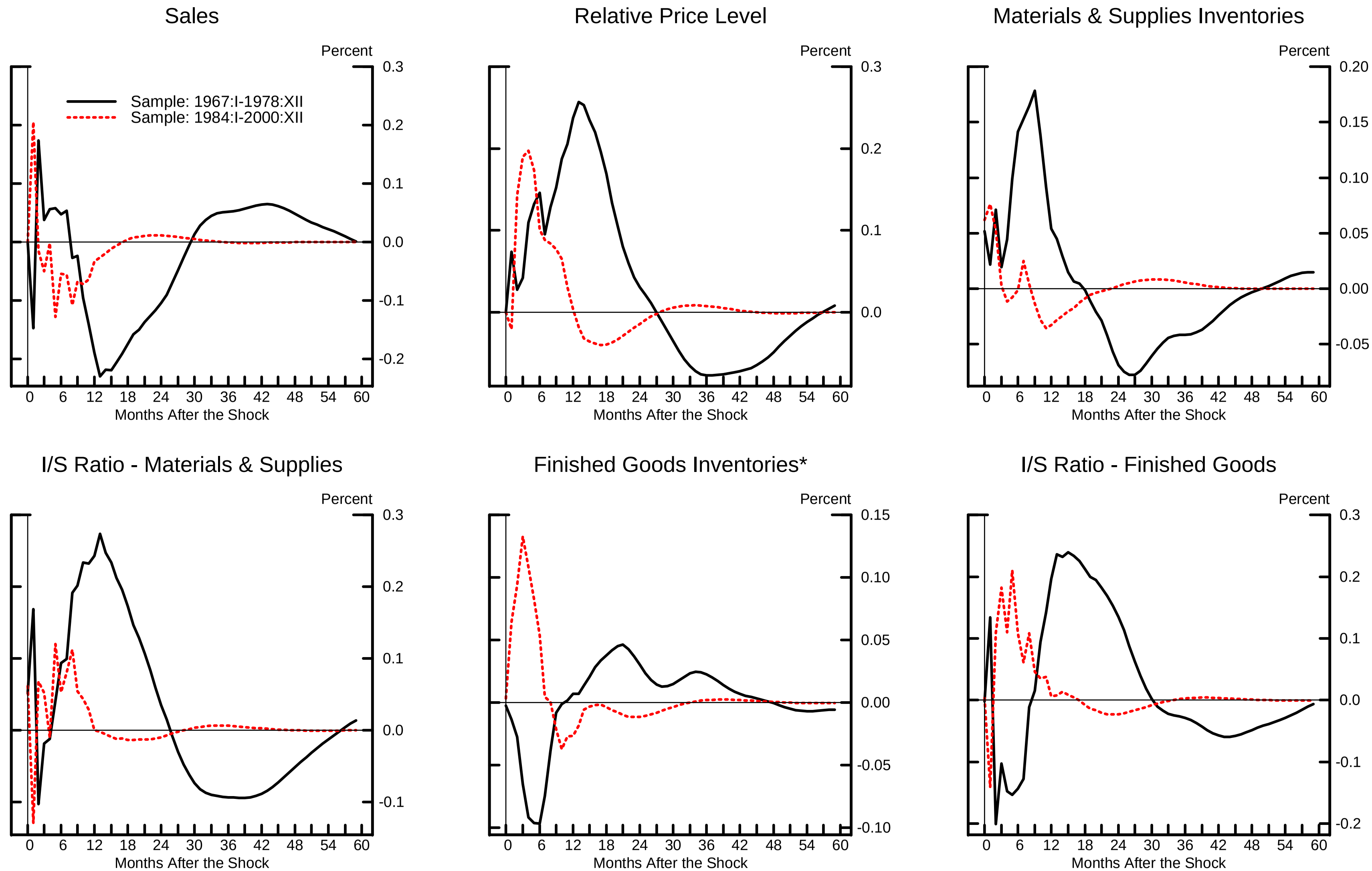



* Finished goods inventories include work-in-progress inventories.

Figure 7c

**Impulse Responses to a 1% Commodity Price Shock**

Manufacturing Nondurable Goods Sector




* Finished goods inventories include work-in-progress inventories.
Note: SIC 21 (Tobacco & Related Products) is omitted from the analysis because of suspect data.