Bank of Japan Working Paper Series

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No.07-E-23
October 2007

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Abstract

In Japan, like many other industrialized countries, output volatility declined dramatically in the 1980s. In order to investigate the cause of this decline, we decompose the variance of output growth by frequency. Our important findings are: (1) The total variance of output growth decreased, which resulted from a reduction in the volatility at business-cycle frequencies; (2) At business-cycle frequencies, the variance of production fell by a larger percentage than did the variance of sales; and (3) In stark contrast, at high frequencies, the variance of production increased, while the variance of sales decreased. These features of production at different frequencies cannot be explained by changes in the sales process and cost-shock process. Instead, improved business practices—such as the adoption of the just-in-time technique—played a direct role in stabilizing the business cycles, while increasing output volatility at high frequencies.

JEL classification: E22; E23; E32

Keywords: Output volatility; Inventories; Business cycle

[◊] We are grateful for helpful discussions and comments from Kazuo Momma, Masahiro Higo, Takatoshi Sekine, Hiroshi Fujiki, Ichiro Fukunaga, as well as seminar participants at the Bank of Japan. The views expressed herein are those of the authors alone and do not necessarily reflect those of the Bank of Japan.

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1. Introduction

In Japan, like many other industrialized countries, output volatility declined dramatically in the 1980s.[1] In this paper, we investigate the cause of this decline and show that changes in production and inventory behavior at different frequencies hold the key to explaining the decline in output volatility.

The variance of Japanese industrial production (quarterly growth rate) declined in the 1980s, falling by about 40% relative to its past level. While the variance of sales also receded, this decline was smaller than the decline in output volatility. Moreover, the covariance of inventory investment with sales became negative in the 1980s, suggesting that inventories had begun to more actively insulate production from sales shocks. These changes in production, sales, and inventories may reflect three broad types of changes in the economic environment since the early 1980s.

The first type of explanation relates to the supply side of the economy—structural changes in business practices. The so-called "Just-In-Time (JIT) technique" and "Flexible Manufacturing System (FMS)" were introduced to the manufacturing sector in the late 1970s and early 1980s. These have led to improved inventory management and greater production flexibility, which may have resulted in lower volatility of output.[2]

The second type of explanation is based on another supply-side factor—smaller cost shocks. Firms will use periods of low costs to produce a lot and to build up inventory stocks, whereas they will use periods of high costs to produce little and instead sell out their inventory stocks which have already been built up. Therefore, while large cost shocks make production more volatile than sales, smaller cost shocks—due to, for example, greater energy efficiency—make production less volatile than sales under

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[1] With regard to the decline in output volatility in the United States and other advanced countries, see, for example, Ahmed, et al. (2004), Blanchard and Simon (2001), Ceccetti, et al. (2006), Kahn, et al. (2002), McConnell, et al. (1999), Summers (2005), Stock and Watson (2002).

[2] Kahn et al. (2002) uncovered similar empirical facts with U.S. data, and suggested that they can be explained by improved business practices.

production-smoothing.

The third type of explanation relates to the demand side of the economy—a decline in the persistence of sales. When the persistence of sales is high, firms anticipate that sales will remain elevated for a longer time following a positive shock to sales, and they raise production more in order to prevent the inventory-to-sales ratio from dipping too low for an extended period. Such firms' behavior makes production more volatile than sales, and makes the covariance between sales and inventory investment positive. But, if the persistence of sales declines, production becomes less volatile than sales, and the covariance between sales and inventory investment becomes negative, as the traditional production-smoothing model suggests.[3]

In order to distinguish among these competing explanations, we focus on the spectrum of monthly growth of output to decompose its variance by frequency. Most of the studies which investigate the decline in output volatility are based on quarterly data. In a JIT-based environment where production is tied more directly to short-term customer demand patterns, however, firms' production plans are revised very frequently. This implies that an analysis based on quarterly data is not appropriate for distinguishing the effects of improved inventory management from those of changes in the sales process and cost shocks.

Our important findings are: (1) In the 1980s, the total variance of monthly growth of industrial production decreased, which resulted from a reduction in volatility at business-cycle frequencies; (2) At business-cycle frequencies, the variance of production fell by a larger percentage than did the variance of sales; and (3) In stark contrast, at high frequencies, the variance of production increased, while the variance of sales decreased. Although competing explanations are not exclusive of each other, the demand-side factor is not compelling to explain these three findings consistently. That is, a decline in the

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[3] Ramey and Vine (2006) found reduced volatility in the U.S. automobile industry, and suggested that it can be explained by a decline in the persistence of sales.

persistence of sales would be expected to reduce the spectrum primarily at business-cycle frequencies, but it would never raise the spectrum of production at high frequencies. In addition, smaller cost shocks are also not compelling to explain our findings, since a reduced innovation variance would generate a proportional decline in the spectrum at all frequencies.[4]

We show that the above features of output volatility at different frequencies has stemmed from one underlying factor—improved business practices. The intuition behind this is: (1) Since improved inventory management helps firms adjust their production flexibly (and quickly) in response to changes in sales, production has recently become more volatile at high frequencies; (2) On the other hand, because firms can prevent unintended inventory accumulation more effectively in the face of adverse sales shocks, this reduces the need for firms to subsequently cut back production to run down inventories; and (3) As a result, the amplitude of the inventory cycle and business cycle is reduced.

We reinforce this intuition with the linear quadratic inventory model. We examine how the effects of improved inventory management and other relevant changes in business practices are transmitted to the movements of production at different frequencies, and show that structural changes in business practices can replicate the stabilized business cycles with increased output volatility at high frequencies. Ahmed et al. (2004), and Stock and Watson (2002) suggest that improved inventory management would tend to be manifested more at relatively high frequencies. Using the linear quadratic inventory model, however, we show that improved inventory management affects economic fluctuations significantly not only at high frequencies but also at business-cycle frequencies.

The rest of this paper is organized as follows. Section 2 presents stylized facts

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[4] See Ahmed et al. (2004) for this point.

about Japanese production and inventory behavior. Section 3 presents the linear quadratic inventory model and Section 4 shows simulation results. Conclusions are given in Section 5.

2. Facts to be Explained

In this section, we first point out three facts about the volatility of Japanese industrial production over the postwar period of 1954 to 2005.[5] We then go on to survey possible explanations for the facts.

2.1. Production, Sales, and Inventory Variances

The first fact: decline in output volatility

Figure 1 shows the quarterly growth rates of Japanese industrial production for a period of about 50 years from 1954 to 2005. We split the sample periods in half: the first sample from 1954 to 1979 and the second sample from 1980 to 2005. The solid line in the figure is the mean of the growth rates, while the dotted line is the standard deviation for each sample period. As the figure clearly shows, output fluctuation declined after 1980, and the standard deviation dropped from 2.7% to 1.7%, by roughly 40%.[6]

Table 1 shows the standard deviation of the quarterly growth rate by goods: final demand goods and producer goods, and by industry: basic materials and processing.[7]

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[5] A lot of previous literature on the increased stability of the economy uses GDP growth. The reason why we do not use GDP statistics in our analysis is that there are several discontinuities in the estimation method of the Japanese GDP (especially in inventory investment), which causes a difficulty in analyzing output volatility in the long-term perspective. In addition, as Eggers and Ioannides (2006) suggest, the change in the composition of GDP – the increasing importance of stable sectors and diminishing importance of volatile sectors – may affect the volatility of GDP growth. We can avoid these two problems by using industrial production.

[6] In this paper, we use the standard deviation of the growth rate as a measure of volatility. When we use the standard deviation of the HP (Hodrick and Prescott)-detrened output gap as an alternative measure of volatility, the result does not change. That is, the standard deviation of the detrened output gap dropped from 5.3% to 3.3%, by roughly 40%.

[7] Basic materials consists of nine industries: iron & steel; nonferrous metals; chemicals; textiles; pulp & paper; ceramics; stone & clay; petroleum & coal products; and plastic. Processing consists of five industries: industrial machinery; electrical machinery; transportation machinery; precision machinery;

Although the degree of decline in the standard deviation differs across goods and industry, it reveals that output volatility of all goods and industries declined substantially in the second period.

Blanchard and Simon (2001) pointed out that the standard deviation of Japanese output growth rose in the 1990s, i.e. during the so-called "lost decade." Indeed, the standard deviation in the 1990s (1.8%) is slightly higher than that in the 1980s (1.4%). However, the standard deviation in the 1990s (1.8%) is still much lower than that in the 1954-79 period (2.7%), which implies that output became less volatile from a longer-term perspective.[8] One might think that the oil shocks in the early 1970s resulted in higher volatility in the first period, while the lack of such large shocks resulted in lower volatility in the second period. Even with the sample of the 1970s excluded, however, the results do not change. The standard deviation in the 1954-69 period (2.5%) is much higher than that in the 1980-2005 period (1.7%). Therefore, we can conclude that Japanese output volatility declined in a long-term perspective.

The second fact: decline in the ratio of output-to-sales variance

To illustrate the role of sales and inventory behavior in explaining output volatility in a simple growth-accounting framework, Table 2 decomposes the variance of output growth into the variance of the growth contributions of sales and inventory investment along with their covariance. Here, the inventory identity ($\widehat{y}_t = \widehat{s}_t + \Delta\widehat{i}_t$) holds, and $\widehat{y}_t$ refers to the quarterly growth rate of output, while $\widehat{s}_t$ is the quarterly growth contribution of sales and $\Delta\widehat{i}_t$ is the quarterly growth contribution of inventory investment.[9] As seen in

and processed metals.

[8] Blanchard and Simon (2001) pointed out that the standard deviation of GDP growth in the 1990s is higher than that in the 1960s. However, as noted in footnote 5, there are several discontinuities in the estimation method of the Japanese GDP and it is not appropriate to evaluate the GDP growth volatility in a long-term perspective.

[9] See Appendix for details on data.

the table, the variance of production fell by a larger percentage than did the variance of sales, which resulted from the decline in the variance of inventory investment as well as that in the covariance between inventory investment and sales. More specifically, the covariance switched from being positive to negative.

These changes in production, sales, and inventory behavior can be summarized as the decline in the ratio of output-to-sales variance. As shown in Table 3, while the ratio for each goods and industry is uniformly greater than 1 in the 1954-79 period, it has fallen to a value approximately equal to 1 in the 1980-2005 period. Moreover, if we focus on the 1991-2005 period, the ratio for final demand goods and processing is significantly lower than 1. Thus, the manufacturing sector has experienced a contraction not only in overall output volatility, but also in output volatility relative to sales volatility.

The third fact: stabilized business cycles with increased output volatility at high frequencies

Following a lot of previous literature which analyzed the decline in output volatility, we used the *quarterly* growth rate to point out the above two facts. But now, in order to investigate how output volatility changed at different frequencies, we use the spectrum of the *monthly* growth rate of industrial production and decompose its variance by frequency. The reason why we focus on the monthly growth rate is that firms' production plans are revised very frequently, especially in the 1980-2005 period when many firms adopted the JIT and FMS. Consider, for example, the adoption of just-in-time ordering methods. Firms have significantly reduced the number of days in advance of production that they order their materials and supplies. By purchasing materials much closer to the actual day of production, firms can change their production plans frequently and thus react more quickly to unexpected shifts in demand. Such production behavior is reflected well in the monthly data rather than the quarterly data. In the frequency domain analysis based on the quarterly data, the shortest-period cycle is two quarters (six months), which is too long to analyze the effects of improved inventory management.

We use the band-pass filter (Baxter and King, 1999) to isolate movements of production and sales in the frequency range of 2-6 months per cycle (called the "high frequency" interval) and the frequency range of 18-96 months per cycle (called the "business-cycle frequency" interval).[10] The band pass filtered series of production growth are shown in Figure 2.[11] Several important findings emerge from Table 4 which shows the variances of production and sales at different frequencies.

(1) Production is less volatile than sales at high frequencies, but it is more volatile than sales at business-cycle frequencies. Hence, inventories stabilize economic fluctuations at high frequencies but destabilize them at business-cycle frequencies.[12]

(2) Although this finding holds for both periods, the variance of production changed dramatically in the second period. At business-cycle frequencies, the variance of production fell by a larger percentage than did the variance of sales, which resulted in the decline in the ratio of output-to-sales variance. (Note that this is consistent with the first and second facts based on the quarterly data.)

(3) In stark contrast, at high frequencies, the variance of production increased in the second period, while that of sales decreased. As a result, the ratio of output-to-sales variance rose at high frequencies in the second period.

(4) Because of the decline in output volatility at business-cycle frequencies, the total variance of production, i.e. the integral of the spectrum across all frequencies, decreased in the second period. However, because of the increase in the ratio of output-to-sales variance at high frequencies, the total variance of production relative

[10] We exclude the frequency range of 6-18 months from our analysis in order to avoid a possible distortion of seasonal adjustment. With regard to the definition of business-cycle frequency, we follow Baxter and King (1999). The results were largely similar when using a narrower range of 24-48 months per cycle (as in Sargent, 1979).

[11] The band-pass filter uses a maximum lag length of k=12 as the truncation window parameter, implying that 12 observations are lost from each end of the data series. This choice is based on the length of samples. See Baxter and King (1999) for details on discussions regarding this issue.

[12] This finding is consistent with Wen (2005).

to the that of sales increased in the second period.

Thus, the production (and inventory) behavior changed differently across frequencies; output volatility decreased at business-cycle frequencies but increased at high frequencies.

2.2. Competing Explanations

The above three facts may reflect three broad types of changes in the economic environment since the early 1980s. The first type of explanation relates to the demand side of the economy: changes in the sales process. The second and third type of explanation relates to the supply side of the economy: smaller cost shocks and improved business practices.

Changes in the sales process

Smaller demand shocks played a direct role in the first fact: the decline in output volatility. Indeed, as shown in Table 2, the decline in sales volatility accounts for 65% of the decline in output volatility. In addition, if the persistence of sales declined in the second period, this also can explain the second fact: the decline in the ratio of output-to-sales variance. Specifically, when the persistence of sales is high, firms anticipate that sales will remain elevated for a longer time following a positive shock to sales, and they raise production more in order to prevent the inventory-to-sales ratio from dipping too low for an extended period. Such firms' behavior makes production more volatile than sales, and makes the covariance between sales and inventory investment positive. To put it differently, if the persistence of sales declines, production becomes less volatile than sales under production-smoothing, and the covariance between sales and inventory investment becomes negative.

Changes in the sales process, however, cannot explain the third fact, i.e. the stabilized business cycles with increased output volatility at high frequencies. Since the reduced innovation variance would generate a proportional decline in the spectrum at all frequencies, smaller demand shocks cannot explain the features of production behavior at different frequencies. In addition, a decline in the persistence of sales would be expected to reduce the spectrum primarily at business-cycle frequencies, but it would never raise the spectrum of production at high frequencies.

Smaller cost shocks

Smaller cost shocks are one of the supply-side factors which can explain the first fact, i.e. the decline in output volatility. Firms will use periods of low costs to produce a lot and to build up inventory stocks, while using periods of high costs to produce little and instead sell out their inventory stocks that have already been built up. Therefore, while large cost shocks make production more volatile than sales, smaller cost shocks make it less volatile than sales under production-smoothing.

Taking the energy cost as an example, the variance of cost shocks depends not only on the variance of energy prices but also on the basic unit for energy (energy consumption per unit of output). As shown in Figure 3, the basic unit for crude oil has fallen by half from the early 1970s to the recent period, because Japanese firms have promoted the widespread use of energy-saving technology since facing the oil shocks in the 70s. This improvement of energy efficiency has led to smaller cost shocks and hence the decline in output volatility. If the variance of cost shocks has reduced sufficiently, this also can explain the second fact, i.e. the decline in the ratio of output-to-sales variance.

Additional evidence for smaller cost shocks can be found from a simple vector autoregression on sales and inventories.[13] The bivariate VAR is based on monthly data and identified by using the Cholesky decomposition, with sales placed first in the ordering. This ordering assumes that inventories are affected contemporaneously by sales

[13] Sales and inventories are detrended by the Hodrick–Prescott filter. We use the percent deviation of each variable from its trend, and include five lags in the VAR according to the AIC.

shocks, but sales are not affected contemporaneously by inventories shocks. If we interpret inventories shocks as cost shocks, this assumption is very reasonable because some nominal rigidities prevent cost shocks from affecting prices (and hence sales) contemporaneously.[14] Table 5 presents results of the variance decomposition after 30 months: (1) While inventory shocks account for 43% of the variance of sales in the first period, this proportion falls to 8% in the second period; (2) While 75% of the variance of inventories is attributable to their own shocks in the first period, this proportion drops to 38% in the second period. This implies that the variance of cost shocks declined dramatically in the second period.

Improved business practices

Although smaller cost shocks can explain the first fact (and probably the second fact), they can not explain the third fact, i.e. the stabilized business cycles with increased output volatility at high frequencies. This is because the reduced innovation variance would generate a proportional decline in the spectrum at all frequencies. On the other hand, improved business practices, another supply-side factor, may explain all the three facts consistently.

Figure 4 displays the impulse response functions to one standard deviation increase in sales for each sample period. A positive unanticipated shock to sales is met, in the first instance, by running down inventories. This fall in inventories then increases the probability of running out of stock and so leads to an additional increase in output in the subsequent period to rebuild stocks. The key result from the comparison across sample periods is that the response of inventories is much less pronounced in the second period than in the first, while that of sales is roughly the same across samples. This change in inventory behavior has been caused by improved business practices. The JIT and FMS

[14] This interpretation can be justified because our VAR is based on monthly data. If the VAR is estimated with the lower frequency data, cost shocks may affect prices (and hence sales) within the current period.

were introduced to the manufacturing sector in the late 1970s and early 1980s, and these have led to greater production flexibility. Since firms can flexibly (and quickly) adjust their production in response to an unanticipated increase in sales, production has become more volatile at high frequencies. On the other hand, because firms can more effectively prevent inventories from running down, this reduces the need for firms to subsequently increase production to rebuild inventory stocks. As a result, the amplitude of the inventory cycles (and hence business cycles) is reduced. If this mechanism works sufficiently enough, structural changes in business practices can explain all the three facts about Japanese output volatility.

3. Model

In the following two sections, by using the linear quadratic inventory model, we attempt to distinguish among competing explanations for the three facts about Japanese output volatility.

3.1. Linear Quadratic Inventory Model

The main idea of the linear quadratic inventory model is that firms face quadratic cost of changing the level of production and of deviating from a target ratio of sales to inventories, and they must choose the level of output in order to minimize the discounted present value of quadratic cost.[15] The cost-minimization problem is shown in the following expression:

$$\underset{\{Y_t\}}{Min} \quad C_t = E_t\left\{\lim_{J\to\infty}\sum_{j=0}^{J}\beta^{t+j}\left[\frac{\gamma_1}{2}Y_{t+j}^2+\frac{\gamma_2}{2}\left(Y_{t+j}-Y_{t+j-1}\right)^2+\frac{\alpha_1}{2}\left(I_{t+j-1}-\alpha_2 S_{t+j}\right)^2+U_{t+j}Y_{t+j}\right]\right\}, \quad (1)$$

where Y_t is production during period *t*, I_t is the stock of inventories at the end of period *t*, and S_t is sales in period *t*; U_t is an exogenous cost shock; $E_t(\cdot)$ denotes the

[15] The linear-quadratic inventory model is very traditional and used in a lot of existing literature. See, for example, Blinder and Maccini (1990), Ramey and West (1999), and Ramey and Vine (2006).

conditional expectation operator associated with firms' information set; γ_1, γ_2, α_1, and α_2 are positive parameters; β is a discount factor ($0 < \beta < 1$).

The first term on the right-hand side of equation (1), $\gamma_1 Y_{t+j}^2$, reflects costs of production. It can be interpreted as the second order term in a quadratic approximation to an arbitrary convex cost function associated with a decreasing returns to scale technology. A positive γ_1 means that the firm has a motive to smooth production. The second term $\gamma_2(Y_{t+j} - Y_{t+j-1})^2$ captures increasing costs of changing production, which represents, for example, the cost of adjusting labor force (hiring and firing cost) and reassigning tasks. A positive γ_2 means an additional incentive to smooth production because short-run marginal costs depend on both γ_1 and γ_2. The last term $U_{t+j}Y_{t+j}$ captures exogenous stochastic variation in costs.

The third term $\alpha_1(I_{t+j-1} - \alpha_2 S_{t+j})^2$ embodies inventory holding and backlog costs. Consider first when $\alpha_2 = 0$, so that the term becomes $\alpha_1 I_{t+j-1}^2$. Then, this can be interpreted as the second order term in a quadratic approximation to an arbitrary convex inventory holding cost function. When $\alpha_2 \neq 0$, the term is intended to reflect backlog (stockout) as well as inventory holding costs, and thus captures a revenue-related motive for holding inventories. Stockout costs arise when sales exceed the stock on hand, perhaps entailing lost sales, perhaps entailing delayed payment if orders instead are backlogged. Ceteris paribus, the higher the stock of inventories, the less likely is a stockout and the lower are stockout costs. On the other hand, higher stocks entail higher inventory holding costs. With the target level for inventories, $\alpha_2 E_t S_{t+j}$, this quadratic term approximates the tradeoff between the two costs.

3.2. Rational Expectations Equilibrium

The firm observes sales S_t and cost shock U_t before it chooses production Y_t in period *t*. Here, we assume that the process governing sales and cost shocks follows the stationary autoregressive process:

$$\rho(L)S_t = \varepsilon_t^s , \tag{2}$$

$$\tau(L)U_t = \varepsilon_t^u , \tag{3}$$

where ε_t^s and ε_t^u are i.i.d. shocks with mean zero and variance σ_s^2 and σ_u^2; $\rho(L)$ and $\tau(L)$ are the functions of the lag operator L given by $\rho(L) = 1 - \rho_1 L - \rho_2 L^2 - \cdots - \rho_p L^p$ and $\tau(L) = 1 - \tau_1 L - \tau_2 L^2 - \cdots - \tau_p L^p$ respectively. The cost minimization is subject to the inventory identity ($Y_t = S_t + \Delta I_t$) and equations (2) and (3). While the firm takes sales as given in this cost minimization problem, this does not imply that sales are exogenous to the firm. Rather, following Ramey and Vine (2006), we use a standard micro result that allows one to focus on only the cost minimization part of the overall profit maximization problem.

The first-order condition with respect to inventories in the current period is written as

$$E_t\left[\gamma_1(Y_t - \beta Y_{t+1}) + \gamma_2(\Delta Y_t - 2\beta\Delta Y_{t+1} + \beta^2\Delta Y_{t+2}) + \alpha_1\beta(I_t - \alpha_2 S_{t+1}) + U_t - \beta U_{t+1}\right] = 0 \quad . \tag{4}$$

This condition states that the firm equates the marginal gain from producing one unit today instead of tomorrow to the cost of holding the extra unit in inventory. The difference in costs between two periods depends on production because marginal costs vary with the level of production.

The rational expectations equilibrium is a triplet of stochastic processes for production, inventories, and sales such that it is a bounded solution to the system consisting of the first-order condition (4) and inventory identity ($Y_t = S_t + \Delta I_t$), together with the stationary autoregressive processes of sales and cost shocks (2) and (3).[16]

4. Simulation

We now turn to a simulation of the model. The goal of this simulation is to investigate

[16] The Blanchard and Kahn (1980) conditions for a unique rational expectations equilibrium are satisfied for each calibrated case.

how changes in both the demand and supply side of the economy affect output volatility at different frequencies.

4.1. Benchmark Parameters

The first-order condition (4) and the autoregressive processes (2) and (3) contain parameters for which values must be specified. The baseline set of parameters are chosen so that the model can replicate the observed data in the 1954-79 period (see middle column of Table 6). Specifically, β is preset to 0.997 (4-percent annual), γ_1 is normalized to unity,[17] and α_2 is set to 0.655, which is the average inventory-to-sales ratio.[18] The autoregressive process of sales, shown in equation (2), is estimated and the sample partial autocorrelations indicate that the AR(2) model is appropriate: $\rho_1 = 0.709$, $\rho_2 = 0.198$ and $\sigma_s = 1.576$.[19] With regard to the other remaining parameters (α_1, γ_2, τ_i, σ_u / σ_s), we do not have appropriate estimated values, and they are set so that the ratio of output-to-sales variance and the correlation between sales and inventory investment are consistent with the empirical counterparts in the 1954-79 period.[20] We set $\alpha_1 = 0.58$, $\gamma_2 = 1.5$, and use the AR(1) model for the cost shock process with $\tau_1 = 0.75$ and $\sigma_u / \sigma_s = 3.5$. The AR(1) model is very simple but enough to describe the observed data. Indeed, as shown in the middle column of Table 7, the baseline set of these parameters yield the rational expectation solutions in which the ratio of output-to-sales variance, the correlation between sales and inventory investment, the variance of inventory investment, and the variance decomposition of inventories match their

[17] The solution depends only on relative values of γ_1, γ_2 and α_1: multiplying these three parameters by any nonzero constant leaves the first-order condition (4) unchanged, apart from a rescaling of the cost shock.

[18] See Appendix for the estimation of parameter α_2.

[19] Sales are normalized by the HP-filtered trend in the estimation of the AR(2) model.

[20] While having the advantage of being simple and intuitive, the model does not capture the important nonconvexities in the manufacturing industry. So, following Ramey and Vine (2006), we do not attempt to estimate the other remaining parameters from our model.

empirical counterparts very closely. Moreover, at both high and business-cycle frequencies, the ratios of output-to-sales variance are consistent with the actual data.

4.2. Results

By using the above parameters as a benchmark, we present the simulation results.

Changes in the sales process

To see the changes in the sales process, we first compare the estimation results of the autoregressive process of sales across sample periods. As shown in Table 6, it appears that the process governing sales, depicted in equation (2), changed between the two periods. A simple calculation based on the Yule-Walker equations with the estimated AR(2) coefficients (ρ_1, ρ_2) indicates a decline in the autocorrelation of sales in the second period, that is, a decline in the persistence of sales.[21] The standard deviation of the shocks (σ_s) also declined in the second period, which means smaller demand shocks.

We then simulate the model economy and compute the ratio of output-to-sales variance at different frequencies for each sales process, holding all the other parameters fixed. Table 8 shows that the change in the sales process reduces the total variance of production, i.e. the integral of the spectrum across all frequencies, relative to the total variance of sales. This result is the same as that in Ramey and Vine (2006), who suggest that a reduction in sales persistence, all else equal, lowers the volatility of output relative to sales. Focusing on the ratio of output-to-sales variance at different frequencies, however, we find that the change in the sales process lowers the ratio at high frequencies while keeping the ratio constant at business-cycle frequencies. This is not consistent with the third fact: the stabilized business cycles with increased volatility at high frequencies.

[21] The persistence of sales could have changed for a number of reasons. One possibility is that manufacturing firms began responding to shocks more aggressively with their pricing policies. Another possibility is that monetary policy shocks became more or less persistent. Our linear-quadratic inventory model does not depend on the source of changes in the persistence of sales. We take the change in persistence as given, and examine the implications for the behavior of production and inventories.

Smaller cost shocks

Next, we show the relationship between the ratio of output-to-sales variance and the variance of cost shocks. We simulate the model and compute the ratio of output-to-sales variance at different frequencies for low σ_u and high σ_u, holding all the other parameters fixed. In Figure 5(1), the relative variance of cost shocks (σ_u / σ_s) is used as the horizontal axis. Simulation results show that smaller cost shocks lead to a decline in the ratio of output-to-sales variance at both high and business-cycle frequencies. Therefore, smaller cost shocks can explain the first and second facts, but not the third.

Leaner inventories and greater cost concern

As noted in Section 3.1, the term $\alpha_1(I_{t+j-1} - \alpha_2 S_{t+j})^2$ in cost function (1) captures a revenue-related motive for holding inventories. Improved inventory management and other relevant changes in business practices have the effect of reducing the parameter α_2 and raising the parameter α_1.

Consider the adoption of JIT methods. In the JIT-based operation, day-to-day activities are driven by continuously replenishing the customer-demand-driven goods inventory targets. That is, the JIT requires production to be tied more directly to short-term customer demand patterns; this helps firms predict changes in demand earlier and with much more accuracy. Decreased uncertainty about product demand reduces the level of safety stock which must be carried to guard against stockout, and this in turn leads to a decline in the inventory-to-sales ratio (α_2). Moreover, in today's competitive environment, while keeping the inventory-to-sales ratio (α_2) low, firms need to stay much closer to their target level of inventories ($\alpha_2 E_t S_{t+j}$) in order to reduce both the probability of stockouts and inventory holding costs as much as possible. In other words, the deviation of inventories from the leaner target is more costly in the JIT-based environment.[22] Firms become more concerned with costs in order to gain competitive

[22] Kahn, et al. (2002) shows that the size of deviations of the inventory-to-sales ratio from the target

advantage, and such firms' behavior is reflected in the rise in the parameter α_1.

Figure 5(2) and (3) shows simulation results on how changes in parameters α_2 and α_1 affect the ratio of output-to-sales variance. All the other parameters are fixed in the simulation. The figure suggests that leaner inventories, i.e. smaller α_2, leads to a decline in the ratio of output-to-sales variance at both high and business-cycle frequencies. This means that leaner inventories weaken the mechanism of the inventory accelerator. On the other hand, greater cost concern, i.e. larger α_1, leads to a rise in the ratio of output-to-sales variance at high frequencies, while leading to a decline in the ratio at business-cycle frequencies. This is consistent with the third fact, i.e. the stabilized business cycles with increased output volatility at high frequencies. The mechanism behind this result is: (1) Since firms try to stay much closer to their inventory target which is directly proportional to sales, production becomes more volatile at high frequencies; (2) On the other hand, because firms can avoid large fluctuations of unintended inventory adjustment more effectively in the face of sales shocks, the amplitude of the inventory cycles (and hence business cycles) is reduced.

Greater production flexibility

While the adoption of the JIT enables firms to monitor directly the short-term customer demand patterns and predict changes in demand earlier, the introduction of the FMS helps firms increase or decrease their production levels rapidly or shift their capacity quickly from one product to another. The FMS consists of several Computer Numerical Controlled (CNC) machines along with part and tool handling devices such as robots, arranged so that it can handle any family of parts by automation. This automation leads to lower direct labor costs, i.e. the reduction in the number of workers. Such greater production flexibility is reflected in the decline in the parameter γ_2 of the production smoothing term $\gamma_2(Y_{t+j}-Y_{t+j-1})^2$ in equation (1).

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has been reduced significantly since the early 1980s.

Figure 5(4) shows simulation results on how changes in the parameter γ_2 affect the ratio of output-to-sales variance. Greater production flexibility, i.e. smaller γ_2, leads to a decline in the ratio of output-to-sales variance at business-cycle frequencies, while leading to a rise in the ratio at high frequencies. This result is consistent with the third fact, and the mechanism behind this is: (1) Since the FMS enables firms to react more quickly to unexpected shifts in demand, production becomes more volatile at high frequencies; (2) On the other hand, because firms can avoid extreme fluctuations of unintended inventory adjustment more effectively, the amplitude of the inventory cycles (and hence business cycles) is reduced.

Total effects

As shown in the middle column of Table 7, our model with the baseline set of parameters can replicate firms' production behavior in the first period (1954-1979). We finally examine whether our model with changes in parameters can replicate firms' production behavior in the second period (1980-2005). See the right column of Table 6 for the set of parameters in the second period. The autoregressive process of sales is set by using the estimated parameter for the second period: $\rho_1 = 0.526$, $\rho_2 = 0.325$ and $\sigma_s = 1.366$. Based on the actual data, the average inventory-to-sales ratio α_2 in the second period is set to 0.432, which is lower than that in the first period. The parameter τ_i is held the same across periods. Given these parameters, other supply-side parameters (α_1, γ_2, σ_u / σ_s) are chosen so that the ratio of output-to-sales variance, the correlation between sales and inventory investment, the variance of inventory investment, and the variance decomposition of inventories match their empirical counterparts in the 1980-2005 period: (1) smaller γ_2 which means greater production flexibility ($\gamma_2 = 0.175$); (2) larger α_1 which means greater cost concern ($\alpha_1 = 1.75$); (3) smaller σ_u which means smaller cost shocks ($\sigma_u / \sigma_s = 1.8$).

As shown in the right column of Table 7, the set of these parameters yield the rational expectation solutions in which the ratio of output-to-sales variance is roughly consistent with the actual data in the second period at both high and business-cycle frequencies. Although the simulated ratio at business-cycle frequencies is slightly lower than the empirical counterpart, the direction and the degree of change in the ratio is consistent with the actual data. Therefore, our model with changes in parameters can replicate firms' production behavior in the second period (1980-2005), and structural changes in business practices can explain the stabilized business cycles with increased output volatility at high frequencies.

5. Conclusion

This paper has documented significant changes in the behavior of Japanese industrial production. In the 1980s, the variance of production fell by a larger percentage at business-cycle frequencies than did the variance of sales. In stark contrast, at high frequencies, the variance of production increased while that of sales decreased. We examined which of the competing explanations—the decline in the persistence of sales, smaller cost shocks, and improved business practices—are consistent with our finding. Our analysis showed that the features of production and inventory behavior at different frequencies provide a litmus test for explaining the stylized facts about Japanese output volatility. Although competing explanations are not exclusive of each other, the stylized facts cannot be explained consistently without improved business practices. Using the linear quadratic inventory model, we demonstrated how the effects of improved business practices are transmitted to the movements of production at both high and business-cycle frequencies.

Further work needs to be done, in order to complete our understanding about changes in production and inventory behavior. For example, since we used calibration parameters and did not estimate the linear quadratic inventory model, it would be very fruitful to estimate the model and examine how quantitatively the improved business practices were reflected in the estimated parameters. International comparison would also be useful.[23] Although a number of studies have examined the source of decline in output volatility in other industrialized countries, most of them have not focused on the spectrum of production and inventory. Therefore, it would be beneficial to investigate how the behavior of production and inventory changed at different frequencies in other countries as well.

[23] By using the data of 42 countries, Fukuda and Teruyama (1988) examined the international comparison about how demand shocks and cost shocks affect production and inventory behavior. But their data are annual, whose sample periods are from 1965 through 1986, and they did not investigate the effects of improved business practices.

Appendix: Index of Industrial Production and Inventory Identity

In our analysis, we use the *Index of Industrial Production* (IIP) released by the Ministry of Economy, Trade and Industry. Since the IIP is literally an index, it does not satisfy an inventory identity. In order to find the relationship among indices of production, sales and inventory, we estimate the following equation:

$$Y_t = Y_t^{index} = \beta_1 S_t^{index} + \beta_2 \Delta I_t^{index} + Z_t \,, \tag{A1}$$

where Y_t^{index}, S_t^{index}, I_t^{index} are indices of production, sales and inventory respectively. The variable Z_t is an error caused by differences in the coverage of indices or the weight of items. We define sales as the first term on the right-hand side ($S_t = \beta_1 S_t^{index}$). In order to form a perfect identity in our analysis, we define inventory investment as the sum of the second and third terms ($\Delta I_t = \beta_2 \Delta I_t^{index} + Z_t$); it should be noted, however, that defining inventory investment as the second term ($\Delta I_t = \beta_2 \Delta I_t^{index}$) does not change our main results.

We estimate parameters β_1 and β_2 by OLS for each industry or goods. The parameter β_1 is estimated to be nearly 1.0 for all industries and goods, and the estimated β_2 differs across industry and goods. Then, we obtain the following growth contribution equation.

$$\underbrace{\frac{\Delta Y_t}{Y_{t-1}} = \frac{\Delta Y_t^{index}}{Y_{t-1}^{index}}}_{\hat{y}_t} = \underbrace{\beta_1 \frac{\Delta S_t^{index}}{Y_{t-1}^{index}}}_{\hat{s}_t} + \underbrace{\beta_2 \frac{\Delta^2 I_t^{index}}{Y_{t-1}^{index}} + \frac{\Delta Z_t}{Y_{t-1}^{index}}}_{\Delta \hat{i}_t} \,. \tag{A2}$$

Next, we define the average inventory-to-sales ratio as the ratio of inventories trend and sales trend. Dividing equation (A1) by production trend leads to

$$\frac{Y_t}{\overline{Y}_t} = \frac{\overline{S}_t}{\overline{Y}_t}\frac{S_t}{\overline{S}_t} + \frac{\overline{I}_t}{\overline{S}_t}\frac{\overline{S}_t}{\overline{Y}_t}\frac{\Delta I_t}{\overline{I}_t} = \lambda \frac{S_t}{\overline{S}_t} + \alpha_2 \lambda \frac{\Delta I_t}{\overline{I}_t} \,, \tag{A3}$$

where $\overline{Y}_t = \overline{Y}_t^{index}$, $\overline{S}_t = \beta_1 \overline{S}_t^{index}$, $\overline{I}_t = \beta_2 \overline{I}_t^{index}$, $\lambda = \overline{S}_t / \overline{Y}_t$, $\alpha_2 = \overline{I}_t / \overline{S}_t$. Here, the variable with hat ($\bar{}$) denote the trend level of each variable. The parameter α_2 is the average inventory-to-sales ratio ($\alpha_2 = \bar{I}_t / \vec{S}_t$), and λ is the ratio of sales trend to production trend ($\lambda = \overline{S}_t / \overline{Y}_t$). These two parameters for manufacturing are estimated by OLS for each sample period; we obtain $\lambda = 1$ for both samples, $\alpha_2 = 0.655$ for the first sample and $\alpha_2 = 0.432$ for the second sample.

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Table 1 Volatility of Growth in Industrial Production and Its Components

Standard Deviations of Quarterly Growth Rates

	1954:1～1979:4 (A)	1980:1～2005:4 (B)	$\frac{(B)-(A)}{(A)}$
Industrial production	2.7	1.7	-39.0%
Final demand goods	2.8	1.7	-41.0%
Consumer goods	2.8	1.4	-51.6%
Capital goods	3.8	2.4	-37.3%
Producer goods	3.0	2.0	-34.4%
Basic materials	3.2	1.4	-58.1%
Processing	3.9	2.4	-38.7%

Source: Authors' calculation based on the Ministry of Economy, Trade and Industry's "Indices of Industrial Production.",.

Table 2 Decomposition of Output Growth Volatility

	1954:1～1979:4 (Quarterly)	1980:1～2005:4 (Quarterly)	Percentage of $\Delta Var[\hat{y}_t]$
$\mathrm{Var}[\hat{y}_t]$	7.55	2.85	100.0%
$\mathrm{Var}[\hat{s}_t]$	5.86	2.79	65.3%
$\mathrm{Var}[\Delta\hat{i}_t]$	1.50	0.32	25.1%
$2\,\mathrm{Cov}\,[\hat{s}_t, \Delta\hat{i}_t]$	0.20	-0.26	9.8%

Note: See Appendix for calculations.

Table 3 Ratio of Output-to-Sales Variance ($Var[\hat{y}_t]/Var[\hat{s}_t]$)

	1954:1～1979:4 (Quarterly)	1980:1～2005:4 (Quarterly)	
			91:1～2005:4
Industrial production	1.29	1.02	0.97
Final demand goods	1.45	0.96	0.88
Consumer goods	1.79	0.96	0.83
Capital goods	1.28	1.17	1.13
Producer goods	1.16	1.11	1.09
Basic materials	1.26	0.95	0.95
Processing	1.30	0.89	0.85

Source: Authors' calculation based on the Ministry of Economy, Trade and Industry's "Indices of Industrial Production.",.

Table 4 Variance of Production and Sales at Different Frequencies

		1954:1～1979:12 (Monthly)	1980:1～2005:12 (Monthly)	Difference
All frequencies	$Var[\hat{y}_t]$	2.23	2.00	-0.23
	$Var[\hat{s}_t]$	3.07	2.25	-0.82
	$Var[\hat{y}_t]/Var[\hat{s}_t]$	0.73	0.89	+0.16
High frequency	$Var[\hat{y}_t]$	1.32	1.64	+0.32
	$Var[\hat{s}_t]$	2.46	1.96	-0.50
	$Var[\hat{y}_t]/Var[\hat{s}_t]$	0.54	0.83	+0.29
Business-cycle frequency	$Var[\hat{y}_t]$	0.53	0.21	-0.32
	$Var[\hat{s}_t]$	0.37	0.17	-0.20
	$Var[\hat{y}_t]/Var[\hat{s}_t]$	1.43	1.21	-0.22

Source: Authors' calculation based on the Ministry of Economy, Trade and Industry's "Indices of Industrial Production.",.

Table 5 Variance Decomposition

	Variance of sales		Variance of inventories	
	Contribution of sales shocks (Percent)	Contribution of inventory shocks (Percent)	Contribution of sales shocks (Percent)	Contribution of inventory shocks (Percent)
1954:1～1979:12	56.8	43.2	24.8	75.2
1980:1～2005:12	92.1	7.9	62.2	37.8

Source: Authors' calculation based on the Ministry of Economy, Trade and Industry's "Indices of Industrial Production.",.

Table 6 Parameters

	1954-79 (Benchmark)	1980-2005
β	0.997	0.997
γ_1	1	1
γ_2	1.5	0.175
α_1	0.575	1.75
α_2	0.655	0.432
ρ_1	0.709	0.526
ρ_2	0.198	0.325
σ_s	1.576	1.366
τ_1	0.75	0.75
σ_u	5.5	2.5

Table 7 Simulation Results

	1954-79		1980-2005	
	Data	Model	Data	Model
$\mathrm{Var}(\Delta Y)/\mathrm{Var}(\Delta S)$	0.73	0.72	0.89	0.87
High frequency	0.54	0.51	0.83	0.79
Business-cycle frequency	1.43	1.23	1.21	1.07
$Correl(\Delta S, \Delta^2 I)$	-0.54	-0.53	-0.41	-0.37
$Var(\Delta I)$	2.15	2.06	0.69	0.74
$Var(I)$ due to inventory shocks	75.2	74.7	37.8	36.2

Note: We conduct stochastic simulations and obtain the stochastic distributions of endogenous variables in order to calculate the ratio of output-to-sales variance at different frequencies. We generate five sets of artificially normally-distributed shocks with 10,000 months of shocks in each set. We use these shocks to conduct stochastic simulations under alternative parameter sets.

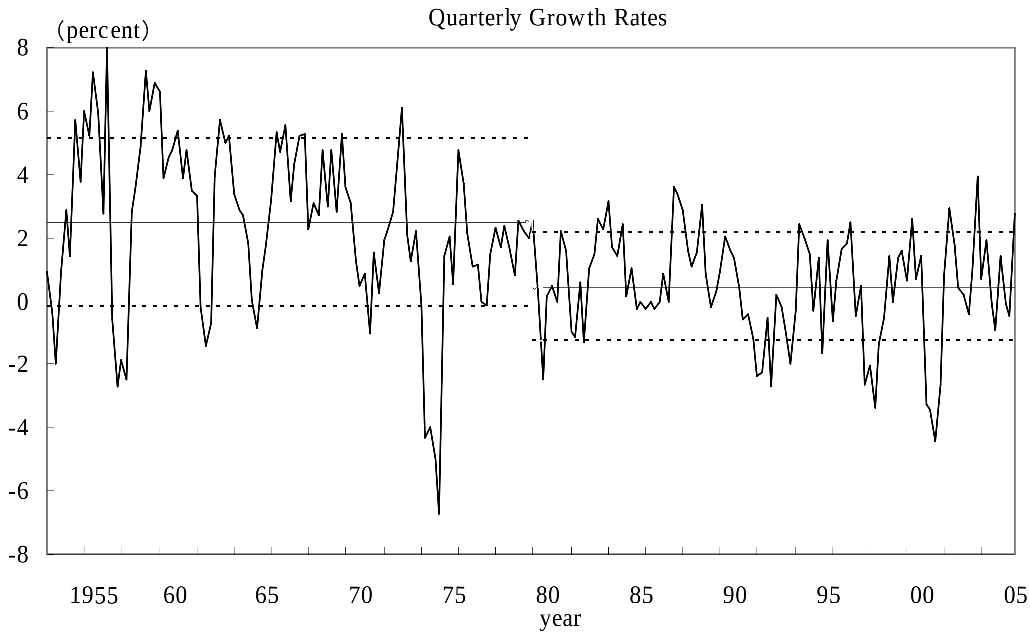
Table 8 Simulation Results: Ratio of Output-to-Sales Variance **(** $\mathrm{Var}[\hat{y}_t]/\mathrm{Var}[\hat{s}_t]$ **)**

Effects of Change in Sales Process

	Benchmark (1954-79 Model)	Change in sales process (1980-2005 Model)
All frequencies	0.72	0.55
High frequency	0.51	0.37
Business-cycle frequency	1.23	1.23

Note: See note of Table 7 for the simulation method.

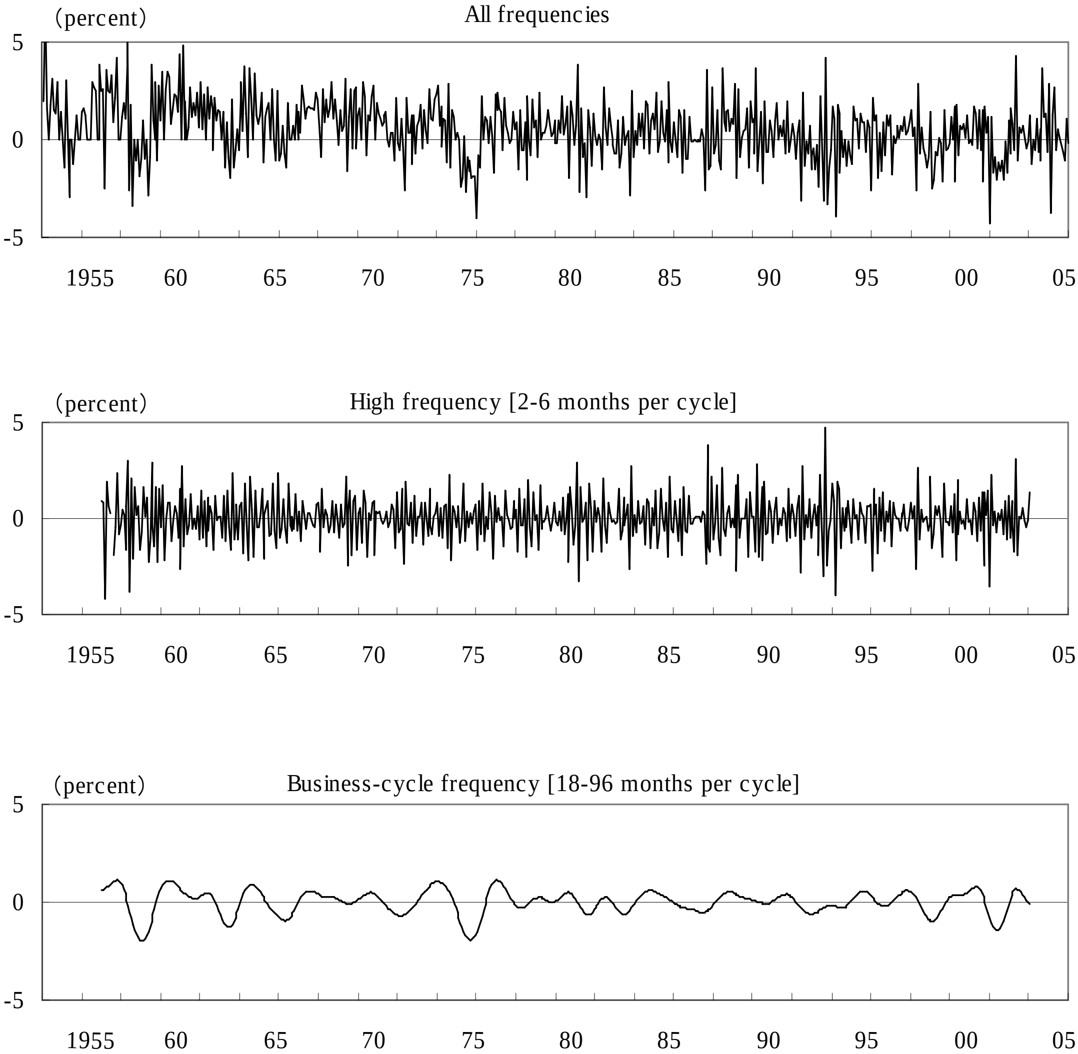
Figure 1 Industrial Production



Note: The solid line is the mean of the growth rates; the dotted line is the standard deviation of the growth rates for each sample period.

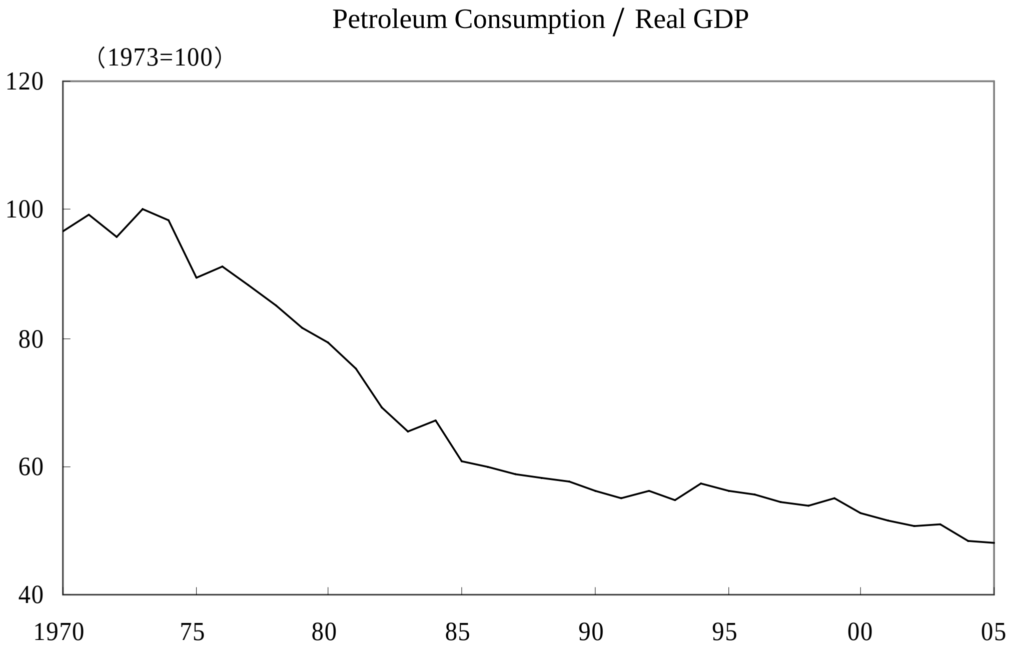
Source: Ministry of Economy, Trade and Industry, "Indices of Industrial Production."

Figure 2 Monthly Growth in Industrial Production



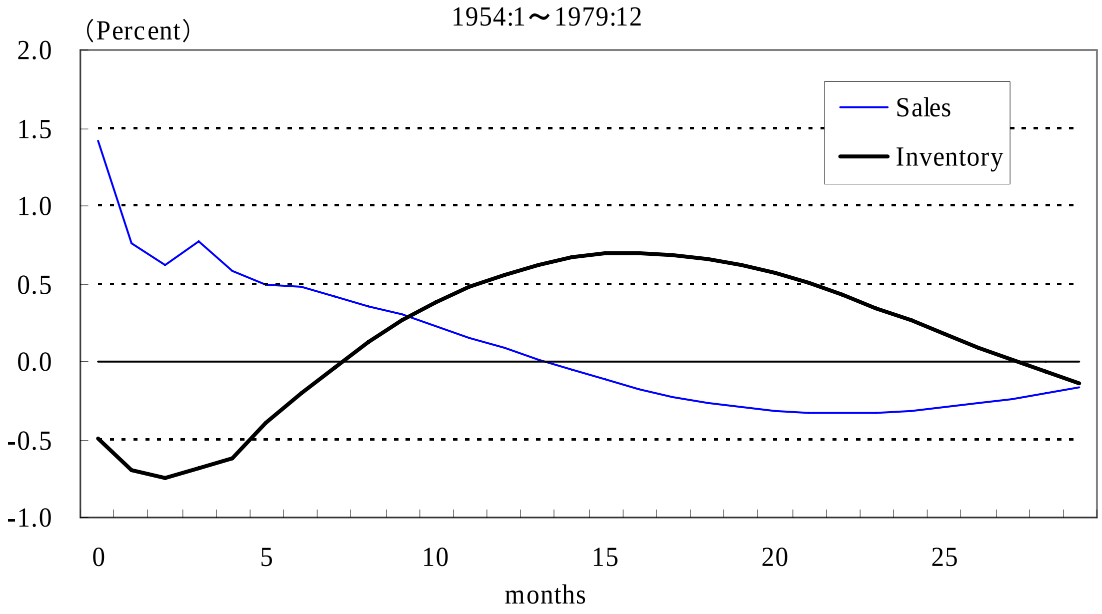
Source: Authors' calculation based on the Ministry of Economy, Trade and Industry's "Indices of Industrial Production.",.

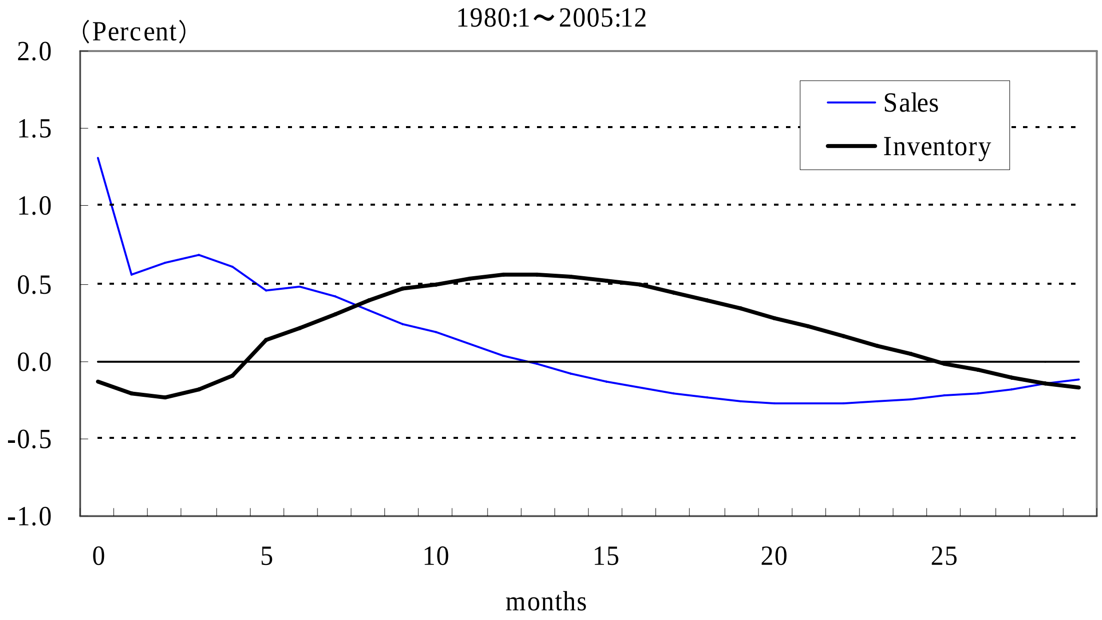
Figure 3 Basic Unit for Crude Oil



Sources: U.S. Department of Energy
Cabinet Office, Government of Japan

Figure 4 Impulse Responses to a Sales Shock over Different Samples

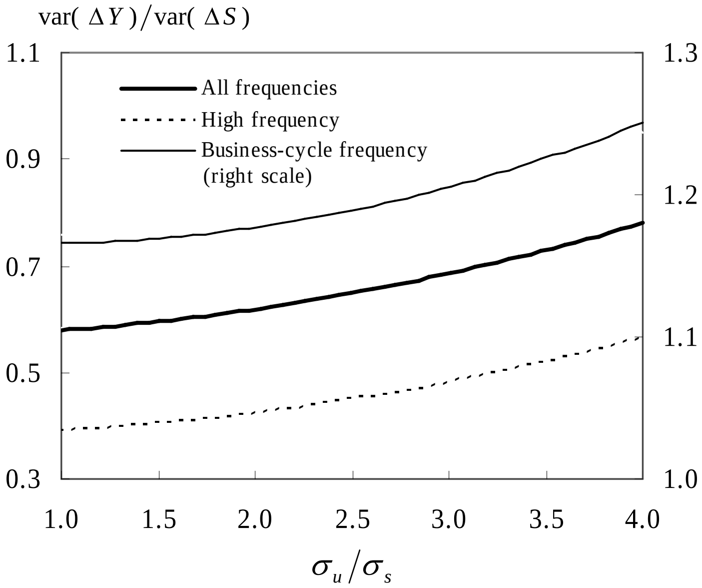




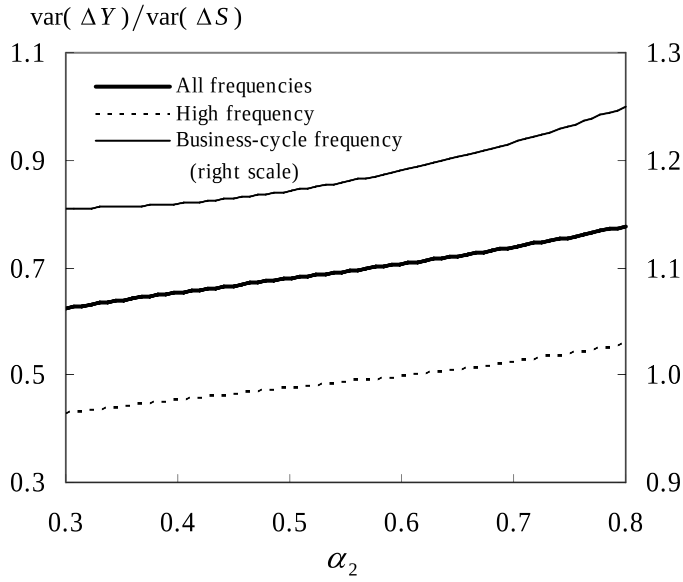
Source: Authors' calculation based on the Ministry of Economy, Trade and Industry's "Indices of Industrial Production.",.

Figure 5 Simulation Results: Ratio of Output-to-Sales Variance

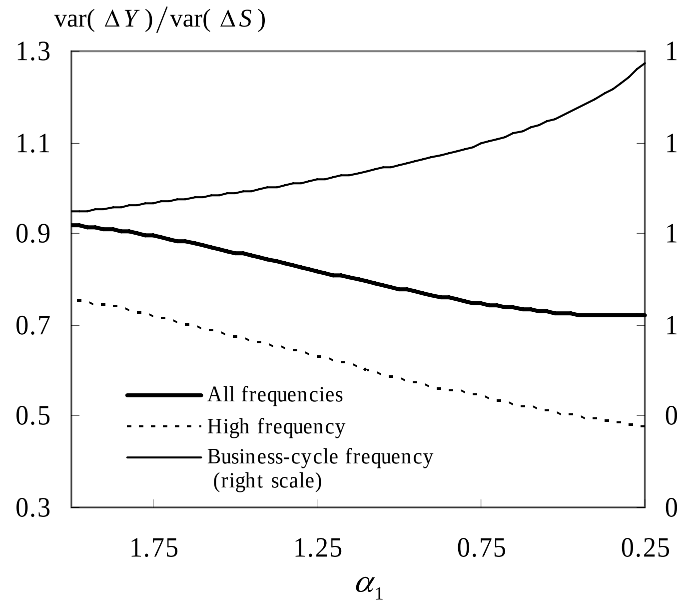
(1) Effects of σ_u/σ_s



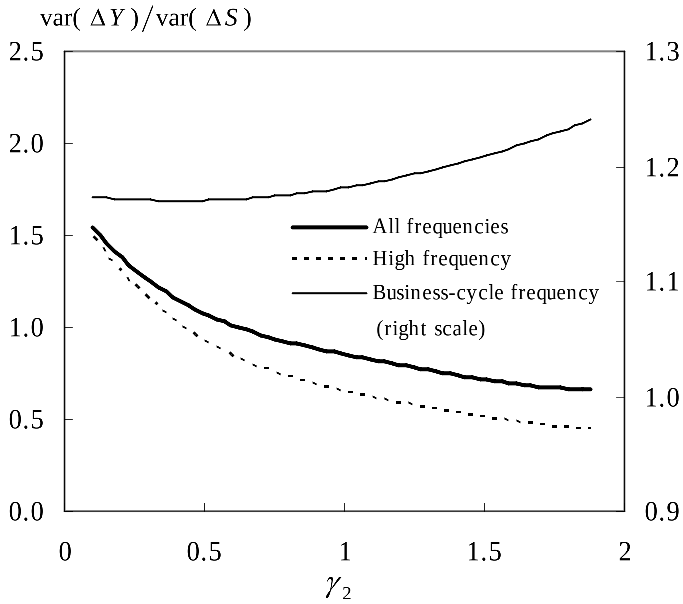
(2) Effects of α_2



(3) Effects of α_1



(4) Effects of γ_2



Note: See note of Table 7 for the simulation methods.