The Great Moderation in the Japanese Economy *

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Abstract

This paper examines changing dynamics and sources of volatility of the postwar output growth in Japan. We document two major facts in the postwar Japanese business cycle: (i) the Great Moderation phenomenon in Japan has occurred in the middle of 1970s, but was not persistent with some volatile movements of output from the late 1980s to the beginning of 1990s, and in the late 2000s, and (ii) the correlation between labor input and productivity has been overall negative. To find the source of output and labor input behaviors of the postwar Japanese economy, a time-varying VAR with drifting coefficients and stochastic volatilities is modeled in line with Galí and Gambetti (2009). We find that technology shocks are responsible for significant changes of the output volatility throughout the total sample period while the volatility of labor input is largely attributed to nontechnology shocks.

Keywords: Japanese economy, Great Moderation, time-varying coefficient VAR, stochastic volatility, technology shocks
JEL classification: E32

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1 Introduction

Most industrialized economies have experienced a substantial decline in output growth volatility in the postwar period, which is known as "the Great Moderation". The Japanese economy is one of them with decreasing output growth volatility but the timing and the changing pattern seem quite different. The aim of this paper is to shed light on the following questions: (i) When is the timing of so-called Great Moderation over the last several decades in Japan? (ii) Did the sequence of output growth volatility show changing patterns in the perspective of labor market dynamics? (iii) What is the source of the significant changes of output and labor input volatility: were there any structural changes in the labor market or has the size of technology shocks changed? (iv) Is the changing pattern of Japanese labor market dynamics different from that of U.S. labor market?

In the U.S. case, many authors have investigated characteristics and reasons of the Great Moderation that started in the middle of 1980s.[1] In the Japanese case, there are some papers to analyze the postwar Japanese business cycles[2] but they do not pay much attention to the changing patterns of the volatility. There are few papers to investigate time-varying properties of Japanese business cycles in the postwar period. Sakura, Sasaki, and Higo (2005) find that the output volatility in the period from 1990s to early 2000s became larger compared to that in mid-1970s to mid-1980s. Shibamoto and Miyao (2008) use the data of IIP and CPI from February 1978 to December 2006, and find the possibility of structural change in 1992 based on the stability test. They attempt to explain the decline of inflation and output volatility in the latter period based on aggregate demand and supply framework. Kimura and Shiotani (2009) saparate the postwar economy into pre-1980 and post-1980, decompose the variance of output growth by frequency, and investigate the cause of the decline of output variance in the latter period. They conclude that business practices played a direct role in stabilizing business cycles.

In this paper, we document two important aspects of the postwar Japanese economy. First, timing and persistence of the Great Moderation in the Japanese economy are very different from those for other G7 countries. There is a significant decline in output growth volatility in the middle of 1970s. However, there are two upheavals: in the bubble period from mid-1980s to early 1990s, and in the recent global financial crisis period. Second, the correlation of labor input with productivity has been negative throughout the postwar period.[3]

[1] Based on time-varying or Markov-switching structural VAR methods, the good luck hypothesis has been advocated by many authors including Stock and Watson (2002, 2005), Primiceri (2005), Sims and Zha (2006), Arias, Hansen, and Ohanian (2006), and Gambetti, Pappa, and Canova (2006). On the other hand, good policy hypothesis was also supported by many other authors such as Clarida, Galí, and Gertler (2000), Lubik and Schorfheide (2004), Boivin and Giannoni (2006), and Benati and Surico (2009). There are different approaches to look at the result as structural changes: Campbell and Hercowitz (2005), and Galí and Gambetti (2009). Especially Galí and Gambetti (2009) capture the changing patterns of the correlations among macro variables and unconditional and conditional second moments.

[2] For example, please refer to Braun, Esteban, Okada, and Sudo (2006) and Braun, Okada, and Sudo (2008).

[3] To the best of our knowledge, Galí (1999) was the first to provide evidence of negative correlation between labor input and productivity in Japan. According to Galí (1999, 2005), Japan was the only country with the negative correlation among G7 countries. However, he did not check the changing patterns. We reconfirm this finding with several data and analyze the changing pattern and the relationship with output volatility.

We estimate a time-varying coefficient vector autoregressive model (TVC-VAR) of labor input and productivity to find the dominant source of volatilities of output and labor input growths. In order to correctly identify the sources of the Great Moderation, we impose the long-run restriction in line with Galí (1999), and Galí and Gambetti (2009), where the technology shock is the only source that may shift the labor productivity permanently. We estimate the model via Bayesian methods, and explore theoretical properties of the estimated structure.

We find that the source of the volatility is different for each macro variable. Technology shocks play the major role in explaining the volatility of output and productivity growth during the sample period, while nontechnology shocks contribute more fraction of the volatility of labor input. The fact that technology shocks contribute output volatility most is very closely related to the persistently negative correlation of labor input with labor productivity. Countercyclical behavior of labor productivity in response to nontechnology shocks diminishes the volatility of output growth. As a result, the volatile movement of output growth is less explained by nontechnology shocks.

The consistently negative sign of correlation in Japan is contrast to the findings of the U.S. economy. In the U.S. economy, the sign of the correlation between labor input and productivity has changed from positive to negative on the onset of the Great Moderation.[4] Galí and Rens (2010) and Barnichon (2010) argue that there is a strong possibility of a structural change within the labor market: the most volatile component in the labor input has switched from the effort level into hours and employment on the onset of the Great Moderation. In the Japanese labor market, however, working hours always have been fluctuating more than employment and effort level. Therefore, these differences may reflect that the characteristics of labor market dynamics are different between the U.S. and Japan.

The paper is organized as follows. In Section 2, we document some facts with respect to macro variables such as output, labor input, and productivity in Japan. Section 3 describes the time-varying VAR model, estimation, and the identification scheme. Section 4 displays the benchmark results. In Section 5, we check the robustness of the main results. In Section 6, we discuss the results with the U.S. case. Section 7 concludes.

2 Japanese Economy and the Great Moderation

In this section, we document some facts pertaining to the growth behavior of output, labor input, and labor productivity. We employ quarterly data, and the sample size is 1955Q2 to 2009Q4. Output is calculated connecting GDP data sources from 68SNA and 93SNA. Employment and working population aged-15-and-over are taken from *Japan's Labor Force Survey* and *Japanese Census Population*, respectively. We use hours data by *Monthly Labor Survey*. We use working hours in the manufacturing sector since we do not have the aggregate data that covers the total sample period. In the robustness check, we use the aggregate data from 1970Q1 to 2009Q4. Labor input is measured by multiplying working hours by employment. In all cases, we normalize the output and

[4]Stiroh (2008), Galí and Gambetti (2009), and Galí and Rens (2010) have common findings that the positive correlation between labor input and productivity became significantly negative. Barnichon (2010) shows the similar results that the correlation between unemployment rate and labor productivity has changed from negative to positive.

labor input measures by the size of the working population. Labor productivity measure is constructed as the ratio between the corresponding output and labor input.

2.1 Timing of the Great Moderation

Figure 1 displays the rolling standard deviations of output, labor input, and labor productivity. All variables are transformed by taking the natural logarithm and applying first-difference transformation. The standard deviations are calculated every three years.[5] We find that the output is moderated in two subsample periods: from late 70s to early 80s and 90s to the middle of 2000s. However, the moderation periods are not persistent, which is a different feature compared to other G7 countries. Thus, we can conclude that the timing and the persistency of the Japanese Great Moderation is very unique.[6] However, the labor input volatility is relatively moderated from late 70s to the middle of 2000s. The labor productivity is also moderated since the end of 70s but the volume is relatively small.

Figure 1 is inserted here.

2.2 Changing Dynamics of Japanese Economy

Figure 2 shows rolling correlations among macro variables. The signs of conditional correlations are relatively persistent in all cases but the movements are highly volatile. Overall, output is positively correlated with other macro variables throughout the sample period. However, there are considerable declines in 70s and 2000s for labor productivity and early 80s and 90s for labor input. These unstable relationships among output and labor market variables may reflect that there are several structural changes in the labor market. More interestingly, the correlation between labor input and labor productivity is negative, although it becomes almost zero in the bubble period.

Figure 2 is inserted here.

To confirm the results, we split the sample into several sub-periods.[7] We use three kinds of transformations in order to get the original times series stationary. The first transformation corresponds to the first difference (1D) of logged variables so that we can compare sub-sample results with rolling volatility and correlation. Our second and third transformations use Hodrick-Prescott (HP) and Band-Pass (BP) filters. We set λ as 1600 to remove the trend components. Using BP filter, we isolate the movement of variables in the frequency range of 6-32 quarter, which is associated with business cycle frequencies. For the data robustness, we also use hours data taken from *Labor Force Survey* (LFS) in the 1D case.

Table 1 reports standard deviations in each sub-sample period. In all cases, we find that there is a dramatic decline of output volatility in the post-1974 period, which is consistent with rolling standard deviation results in Figure 1. In the 1D case, for example,

[5] We also calculated other length such as four years but the results did not change much.

[6] For example, Stock and Watson (2002) and Summers (2005) show time-varying output volatility of G7 countries. They find that the Great Moderation phenomenon in Japan occurred in the middle of 1970s but they tell nothing about the persistency. We compare the U.S. case in the latter section.

[7] Each period is selected so that we can easily compare the results with those in the latter section.

the standard deviation of output growth falls from 1.461 to 0.664 in the 76-85 period. Labor input and productivity also show the large reduction in their volatility: 1.351 to 0.648 and 1.392 to 0.983, respectively. However, the output moderation is not persistent. There are two other volatile periods: 86-91 and 06-09 periods.

Table 1 is inserted here.

Table 2 reports correlations in each sub-sample period. Results for each sub-sample correlation are also consistent with the result for the rolling correlation. Although the signs of correlations are not changing often, the volumes are consistently changing. The changing pattern of correlations among variables and relative standard deviation may reflect the changing pattern of the labor market structure. Generally, the correlations of output with labor productivity and input are positive. This fact may reflect the procyclical movements of labor productivity and input supported by the standard RBC theory.

Table 2 is inserted here.

More interestingly, the correlation between labor input and labor productivity is negative.[8] What is the relationship between this negative correlation and output growth volatility? In the next section, we search for the source of output and labor input growth volatility and link the negative correlation between labor input and labor productivity to the output volatility.

3 Framework of Analysis

In this section, we explain our framework of the analysis: SVAR estimation with time-varying coefficients and stochastic volatility, and the long-run identification scheme. Drifting coefficients let the model permit possible nonlinearities or time variation in lag structures. The changing parameter can capture the changing pattern of the economy structure that we find from the basic statistics in the previous section. Multivariate stochastic volatility enables possible heteroskedasticity of shocks, which is often observed in the postwar Japanese economy. In addition, the stochastic volatility can capture the different size of shocks, Therefore, our model has more advantage in studying structural changes of Japanese economy than VAR with constant coefficients and a constant covariance matrix of errors.

3.1 TVC-VAR with stochastic volatility

We introduce a TVC-VAR(p) model with a time-varying covariance matrix of errors:

$$x_t = B_{0,t} + B_{1,t}x_{t-1} + B_{2,t}x_{t-2} + \cdots + B_{p,t}x_{t-p} + u_t \tag{1}$$

where x_t is defined as $x_t \equiv [\Delta lp_t, li_t]'$, with y_t, li_t, and lp_t ($\equiv y_t - li_t$) being output, labor input (both in logarithm), and labor productivity. $B_{0,t}$ is a vector of time-varying

[8] This acyclical feature of labor productivity is very similar to that of the Great Moderation period in the U.S.. The asymmetric movements between these two variables may link to the stable output movements.

intercepts, and $B_{i,t}$ $(i = 1, \cdots, p)$ are matrices of time-varying coefficients. u_t are error terms of the reduced form, and are assumed to be conditionally normal with mean zero and a time-varying covariance matrix R_t.

Letting $B_t = [B_{0,t}, B_{1,t}, \cdots, B_{p,t}]$, we define $\theta_t = vec(B_t')$, where $vec(\cdot)$ is a column stacking operator. We assume that θ_t evolves over time according to the process

$$\theta_t = \theta_{t-1} + \omega_t, \tag{2}$$

where ω_t is a Gaussian white noise process with zero mean and a constant covariance Q, and independent of u_t at all leads and lags.

We model the time variation for R_t as follows. Let $R_t \equiv A_t^{-1} H_t A_t^{-1\prime}$, where A_t is lower triangular with ones in the main diagonal, and H_t is a diagonal matrix.

$$H_t = \begin{bmatrix} h_{1t} & 0 \\ 0 & h_{2t} \end{bmatrix}, \quad A_t = \begin{bmatrix} 1 & 0 \\ \alpha_t & 1 \end{bmatrix} \tag{3}$$

The diagonal elements of H_t are assumed to be unvariate stochastic volatilities that evolve as driftless, geometric random walks:

$$\log h_{i,t} = \log h_{i,t-1} + \xi_t. \tag{4}$$

We also assume

$$\alpha_t = \alpha_{t-1} + \zeta_t, \tag{5}$$

where ξ_t and ζ_t are Gaussian white noise processes with zero mean and constant covariance matrices Ψ and Ξ, respectively. Random walk specification is designed for permanent shifts in the innovation variance. The factorization of R_t and log specification guarantee that R_t is positive definite.

3.2 Long-run Identification

To identify the structural shock in the TVC-VAR scheme, we follow the long run restriction in Galí and Gambetti (2009). We assume that VAR innovations can be written as

$$u_t = R_t^{\frac{1}{2}} \varepsilon_t, \tag{6}$$

where we assume that the vector of the structural shocks, $\varepsilon_t \equiv \left[\varepsilon_t^T, \varepsilon_t^{NT}\right]'$, has the identity covariance matrix I, and that ε_t^T and ε_t^{NT} represent technology and non-technology shocks, respectively. The identification and interpretation is in line with Galí (1999) and Galí and Gambetti (2009): only technology shocks may affect labor productivity in the long run.

The companion form of the original model can be expressed as

$$\mathbf{x}_t = \mu_\mathbf{t} + \mathbf{B_t x_{t-1}} + \mathbf{u_t}, \tag{7}$$

where $\mathbf{x}_t \equiv [x_t', x_{t-1}', \cdots, x_{t-p+1}']'$, $\mathbf{u}_t \equiv [u_t', 0, \cdots, 0]'$, $\mu_t \equiv [B_{0,t}, 0, \cdots, 0]'$, and $\mathbf{B}_t$ is the corresponding companion matrix.

By using a lag operator, this companion form can be transformed into a VMA representation as

$$
\begin{aligned}
\mathbf{x}_t &= (I - \mathbf{B}_t L)^{-1}(\mu_\mathbf{t} + \mathbf{u_t}) && (8)\\
&= \phi_\mathbf{t} + \mathbf{B_t}(\mathbf{L})\mathbf{u_t} && (9)\\
&= \phi_\mathbf{t} + \sum_{\mathbf{k=0}}^{\infty} \mathbf{B_t^k} \mathbf{u_{t-k}} && (10)
\end{aligned}
$$

where $\phi_\mathbf{t} = (\mathbf{I} - \mathbf{B_t})^{-\mathbf{1}}\mu_\mathbf{t}$ and L denotes a lag operator. Thus the first two rows and two columns of $\mathbf{B}_t^k$ identify the impulse response at $t+k$ of labor productivity growth and hours to innovations u_t. In the mathematical form, this can be written as

$$
\frac{\partial x_{t+k}}{\partial u_t'} = e_{2,2}(\mathbf{B}_t^k) \equiv \mathbf{B}_{t,k} \quad \forall k \geq 0, \tag{11}
$$

where $e_{2,2}(\mathbf{M})$ is a function which selects the first two rows and two columns of any matrix $\mathbf{M}$, and where $\mathbf{B}_{t,0} \equiv I$. Remembering $u_t = R_t^{\frac{1}{2}} \varepsilon_t$, the impulse responses at $t+k$ of labor productivity growth and hours to structural shocks at t are expressed as

$$
\begin{aligned}
\frac{\partial x_{t+k}}{\partial \varepsilon_t'} &= \frac{\partial x_{t+k}}{\partial u_t'} \frac{\partial u_t}{\partial \varepsilon_t'} && (12)\\
&= \mathbf{B}_{t,k} R_t^{\frac{1}{2}} \equiv \mathbf{C}_{t,k} \quad \forall k \geq 0. && (13)
\end{aligned}
$$

Note that the impulse responses depend on t.

From the above equation, the variance of $\mathbf{x}_t$ in the companion form is given by

$$
\begin{aligned}
Var(\mathbf{x}_t) &= \mathbf{B}_t(1) Var(\mathbf{u}_t) \mathbf{B}_t(1)' && (14)\\
&= \left(\sum_{k=0}^{\infty} \mathbf{B}_t^k \right) \begin{bmatrix} R_t & \mathbf{0} \\ \mathbf{0} & \mathbf{0} \end{bmatrix} \left(\sum_{k=0}^{\infty} \mathbf{B}_t^k \right)'. && (15)
\end{aligned}
$$

Note that the variance of productivity growth and labor input is a block in the first two rows and two columns.

Now let us define the accumulated responses as $\mathbf{B}_t(1) = \sum_{k=0}^{\infty} \mathbf{B}_{t,k}$, $\mathbf{C}_t(1) = \sum_{k=0}^{\infty} \mathbf{C}_{t,k}$, which are also referred to a long-run effect on the level of x_t. We assume that non-technology shocks do not have a long-run effect on the level of labor productivity. Thus $\mathbf{C}_t(1)$ is lower triangular. The variance of productivity growth and labor input can be written as

$$
\begin{aligned}
Var(x_t) &= \left(\sum_{k=0}^{\infty} \mathbf{B}_{t,k} \right) R_t \left(\sum_{k=0}^{\infty} \mathbf{B}_{t,k} \right)' && (16)\\
&= \left(\sum_{k=0}^{\infty} \mathbf{C}_{t,k} \right) \left(\sum_{k=0}^{\infty} \mathbf{C}_{t,k} \right)' \equiv \mathbf{C}_t(1)\mathbf{C}_t(1)'. && (17)
\end{aligned}
$$

$\mathbf{C}_t(1)$ is uniquely determined by the Cholesky decomposition. Using the fact $\mathbf{C}_t(1) = \mathbf{B}_t(1) R_t^{\frac{1}{2}}$, the impulse responses at $t+k$ to structural shocks at t can be expressed as

$$
\frac{\partial x_{t+k}}{\partial \varepsilon_t'} = \mathbf{B}_{t,k} \mathbf{B}_t(1)^{-1} \mathbf{C}_t(1) \quad \forall k \geq 0, \tag{18}
$$

without a function of parameters describing the structural form of time-varying VAR.

Given estimates of time-varying coefficients and stochastic volatilities, we can calculate time-varying measures of impulse responses to structural shocks, variances and correlations (unconditional and conditional). The explanation about the method of estimation is provided in appendix.

4 Benchmark Results of the Great Moderation

4.1 Unconditional Second Moments

We report some unconditional second moments. Standard deviation and correlation are calculated from equation (18).[9] Figure 3 displays the evolution over time of the unconditional standard deviation of output, labor input, and labor productivity (all in log first differences). First, there is a sharp decline of output volatility in the middle of 1970s. The observed pattern for output volatility is consistent with what we find in the rolling volatility and the existing evidence on the Great Moderation of Japan such as Stock and Watson (2002), and Summers (2005). The standard deviation experiences a remarkable decline between 1974 and 1975, then stabilizing at a lower level, and growing again in the late 1990s. Furthermore, very high volatility is observed in the late 2000s that reflects the recent financial boom and bust. A similar pattern is observed for the standard deviation of labor input and labor productivity. The volatilities of labor input and labor productivity look stable until the middle of 2000s.

Figure 3 is inserted here.

Figure 4 shows the evolution of the unconditional correlations among output, labor input, and labor productivity. There is a decline in the correlation between labor input and output in some subsample periods. The bulk of the decline takes place at the beginning of 1980s and 1990s. The sign of the correlation between labor input and labor productivity is always zero although it approaches to zero in the late 1980s.

Figure 4 is inserted here.

These two figures are very consistent with the results of rolling volatility and correlations in the former section. In the following subsections, we decompose the standard deviations and correlations into contributions conditional on technology and nontechnology shocks.

4.2 Conditional Standard Deviations

We start by examining the sources of the changes in the standard deviation of output, labor input, and labor productivity over time. Figure 5 shows the estimates of the time-varying standard deviation of each variable conditional on technology and nontechnology shocks. The main finding is that the Great Moderation phenomenon in the Japanese 70s is largely accounted by the decline in the contribution of technology shocks to the variance of output. Timing and magnitude of the fall in the conditional standard deviation of

[9] For specified details, see Galí and Gambetti (2009).

output in 1970s match well those of its unconditional standard deviation. Furthermore, technology shocks play the dominant role in all sample periods. The contribution of nontechnology shocks is more limited although the pattern is very similar.

The middle panel reports the analogous evidence for labor input. In contrast, nontechnology shocks contribute most of the bulk of patterns in the standard deviation of labor input since the middle of 1970s to the present period. Technology shocks play the major role only before the Great Moderation begins. The right panel shows the case for labor productivity. The changing pattern of the standard deviation of labor productivity since 1980s are largely explained by the technology shocks. The contribution of nontechnology shocks shows decreasing pattern until the recent crisis.

Figure 5 is inserted here.

4.3 Conditional Correlations and Structural Change

Why do nontechnology shocks have a limited role to explain the volatility of the output growth? To find the reason, we show the conditional correlations of labor input with productivity.[10]

Figure 6 reports conditional and unconditional correlations between labor input and productivity. We can check the changing pattern of the labor input and productivity correlation conditional on technology shocks: (i) decline until 1985, (ii) increasing until the end of 80s, and (iii) decreasing again. The volatile movement of the unconditional correlation seems to be explained by technology shocks. More importantly, there is a stable process of near-minus-unity correlation generated by nontechnology shocks. The negativity of unconditional correlation between labor input and productivity is largely attributed to nontechnology shocks.

Figure 6 is inserted here.

What is the relationship between this correlation and conditional volatility? The low contribution of nontechnology shocks to output volatility results from the negative correlation between labor input and productivity conditional on nontechnology shocks. The acyclical behavior of productivity under the nontechnology shocks leads to the short-run decreasing returns to scale. As a result, the response of output to nontechnology shocks becomes small.

4.4 Impulse Responses

To reconfirm technology shocks as the driving force to contribute the variance of output volatility, we present the changing pattern of impulse responses in this subsection. For each quarter we collect the posterior mean of the impulse response functions for the impact period to 20 quarters of the horizons. Each figure displays the impulse response in every four quarter: on the x-axis there are time periods, from 1964Q2 to 2009Q2, on the y-axis there are quarters after the shock, and on the z-axis there is a response scale.

[10]The relationship between unconditional and conditional correlations is as follows: $\text{corr}(x_t, z_t) = \lambda_T \text{corr}_T(x_t, z_t) + \lambda_{NT} \text{corr}_{NT}(x_t, z_t)$, where $\lambda_i \equiv [\sigma_i(x_t)/\sigma(x_t)][\sigma_i(z_t)/\sigma(z_t)]$, and $\text{corr}(x_t, z_t)$ and $\sigma_i(z_t)$ denote, respectively, the correlation and standard deviation conditional on i-shocks, for $i = T, NT$.

Figure 7 shows the evolution of the output responses to positive technology shocks. There are three spikes: the first spike is just before the Great Moderation starts, the second spike is during the bubble period in the late 1980s, and the third spike is during the recent financial boom and crisis. This figure is very similar to the output volatility conditional on technology shocks in Figure 4.

Figure 7 is inserted here.

Figure 8A and 8B respectively show the evolutions of impulse responses of labor input and productivity to nontechnology shocks. The figures reflect the results of the conditional correlation in the previous subsection. The opposite directions of responses are observed between labor input and labor productivity throughout total sample periods.

Figure 8A is inserted here.

Figure 8B is inserted here.

Some authors argue the "short-run increasing returns to labor" (SPIRL) phenomenon exaggerated the output volatility in the pre-moderation U.S. economy. However, we cannot find any evidence of SPIRL in the postwar Japanese economy based on our benchmark data. Therefore, the changing pattern of output volatility may come from the technology shocks that was also confirmed by displaying the conditional correlations.

5 Robustness

In this section, we check robustness of the main results. First, we show the estimated volatility and correlations on subsamples. Second, we examine the robustness re-estimating the model with all variables in the difference form. Third, for a data robustness check, we alternatively use the aggregate-sector labor input and corresponding labor productivity.

5.1 Subsample

We present subsample estimates suggesting our main results are robust. In the first subsample period, we limit the end of the sample dates to 2004Q4. It is because we need to check the recent global boom and crisis has an impact on our results. Sample periods are from 1955Q2 to 2004Q4.[11] The second subsample period result, from 1968Q1 to 2009Q4, are listed in Figure 9B. Our posterior periods in the second subsample period start from the Great Moderation period because we use former eight years to estimate priors.

The left panel in Figure 9A shows the unconditional and conditional standard deviations of output under sample periods from 1995Q2 to 2004Q4. The timing of upheavals of the unconditional volatilities are consistent with the benchmark case, while some scales are slightly different. The contributions of technology and nontechnology shocks are consistent with the benchmark result. The right panel displays unconditional and conditional correlations between labor input and labor productivity. The result is consistent with the benchmark case. Figure 9B shows the results based on the sample periods from 1968Q1 to 2009Q4. They are almost consistent with the benchmark case.

[11] The reason why the sample period ends at 2004Q4 is to compare our results with the U.S. case in the latter section.

Figure 9A is inserted here.

Figure 9B is inserted here.

5.2 Difference or Level?

In our benchmark estimation, labor productivity and labor input variable are estimated in the form of difference and level, respectively, which is consistent with Christiano, Eichenbaum, and Vigfusson (2003), Uhlig (2005), and Galí and Gambetti (2009). However it has been argued that the sign of hour responses can be reversed if we estimate the VAR model, using variables in difference and difference.[12] Therefore, we re-estimate the VAR model using both variables in differences.[13]

Figure 10 displays the results based on the difference and difference scheme. The left panel shows unconditional and conditional standard deviations of output growth. The contribution of technology shocks are still noticeable but two upheavals, in mid-70s and late-2000s, are now more explained by nontechnology shocks. The middle panel indicates that nontechnology shocks play a dominant role in explaining the labor input volatility. The right panel shows the unconditional and conditional correlations between labor input and productivity. The value of correlation conditional on nontechnology shocks stays around -0.8 in the total sample period. However, it becomes -0.5 to -0.6 in the mid 70s and late 2000s, which is the same period that the nontechnology shocks explain the output volatility more than technology shocks.

Figure 10 is inserted here.

There are many regions of negative correlations conditional on technology shocks: it reflects the negative response of labor input to technology shocks in the short run. However, this negative relationship under technology shocks do not change our main results.

5.3 Aggregate Data

Hayashi and Prescott (2008) argue that 14 million employed persons were stuck in the agricultural sector in the prewar period. On the contrary, the employment share of the agricultural sector in 1950s and 1960s declines rapidly. It reflects the huge sectoral movement of workers from the agricultural to the non-agricultural sectors. Quarterly data are not available for the aggregate labor input in 1950s and 1960s but we find that the correlations of labor input with productivity in 1950s to 1960s are negative in both non-agricultural and aggregate sectors.

Due to the quarterly data limitation, we re-estimate the model with aggregate data starting from 1970Q1. Figure 11 displays the results based on the aggregate labor input. The technology-shock contribution to output volatility is consistent with the benchmark case. The contribution of labor input volatility is roughly consistent except the recent crisis period. The conditional correlation between labor input and labor productivity is also consistent.

Figure 11 is inserted here.

[12] For the Japanese case, refer to Braun and Shioji (2004), and for the U.S. case from Francis and Ramey (2005, 2009).

[13] It means that labor inputs are difference stationary.

6 Discussion

In this section, we firstly document two stylized facts in the U.S. business cycles to compare with our benchmark case. Secondly, we link the Japanese labor market dynamics to the output volatility.

6.1 Comparison with the U.S.

In this subsection, we document two stylized facts of the postwar U.S. business cycle: (i) the Great Moderation has occurred in the middle of 1980s, and (ii) there is a significant sign change of correlation of labor input with productivity.

To document these facts with our result, we use data constructed by Galí and Gambetti (2009). Output and labor input measures are normalized by the size of the working population.[14] Figure 12 displays rolling standard deviations and correlations. Figure 12A respectively shows the rolling standard deviation of output, labor input, and productivity from left to the panels. There is a large decline of output volatility in the middle of 1980s. Figure 12B shows rolling correlations among three variables. Interestingly, all correlations are shifted to the new paths with the onset of the Great Moderation. Especially, the sign of correlation of labor input with productivity has changed from positive to negative entering the Great Moderation period.

Figure 12 is inserted here.

6.2 Relationship between labor market and output in Japan

Galí and Gambetti (2009) find that decreasing contribution of nontechnology shocks since the middle of 1980s is the main reason of the moderation of output growth. Focusing on the sign change of correlation between labor input and productivity, they argue that acyclicality of labor productivity conditional on nontechnology shocks is a dark horse behind the moderation. Many authors argue that the acyclical behavior of labor productivity in the Great Moderation period reflect the structural change in the U.S. labor market.

On the other hand, the acyclical behavior of labor productivity is observed throughout the total sample period in Japan. It may reflect that the Japanese labor market may have its own characteristics. Structural changes in the labor market may have occurred several times but the impact of changing dynamics of the labor market to volatility of output growth has not changed too much. Therefore, it suggests that output volatility in the Japanese economy is largely influenced not by nontechnology but by technology shocks.

Barnichon (2010), and Galí and Rens (2010) investigate the potential sources of the decline of correlation between labor input and labor productivity, using a dynamic-general-equilibrium labor-search model. Galí and Rens (2010) show that vanishing procyclicality of labor productivity can be explained by a reduction in labor market frictions such as hiring costs. In the presence of labor market frictions, the labor effort level fluctuates more instead of employment. This unobservable effort is included in the measured productivity, making measured labor producitivity more procyclical and volatile. A reduction

[14]For the details of the data, refer to Galí and Gambetti (2009).

in frictions decreases the volatility of effort and therefore the degree of procyclicality of productivity falls. Barnichon (2010) suggests an increase in the elasticity of hours as another factor for the vanishing procyclicality of labor productivity. Fluctuations in hours generate countercyclical productivity movement, whereas fluctuations in effort generate procyclical producitivity movements. As a result, the volatility decline of labor effort can be a driving force in explaining the U.S. sign shift of correlation between labor input and labor productivity.

How can we interpret our results using their structural model? To see more details of labor input dynamics in Japan, we decompose the labor input growth into hours and employment. Figure 13 displays rolling standard deviations of hours and employment as well as labor input.[15]

Figure 13 is inserted here.

It is clear from the graph that the volatility of employment has been low throughout the total sample period. Therefore, the increase in employment volatility due to the decline of labor market friction is not the case for Japan. Moreover, the volatility of labor input is explained mostly by the volatility of hours. Therefore, labor adjustments do not seem to have switched from efforts into hours. This may reflect the elasticity of hours has been higher than that of labor effort. The mechanism of adjustment of labor input seems not to be changed.

7 Concluding Remarks

We document two important issues over the postwar Japanese business cycles. Firstly, we find the timing of the Great Moderation and its changing pattern. The Great Moderation phenomenon has occurred in Japan since the middle of 1970s, with a dramatic decline in macroeconomic volatility. Different from other G7 countries, however, Japan's Great Moderation is not persistent, with some volatile movements in the late 1980s and the late 2000s. Secondly, we find the persistently negative correlation between labor input and labor productivity throughout total sample period.

To find the driving force of the postwar Japanese macroeconomy, we estimate a SVAR model with drifting coefficients and stochastic volatilities. Overall, technology shocks are responsible for output growth volatility including the Great Moderation phenomenon, but the volatility of labor input is considerably attributed to nontechnology shocks.

The correlations among these variables changes in a time-varying manner, which indicates that there may be several structural changes in the Japanese labor market. However, the correlation between labor input and labor productivity is continuously negative, especially under nontechnology shocks. Moreover, the volatility of labor input has always explained by hours. It is a very different feature from the U.S. case so we might need a different model to analyze the Japanese labor market dynamics.

[15] Standard deviation of labor input growth can be decomposed into three parts: $Var(\Delta\text{labor input}_t) = Var(\Delta\text{hours}_t) + Var(\Delta\text{employment}_t) + 2Cov(\Delta\text{hours}_t, \Delta\text{employment}_t)$.

Appendix

Priors

- Let z^T denote a sequence of z's up to time T.
- We assume that the conditional prior density of θ^T is given by

$$p(\theta^T|\alpha^T, h^T, Q, \Psi, \Xi) \propto I(\theta^T) f(\theta^T|\alpha^T, h^T, Q, \Psi, \Xi), \tag{19}$$

  where $I(\theta^T) = \Pi_{t=0}^{T} I(\theta_t)$,

$$f(\theta^T|\alpha^T, h^T, Q, \Psi, \Xi) = f(\theta_0)\Pi_{t-1}^{T} f(\theta_t|\theta_{t-1}, \alpha^T, h^T, Q, \Psi, \Xi), \tag{20}$$

  and $I(\theta^T)$ takes a unit value if all the roots of the VAR polynomial associated with θ_t are larger than one in modulus and 0 otherwise, ruling out a non-stationary process.

- Following Benati and Mumtaz (2007) and Primiceri (2005), we make following assumptions prior distributions and its hyperparameters:

$$\begin{aligned}
p(\theta_0) &\propto I(\theta_0)N(\hat{\theta}_{OLS}, \hat{V}(\hat{\theta}_{OLS})) \\
p(\log h_0) &= N(\log \hat{h}_{OLS}, 10 \times I) \\
p(\alpha_0) &= N(\hat{\alpha}_{OLS}, |\hat{\alpha}_{OLS}|) \\
p(Q) &= IW(\bar{Q}^{-1}, T_0) \\
p(\Psi) &= IW(\bar{\Psi}^{-1}, 2) \\
p(\Xi_{i,i}) &= IG\left(\frac{0.0001}{2}, \frac{1}{2}\right)
\end{aligned}$$

- $\hat{\theta}_{OLS}$ is the vector of OLS estimates of the VAR coefficients.
- $\hat{V}(\hat{\theta}_{OLS})$ is the estimate of their covariance matrix using the initial sample.
- $\hat{h}_{OLS}$ is a vector containing the elements of the diagonal matrix $\hat{H}$.
- $\hat{\alpha}_{OLS}$ is the element (2,1) of the lower triangular matrix $\hat{A}$.
- $\bar{Q} = 0.005 \times \hat{V}(\hat{\theta}_{OLS})$
- T_0 is the number of observations in the initial sample.
- $\bar{\Psi} = 0.001^2 \times |\hat{\alpha}_{OLS}|$

Estimation

We use a Markov Chain Monte Calro (MCMC) method, the Gibbs sampling. The Gibbs sampler partitions the vector of unknowns into blocks and the transition density is defined by the product of conditional densities.

Step 1: $p(\theta^T|x^T, \alpha^T, h^T, Q, \Psi, \Xi)$

- Conditional on $x^T, \alpha^T, h^T, Q, \Psi, \Xi$, the unrestricted posterior of the states is normal.
- The conditional mean and variance of the terminal state θ_T is computed using standard Kalman filter recursions while for all the other states the following backward recursions are employed:

$$\theta_{t|t+1} = \theta_{t|t} + P_{t|t} P^{-1}_{t|t+1} (\theta_{t+1} - \theta_{t|t}), \tag{21}$$

$$P_{t|t+1} = P_{t|t} - P_{t|t} P^{-1}_{t+1|t} P_{t|t}, \tag{22}$$

where $p(\theta^T|x^T, \alpha^T, h^T, Q, \Psi, \Xi) \sim N(\theta_{t|t+1}, P_{t|t+1})$.

Step 2: $p(\alpha^T|x^T, \theta^T, h^T, Q, \Psi, \Xi)$

- Conditional on θ^T, $\hat{y}_t = x_t - B_{0,t} - B_{1,t}x_{t-1} - \cdots - B_{p,t}x_{t-p}$ is observable.
- We can rewrite our system of equations as $A_t\hat{y}_t = H_t\nu_t$, where $\nu_t \sim N(0, I)$.
- Conditional on h^T, we use the algorithm of Carter and Kohn (1994) to obtain a draw for α_t taking the above system as observational equations and (5) as unobserved states equations.
- Given that the α_t and the ν_t are independent across equations, the algorithm can be applied equation by equation.
- In the bivariate case, we have one observable equation and one state.

Step 3: $p(h^T|x^T, \theta^T, \alpha^T, Q, \Psi, \Xi)$

- This is done by using the univariate algorithm by Jacquier et al (1994).

Step 4: $p(\Psi|x^T, \theta^T, \alpha^T, h^T, Q, \Xi)$**,** $p(\Xi_{i,i}|x^T, \theta^T, \alpha^T, h^T, Q, \Psi)$**,** $p(Q|x^T, \theta^T, \alpha^T, h^T, \Psi, \Xi)$

- Conditional on $x^T, \theta^T, \alpha^T, h^T$, all the remaining hyperparameters, under conjugate priors, can be sampled in a standard way from Inverted Wishart and Inverted Gamma densities.

We perform 30,000 repetitions. We discard the first 10,000 draws and keep one for every 20 of the remaining 20,000 draws to break the autocorrelations of the draws. The densities for the parameters are typically well behaved.

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Table 1
Standard deviation in each subsample period

	Pre-1975	76-85	86-91	92-05	06-09
Output					
1D (MLS)	1.461	0.664	1.230	0.748	1.405
	[0.127]	[0.089]	[0.217]	[0.087]	[0.312]
HP	0.884	0.423	0.707	0.497	1.081
	[0.135]	[0.089]	[0.188]	[0.109]	[0.389]
BP	0.407	0.250	0.642	0.519	
	[0.074]	[0.058]	[0.202]	[0.118]	
1D (LFS)	1.585	0.664	1.230	0.748	1.405
	[0.257]	[0.089]	[0.217]	[0.087]	[0.312]
Labor Input					
1D (MLS)	1.351	0.648	0.690	0.792	2.142
	[0.127]	[0.083]	[0.118]	[0.085]	[0.442]
HP	0.822	0.296	0.519	0.487	1.205
	[0.126]	[0.059]	[0.150]	[0.091]	[0.347]
BP	1.036	0.362	0.623	0.583	
	[0.201]	[0.090]	[0.188]	[0.116]	
1D (LFS)	1.077	0.695	0.863	1.402	1.790
	[0.191]	[0.100]	[0.165]	[0.172]	[0.445]
Productivity					
1D (MLS)	1.392	0.983	1.056	0.893	1.632
	[0.124]	[0.134]	[0.227]	[0.112]	[0.388]
HP	0.825	0.476	0.392	0.311	0.501
	[0.117]	[0.088]	[0.071]	[0.036]	[0.119]
BP	0.006	0.006	0.005	0.004	
	[0.001]	[0.001]	[0.001]	[0.001]	
1D (LFS)	1.327	0.903	1.477	1.523	1.935
	[0.196]	[0.138]	[0.290]	[0.190]	[0.485]

notes: (a) Standard errors of variance estimates in brackets are computed based on Priestley (1991). (b) 1D: variables are transformed by taking the natural logarithm and applying first-difference transformation. (c) HP: variables are transformed by HP-filter. (d) BP: varaibles are transfromed by band-pass filter. (e) MLS: labor input is measured using data from monthly labor survey. (f) LFS: labor input is measured using data from labor for survey. (g) In the BP case, 12 observations are lost in the end of data set.

Table 2
Correations in each subsample period

	Pre-1975	76-85	86-91	92-05	06-09
labor input, output					
1D (MLS)	0.512	-0.123	0.515	0.329	0.648
HP	0.534	0.159	0.839	0.801	0.909
BP	0.596	-0.008	0.874	0.877	
1D (LFS)	0.560	0.118	0.036	0.099	0.285
labor input, productivity					
1D (MLS)	-0.433	-0.742	-0.054	-0.611	-0.755
HP	-0.424	-0.482	0.188	-0.285	-0.443
BP	-0.484	-0.638	0.387	-0.163	
1D (LFS)	-0.142	-0.683	-0.554	-0.872	-0.718
output, productivity					
1D (MLS)	0.553	0.756	0.828	0.542	0.010
HP	0.540	0.789	0.693	0.347	-0.030
BP	0.349	0.773	0.785	0.328	
1D (LFS)	0.740	0.645	0.812	0.400	0.462

notes: (a) 1D: variables are transformed by taking the natural logarithm and applying first-difference transformation. (b) HP: variables are transformed by HP-filter. (c) BP: varaibles are transfromed by band-pass filter. (d) MLS: labor input is measured using data from monthly labor survey. (e) LFS: labor input is measured using data from labor for survey. (f) In the BP case, 12 observations are lost in the end of data set.

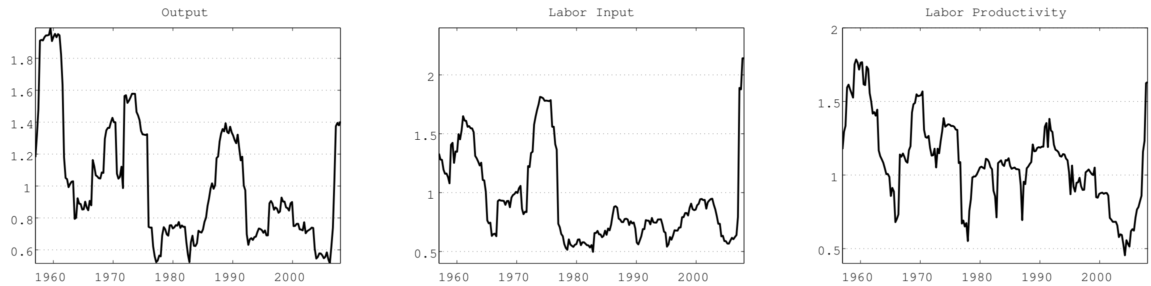

Fig. 1. Rolling standard deviations of output, labor input, and labor productivity.

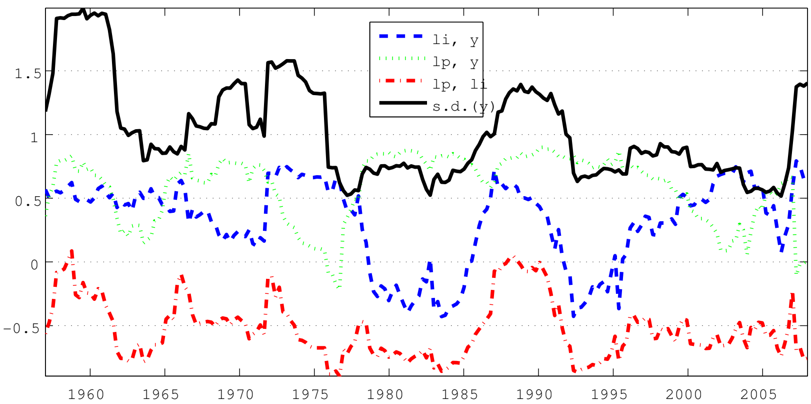

Fig. 2. Rolling Correlations. The black thick line is standard deviation of output. Blue dashed, green dotted, and red dash-dot lines are respectively correlations between labor input and output, labor productivity and output, and labor input and labor productivity.

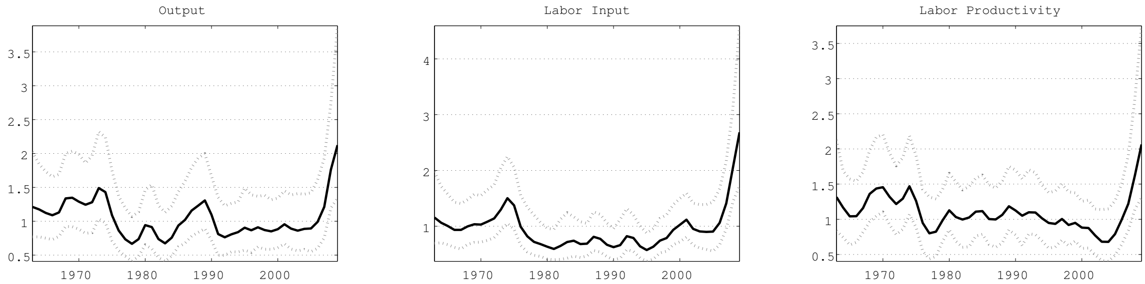

Fig. 3. the unconditional standard deviations based on VAR results. The bold line in each panel is point estmate value. Dotted lines are 90 percent intervals.

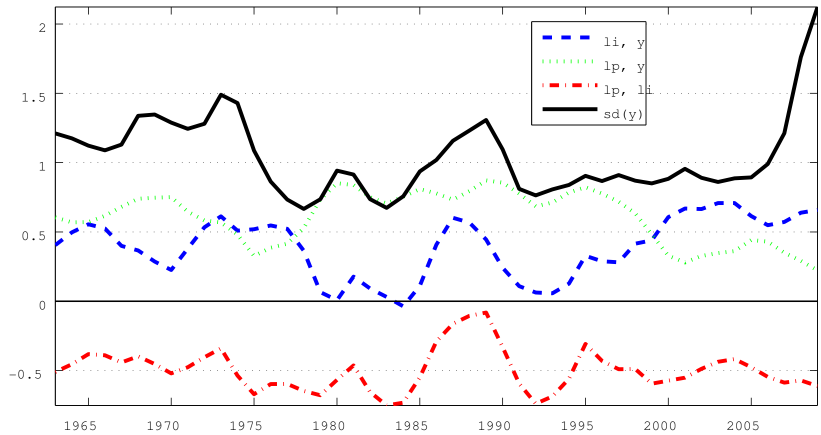

Fig. 4. the unconditional correlations based on VAR results

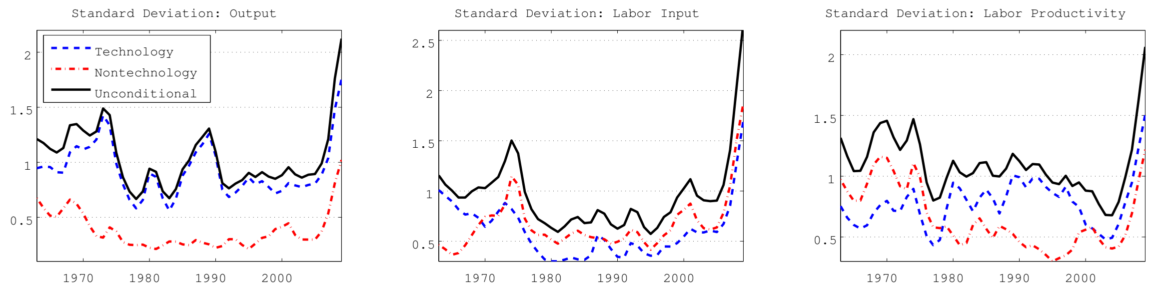

Fig. 5. Conditional standard deviations under the benchmark case. Unconditional and conditional volatilities of output, labor input, and labor productivity are listed from the left to the right panels. The black thick line is the unconditional volatility of each variable. The blue dashed line is the contribution of technology shocks while the red dotted line is the contribution of nontechnology shocks.

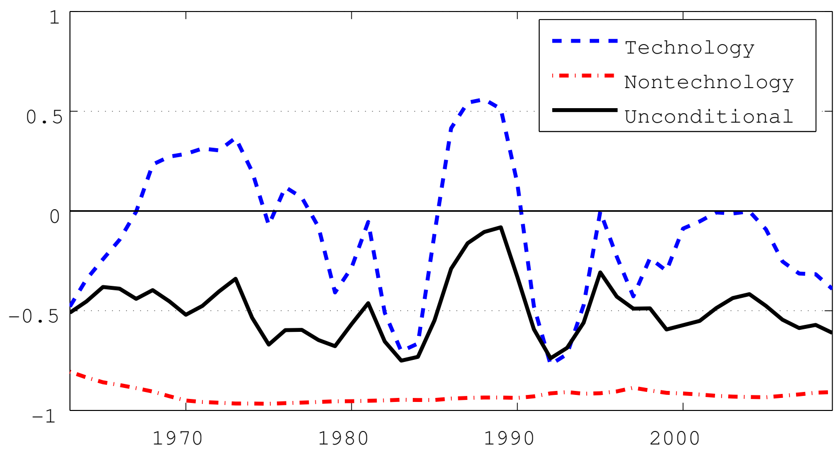

Fig. 6. Conditional Correlation between labor input and productivity. The black thick line is the unconditional correlation between labor input and productivity. The blue dashed line is the contribution of technology shocks while the red dotted line is the contribution of nontechnology shocks.

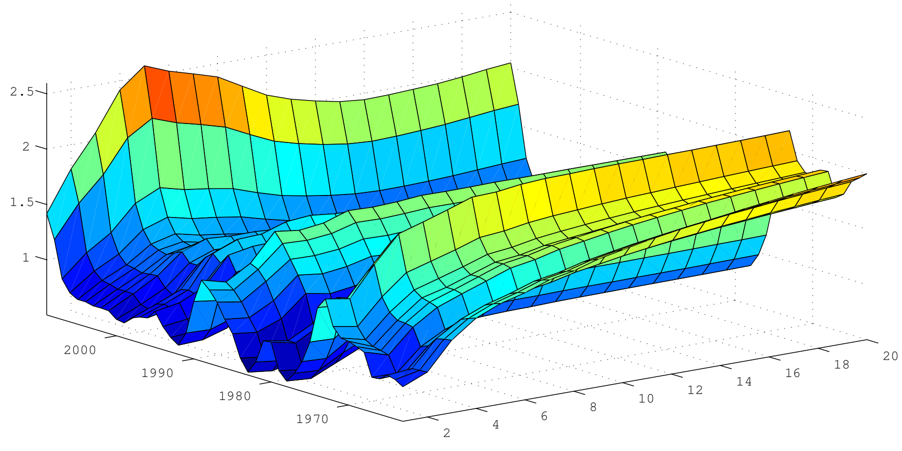

Fig. 7. Impulse Response of Output to Technology shocks.

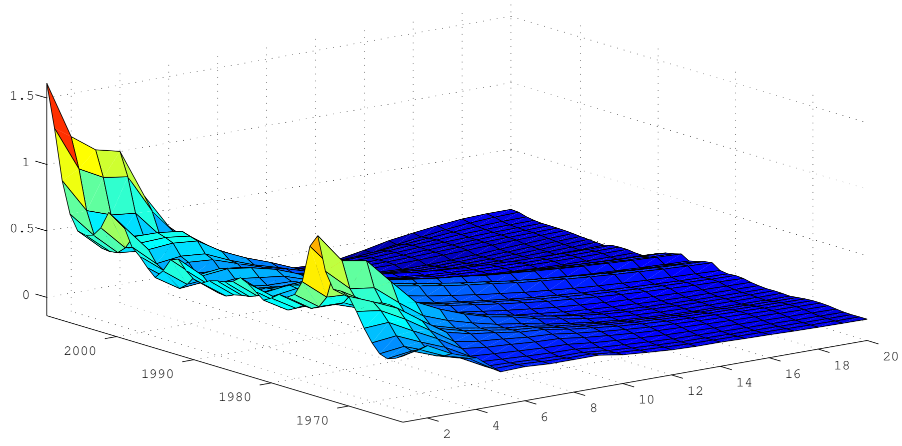

Fig. 8A. Impulse Response of Labor Input to Nontechnology shocks

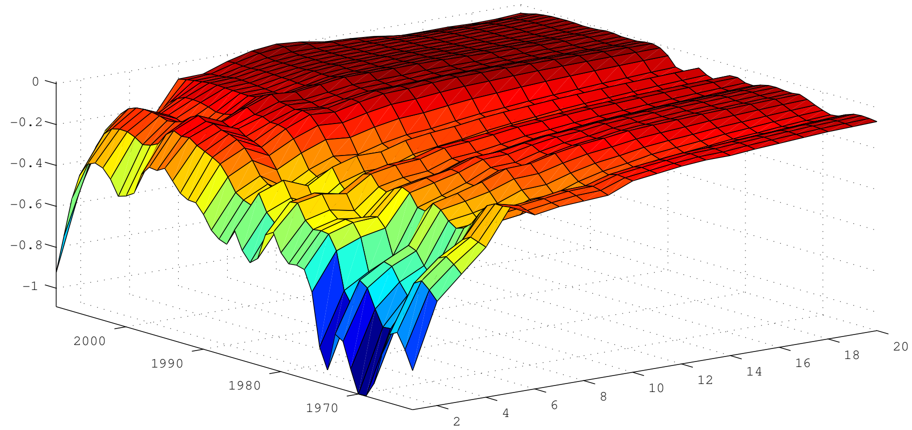

Fig. 8B. Impulse Response of Labor Productivity to Nontechnology shocks

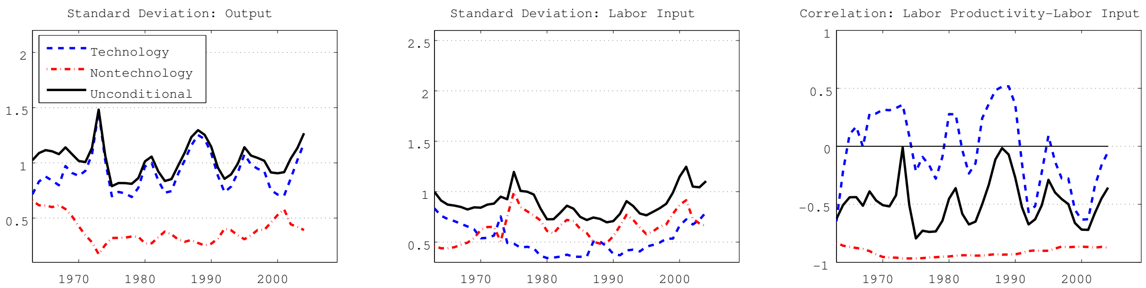

Fig. 9A. Conditional standard deviations and Correlation under sample period 1955q2 to 2004q4. Standard deviations of output and labor input are listed in the left and the middle panels, respectively. The unconditional and conditional correlation between labor input and productivity is listed in the right panel.

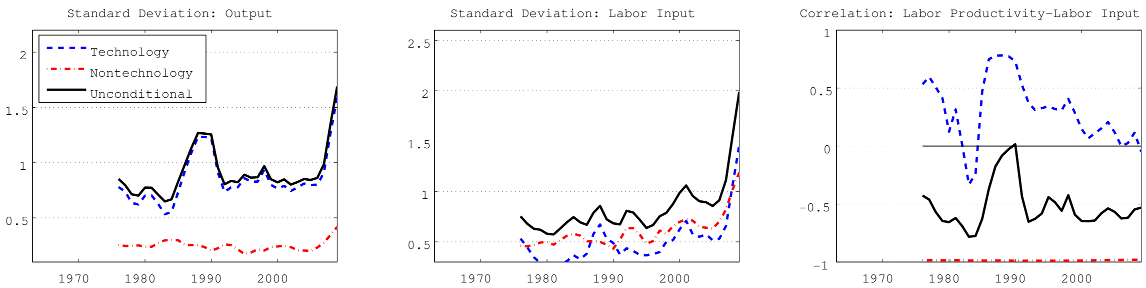

Fig. 9B. Conditional standard deviations and Correlation under sample period 1968q1 to 2009q4. Standard deviations of output and labor input are listed in the left and the middle panels, respectively. The unconditional and conditional correlation between labor input and productivity is listed in the right panel.

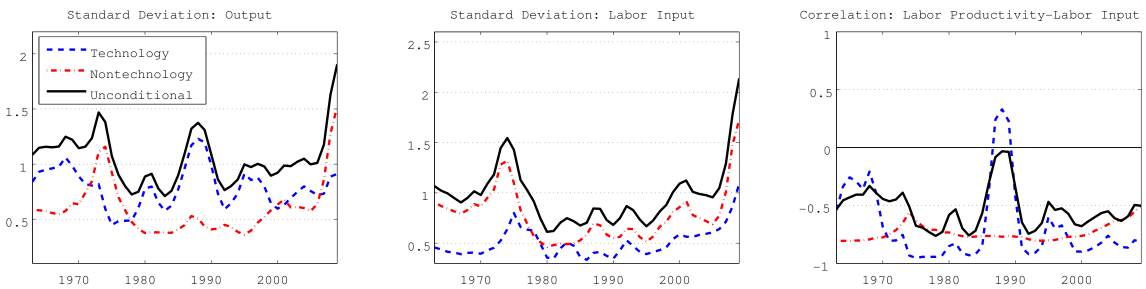

Fig. 10. Conditional standard deviations and Correlation under the difference and difference scheme

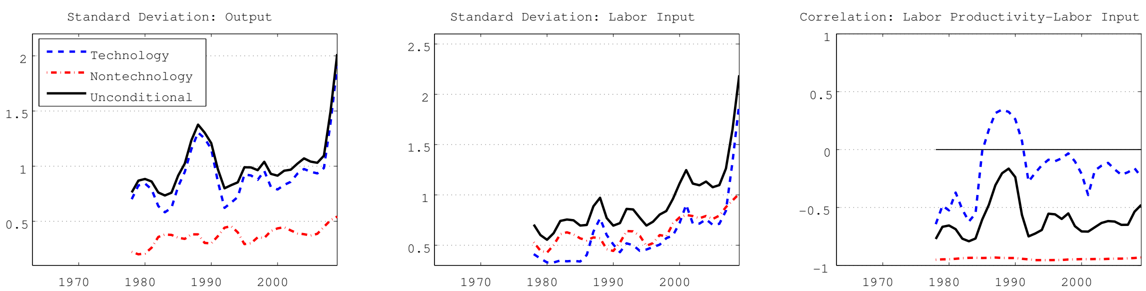

Fig. 11. Conditional standard deviations and Correlation using Aggregate Sector Labor Input

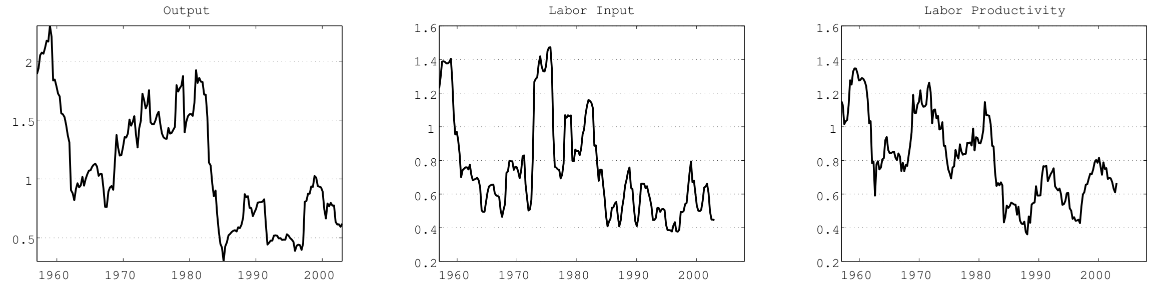

Fig. 12A. Rolling standard deviations of output, labor input, and labor productivity in the U.S.

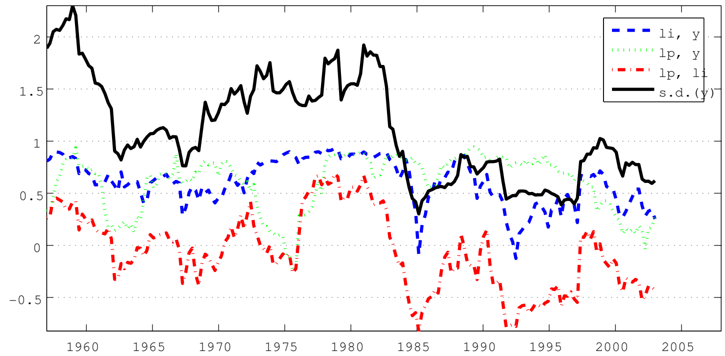

Fig. 12B. Rolling Correlations in the U.S. case. The black thick line is standard deviation of output. Blue dashed, green dotted, and red dash-dot lines are respectively correlations between labor input and output, labor productivity and output, and labor input and labor productivity.

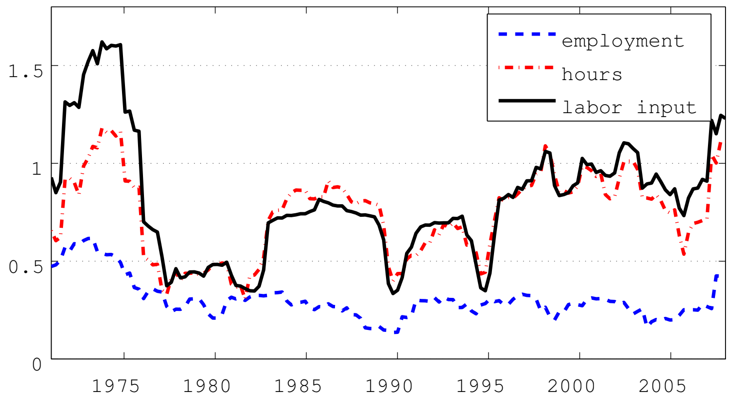

Fig. 13. Rolling standard deviations of Hours and Employment in Japan. The black thick line is the rolling volatility of labor input. The red dashed line is the rolling volatility of hours. The blue bold line is the rolling volatility of employment rate.