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THE GREAT MODERATION IN THE JAPANESE ECONOMY *

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Abstract

This paper investigates the contribution of technology and nontechnology shocks to the changing volatility of output and labor growth in the postwar Japanese economy. A time-varying vector autoregression (VAR) with drifting coefficients and stochastic volatilities is modeled and long-run restriction is used to identify technology shocks in line with Galí (1999) and Galí and Gambetti (2009). We find that technology shocks are responsible for significant changes in the output volatility throughout the total sample period while the volatility of labor input is largely attributed to nontechnology shocks. The driving force behind these results is the negative correlation between labor input and productivity, which holds significantly and persistently over the postwar period.

Keywords: Japanese economy, Great Moderation, Time-varying parameter 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, a phenomenon known as "the Great Moderation." In the U.S. case, many authors have investigated the characteristics of and reasons for the Great Moderation that started in the mid-1980s. Possible explanations include good luck, better monetary policy, and changes in the economic structure, such as inventory management and labor market statistics. Based on the time-varying and 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, the good policy hypothesis has been supported by many other authors including Clarida, Galí, and Gertler (2000), Lubik and Schorfheide (2004), Boivin and Giannoni (2006), and Benati and Surico (2009). There are different approaches to considering structural changes, including Campbell and Hercowitz (2005) and Galí and Gambetti (2009). In particular, Galí and Gambetti (2009) capture the changing patterns of the correlations among the labor market variables.

There exist few papers that investigate the 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 the 1990s to the early 2000s became larger as compared to that from the mid-1970s to the 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 in inflation and output volatility in the latter period based on the aggregate demand and supply framework. Kimura and Shiotani (2009) separate the postwar economy into two periods, pre-1980 and post-1980, decompose the variance of output growth by frequency, and investigate the cause of the decline in output variance in the latter period. They conclude that business practices played a direct role in stabilizing business cycles. A number of recent papers use Bayesian methods such as time-varying and Markov-switching VAR to endogenously find the changes of monetary policy effectiveness but the source of output volatility has not been fully discussed.[1]

In this paper, we provide evidence related to the comovement changes among output, labor input, and productivity. In the business cycle literature, it is very straightforward to interpret the implications of their patterns based on the theoretical model.[2] Therefore, the sizable amount of empirical literature based on the VAR approach examines the relationship between these variables to determine the role of productivity-enhancing technology shocks.[3] In the Japanese case, the limited number of studies on technology shock effects includes Braun and Shioji (2006), Miyagawa, Sakuragawa, and Takizawa (2006), and Watanabe (2006). However, none of these studies have investigated the changing patterns of these variables and the dominant source of the Great Moderation. In this

[1] For example, see Yano and Yoshino (2008), Inoue and Okimoto (2008), and Nakajima, Kasuya, and Watanabe (2011).

[2] For example, a major prediction of real business cycle (RBC) theory is a high positive correlation between productivity and labor input, while a negative effect of productivity-enhancing technology shocks on labor is consistent with sticky price models.

[3] For example, see Galí (1999, 2004), Galí and Rabanal (2004), and Christiano, Eichenbaum, and Vigfusson (2003) on the aggregate level and Chang and Hong (2006) and Franco and Philippon (2007) on the sectoral level.

paper, we estimate a time-varying parameter vector autoregressive (TVP-VAR) model to investigate the dominant source of the output and labor input growth in the Japanese economy. 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 permanently shift labor productivity. We estimate the model via Bayesian methods.

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

The consistently negative sign of the correlation between labor input and productivity in Japan is in contrast to the findings for the U.S. economy. In the U.S. economy, the sign of the correlation changes from positive to negative with 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 beginning of the Great Moderation saw the most volatile component in the labor input switching from effort level to hours worked and employment. In the Japanese labor market, however, we find no sign change for the correlation between labor input and productivity. The decomposition of labor inputs such as working hours, employment, and population supports no sign change for labor input and productivity. We find that the negative correlation holds even in the disaggregated data in the two- and three-digit sectors.

The paper is organized as follows. In Section 2, we document some facts concerning to macro variables such as output, labor input, and productivity in Japan. Section 3 describes the TVP-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 in comparison with those for 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 proceed with a preliminary investigation as follows. First, we depict the rolling standard deviations of output and interested variables, and show some features of the related variables. Second, we display the rolling correlations to investigate the relationship between the interested variables.

We employ seasonally-adjusted quarterly data, and the sample is 1955Q2 through 2009Q4. Output is calculated by connecting the GDP data sources from 68SNA and 93SNA. Employment and working population aged 15 and over are taken from *Japan's Labor Force Survey* (LFS) and *Japanese Census Population*, respectively. In the bench-

[4] For example, see Stiroh (2009), Galí and Gambetti (2009), Galí and Rens (2010), and Barnichon (2010).

mark case, we use the hours data given in the *Monthly Labor Survey* (MLS), and for the robustness check, we use *Japan's Labor Force Survey.* We use working hours in the manufacturing sector since we do not have aggregate data for 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 and employment. In all cases, we normalize the output and labor input measures with the size of the working population. The labor productivity measure is constructed as the ratio between the corresponding output and labor input.

2.1 Timing of the Great Moderation

Fig. 1 displays the rolling standard deviations of the output, labor input, and labor productivity growth rates. All variables are transformed by taking the natural logarithm and applying a first-difference transformation. The standard deviations are calculated every three years.[5] We find that the output growth is moderated in two subsample periods: from the late 1970s to the early 1980s, and from the 1990s to the mid-2000s.[6] In other words, we can divide the post-war Japanese economy into five sub-sample periods.

Figs. 1 and 2 are inserted here.

The first phase, the volatile period until the mid-1970s, was characterized by high growth. The growth rate of GDP was remarkable and the labor market was activated by the participation of baby boomers during this period. There were tremendous geographical and sectoral movements of workers in this phase. Panel A in Fig. 2 shows the migration rates. We can observe the upper trend in the first phase. Both inter- and intra-prefecture migrations took place during this period. This is because a number of migrants from rural areas moved to urban areas to find jobs. Furthermore, the baby boomers, called *dankai sedai*, who were born in 1947-1949, poured into the labor market. Panel B exhibits the rolling standard deviations of the employment rates by age group. The observed pattern of the young aged 15 to 24 is consistent with the high volatility in the first phase.[7] Panel C displays the hiring and turnover rates of firms with more than 30 employees. These were the most volatile in the first phase.

The second phase, from the late 1970s to the mid-1980s, is famous for having a stable economy. The overall indices of the macro variables were stabilized. For example, the unemployment rate was maintained at a low level even though the inflation rate was stable.

The third phase, from the late 1980s to the early 1990s, is also called the "bubble period." Different from the first phase, the standard deviations of labor input and productivity shown in Fig. 1 are not distinctively volatile, while the output is no longer moderated. The rates of migration and employment were stable. However, Panel D in Fig. 2 shows the evolution of the number of firm openings, measured by the right-hand

[5]We also calculated standard deviations for other intervals such as four years, but the results did not change substantially.

[6]This finding is quite consistent with previous works such as Stock and Watson (2002) and Summers (2006).

[7]This unstable movement of the young generation contributing to the high labor input volatility is consistent with Jaimovich and Siu (2009).

scale, and the number of firm bankruptcies, measured by the left-hand scale. The figure confirms that the number of firm openings was the highest and the number of firm bankruptcies the lowest in the bubble period.

In the fourth phase, from the early 1990s to the mid-2000s, the standard deviation of output growth experienced a remarkable decline. The phase is different from the second phase because the standard deviation of labor productivity declined gradually to its lowest level during this period.

In the fifth phase, during the late 2000s, the U.S. and world economies experienced a financial crisis. This crisis also hit the Japanese economy, with high volatility seen in all variables in Fig. 1.

The moderation phenomenon was observed during the second and fourth phases in Japan. These moderation periods are rather brief, unlike those in the U.S. Thus, we can conclude that the timing and persistency of the Japanese Great Moderation is very unique. However, labor input volatility was relatively moderated from the late 1970s to the mid-2000s. Labor productivity was also moderated since the end of the 1970s but the volume was relatively small.

2.2 Changing dynamics of the Japanese economy

Fig.3 shows the rolling correlations among the macro variables. The signs of the conditional correlations are relatively persistent in all cases, but the movements are highly volatile. Overall, the output is positively correlated with the other macro variables throughout the sample period. However, there are considerable declines in the early 1970s and the 2000s for labor productivity and in the early 1980s and the 1990s for labor input. These unstable relationships among output and labor market variables may reflect a number of structural changes in the labor market. Another distinct feature is that the correlation between labor input and labor productivity is negative, except in the bubble period, when it becomes almost zero.

Fig. 3 is inserted here.

To confirm the results, we split the sample into several sub-periods.[8] We use three kinds of transformations to get the original time series to be stationary. The first transformation corresponds to the first difference (1D) of the logged variables so that we can compare the sub-sample results with rolling volatility and correlation. Our second and third transformations use the Hodrick-Prescott (HP) and Band-Pass (BP) filters, respectively. We set λ as 1600 to remove the trend components. Using the BP filter, we isolate the movement of variables in the frequency range of 6-32 quarters, which is associated with the business cycle frequencies. For data robustness, we also use the hours data taken from LFS in the first-difference case.

Table 1 reports the standard deviations in each sub-sample period. In all cases, we find a dramatic decline in output volatility in the post-1974 period, which is consistent with the rolling standard deviation results in Fig. 1. In the 1D case, for example, the standard deviation of output growth falls from 1.461 to 0.664 in the period 1976-1985. Labor input and productivity also show a large reduction in volatility: 1.351 to 0.648 and 1.392 to 0.983, respectively. However, output moderation is not persistent. There are two other volatile periods: 1986-1991 and 2006-2009.

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

Table 1 is inserted here.

Table 2 reports the correlations in each sub-sample period. The results for each sub-sample correlation are also consistent with the result for the rolling correlation. Although the signs of the correlations do not change often, their volumes change consistently. Generally, the correlations of output with labor productivity and input are positive. This may reflect the procyclical movements of labor productivity and input supported by the standard RBC theory if technology shocks dominate these variables. Table 2 shows that the correlation between labor input and labor productivity is negative. If a simple sticky price model holds, the negative relationship to technology shocks in the short run is not a puzzle. However, to investigate the contribution of technology and nontechnology shocks, we require further analysis. The asymmetric movements between these two variables may be linked to the stable output movements. What is the relationship between this negative correlation and output growth volatility? In the next section, we attempt to determine the source of output and labor input growth volatility and link the negative correlation between labor input and labor productivity to the output volatility.

Table 2 is inserted here.

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. The drifting coefficients let the model permit possible nonlinearities or time variation in the 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. The multivariate stochastic volatility enables possible heteroskedasticity of the shocks, which is often observed in the postwar Japanese economy. In addition, the stochastic volatility can capture the different size of shocks, and therefore, our model has an advantage in studying the structural changes of the Japanese economy than over VAR with constant coefficients and a constant covariance matrix of errors.

3.1 TVP-VAR with stochastic volatility

We introduce a TVP-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 ($\equiv y_t - li_t$) denoting the output, labor input (both in logarithms), and labor productivity. $B_{0,t}$ is a vector of the time-varying intercepts, and $B_{i,t}$ ($i = 1, \cdots, p$) are the matrices of the time-varying coefficients. u_t denotes the reduced for error terms, and is 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 univariate 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 the Gaussian white noise processes with zero mean and constant covariance matrices Ψ and Ξ, respectively. The 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 the 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 where ε_t^T and ε_t^{NT} represent the technology and non-technology shocks, respectively. This identification and interpretation is in line with Galí (1999) and Galí and Gambetti (2009): only the 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

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

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 columns of $\mathbf{B}_t^k$ identify the impulse response at $t+k$ of the 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 that selects the first two rows and 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 the labor productivity growth and hours to structural shocks at t are expressed as

$$\frac{\partial x_{t+k}}{\partial \varepsilon_t'} = \frac{\partial x_{t+k}}{\partial u_t'}\frac{\partial u_t}{\partial \varepsilon_t'} \tag{12}$$

$$= \mathbf{B}_{t,k}R_t^{\frac{1}{2}} \equiv \mathbf{C}_{t,k} \quad \forall k \geq 0. \tag{13}$$

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

$$Var(\mathbf{x}_t) = \mathbf{B}_t(1)Var(\mathbf{u}_t)\mathbf{B}_t(1)' \tag{14}$$

$$= \left(\sum_{k=0}^{\infty}\mathbf{B}_t^k\right)\begin{bmatrix} R_t & \mathbf{0} \\ \mathbf{0} & \mathbf{0} \end{bmatrix}\left(\sum_{k=0}^{\infty}\mathbf{B}_t^k\right)'. \tag{15}$$

Note that the variance of productivity growth and labor input is a block in the first two rows and 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 as the long-run effect on the level of x_t. We assume that the nontechnology 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

$$Var(x_t) = \left(\sum_{k=0}^{\infty}\mathbf{B}_{t,k}\right)R_t\left(\sum_{k=0}^{\infty}\mathbf{B}_{t,k}\right)' \tag{16}$$

$$= \left(\sum_{k=0}^{\infty}\mathbf{C}_{t,k}\right)\left(\sum_{k=0}^{\infty}\mathbf{C}_{t,k}\right)' \equiv \mathbf{C}_t(1)\mathbf{C}_t(1)'. \tag{17}$$

$\mathbf{C}_t(1)$ is uniquely determined by the Cholesky decomposition. Using the fact that $\mathbf{C}_t(1) = \mathbf{B}_t(1)R_t^{\frac{1}{2}}$, the impulse responses at $t+k$ to the 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 the time-varying VAR.

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

4 Benchmark results

4.1 Estimated structural shocks and coefficients

We start by displaying the estimated structural shocks and coefficients in our benchmark VAR model. Fig. 4 depicts each element of the posterior mean of $R_t^{\frac{1}{2}}$. The left-hand (right-hand) column portrays the impact size of the technology (nontechnology) shocks on the two current independent variables.[9] These estimates support the evidence that the variation in $R_t^{\frac{1}{2}}$ (or R_t) is crucial in explaining the features of the data. As for the technology shocks, the impact effect on labor productivity increased in the first phase. The effect on the labor input was largest in the first phase. In the 1980s, the effect on both variables decreased and stabilized. Entering the third phase, the impact on the labor input increased again, while that on the labor productivity did not change substantially. This positive effect on the labor input reduced the negative correlation between the labor input and productivity during the bubble period. In the fourth phase, the size of the technology shocks on the labor productivity showed a decreasing pattern, while that on the labor input exhibits an increasing pattern. The impact effect of the nontechnology shocks on the labor productivity are shown in the right panel of the first row. They are negative in all sample periods, limiting the effect on explaining the volatile output in the bubble period. The global financial crisis in the fifth phase is also captured by the nontechnology shock. However, the impact on the labor productivity was negative, while that on the labor input was positive.

Fig. 4 is inserted here.

Fig. 5 displays the coefficients with the time-varying patterns for the two estimated equations in our VAR model. The estimates support the contention that the variation in B_t is an important feature of the data. One distinctive feature is that the coefficients of the lags of labor productivity variables show a very interesting pattern. The first and third rows, respectively, depict the coefficients of the labor productivity lags to explain the current labor productivity and labor input. The coefficient of the one- and third-period lags on the labor productivities in the first row changed from negative to almost zero, and then to negative. On the other hand, the coefficients of the lags in the third row started to rise around 1990.

Fig. 5 is inserted here.

In the third and fourth phases, the impact effect of the technology shocks on the labor productivity became limited, and so did the transition effect from the estimated coefficients. On the other hand, the impact effect of the nontechnology shocks on the labor input increases, and the transition effect from the estimated coefficients increases.

4.2 Unconditional second moments

We report some unconditional second moments. The standard deviation and correlation are calculated from equation (18).[10] Fig. 6 displays the evolution of the unconditional

[9] In the previous studies such as Cogley and Sargent (2005), the diagonal terms of the matrix in the squared values are often interpreted as the variability of the structural shocks.

[10] For more details, see Galí and Gambetti (2009).

standard deviation of the output, labor input, and labor productivity (all in log first differences). First, there was a sharp decline in output volatility in the mid-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 in Japan, which includes Stock and Watson (2002) and Summers (2005). The standard deviation experienced a remarkable decline between 1974 and 1975, stabilized at a lower level, and then increased again in the late 1990s. Furthermore, very high volatility was observed in the late 2000s, which reflects the recent financial boom and bust. A similar pattern is observed for the standard deviation of the labor input and labor productivity. The volatilities of the labor input and labor productivity seemed stable until the mid-2000s.

Fig. 6 is inserted here.

Fig. 7 shows the evolution of the unconditional correlations among output, labor input, and labor productivity. There was a decline in the correlation between the labor input and output in some subsample periods. The bulk of the decline was in the beginning of the 1980s and the 1990s. The sign of the correlation between the labor input and labor productivity was always negative, although it approached zero in the late 1980s.

Fig. 7 is inserted here.

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

4.3 Conditional standard deviations

We start by examining the sources of the changes in the standard deviation of the output, labor input, and labor productivity growth rates over time. Fig. 8 shows the estimates of the time-varying standard deviation of each variable conditional on the technology and nontechnology shocks. The main finding is that the Great Moderation phenomenon in Japan in the 1970s is largely accounted for by the decline in the contribution of technology shocks to the variance of output. The timing and magnitude of the fall in the conditional standard deviation of the output in the 1970s match well with those of the unconditional standard deviation. Furthermore, the technology shocks played a dominant role in all sample periods. The contribution of the nontechnology shocks is more limited, although the pattern is very similar.

The middle panel reports the analogous evidence for the labor input. In contrast, the nontechnology shocks have contributed the bulk of patterns in the standard deviation of the labor input from the mid-1970s to the present period. The technology shocks played a major role only before the Great Moderation. The right panel shows the case for labor productivity. The changing pattern of the standard deviation of labor productivity since the 1980s is largely explained by the technology shocks. The contribution of the nontechnology shocks showed a decreasing pattern until the recent crisis.

Fig. 8 is inserted here.

4.4 Conditional correlations

Why do the nontechnology shocks have a limited role in the volatility of the output growth? To find the answer, we look at the conditional correlations of the labor input with productivity.[11]

Fig. 9 reports the conditional and unconditional correlations between labor input and productivity. We can check the changing pattern of the labor input and productivity correlation conditional on the technology shocks: (i) it declined until 1985, (ii) increased until the end of the 1980s, and (iii) decreased again afterward. The volatile movement of the unconditional correlation seems to be explained by the technology shocks. More importantly, there is a stable process of near-minus-unity correlation generated by the nontechnology shocks. The negativity of the unconditional correlation between the labor input and productivity is largely attributed to the nontechnology shocks.

Fig. 9 is inserted here.

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

4.5 Impulse responses

To reconfirm the technology shocks as the main contributing factor to the variance in output volatility, we present the changing pattern of the 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 for every four quarters: the time period, from 1964Q2 to 2009Q2, is plotted on the x-axis, the quarters after the shock are plotted on the y-axis, and the response scale is plotted on the z-axis.

Fig. 10 shows the evolution of the output responses to the positive technology shocks. There are three spikes: the first is just before the Great Moderation, the second is during the bubble period in the late 1980s, and the third is during the recent financial boom and crisis. This figure is very similar to the output volatility conditional on the technology shocks in Fig. 6.

Fig. 10 is inserted here.

Figs. 11A and 11B show the evolution of impulse responses of labor input and productivity, respectively, to the nontechnology shocks. The figures reflect the results of the conditional correlation in the previous subsection. The responses for the labor input and labor productivity throughout the total sample period are in opposite directions.

Fig. 11A is inserted here.

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

Fig. 11B is inserted here.

Some authors have argued that 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. Rather, the changing pattern of output volatility may have actually come from the technology shocks; this was confirmed using the conditional correlations.

5 Robustness

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

5.1 Subsample

We present the subsample estimates suggesting that our main results are robust. In the first subsample period, we limit the sample period to 2004Q4. This is because we need to check whether the recent global boom and crisis has an impact on our results. The total sample period is from 1955Q2 to 2004Q4. The results for the second subsample period, from 1968Q1 to 2009Q4, are listed in Fig. 12B.[12] Our posterior periods in the second subsample period start from the Great Moderation because we use the previous eight years to estimate the priors.

The left panel in Fig. 12A shows the unconditional and conditional standard deviations of the output under the sample periods from 1995Q2 to 2004Q4. The timing of the upheavals of the unconditional volatilities is consistent with the benchmark case, although some scales are slightly different. The contributions of the technology and nontechnology shocks are consistent with the benchmark result. The right panel displays the unconditional and conditional correlations between the labor input and labor productivity. The result is consistent with the benchmark case. Fig. 12B shows the results based on the sample periods from 1968Q1 to 2009Q4. They are almost consistent with the benchmark case.

Fig. 12A is inserted here.

Fig. 12B is inserted here.

5.2 Differences or levels

In our benchmark estimation, the labor productivity and labor input are estimated, respectively, in the form of differences and levels 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 with both in the form of differences.[13] Therefore, we re-estimate the VAR

[12] In both cases, the first 8 years are used as a prior and actual estimation is done using the left samples.

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

model using both variables in differences.[14]

Fig. 13 displays the results when both variables are estimated in the form of differences. The left panel shows the unconditional and conditional standard deviations of output growth. The contribution of the technology shocks is still noticeable but two upheavals, in the mid-1970s and the late 2000s, are now more explained by the nontechnology shocks. The middle panel indicates that the nontechnology shocks play a dominant role in explaining the labor input volatility. The right panel shows the unconditional and conditional correlations between the labor input and productivity. The value of the correlation conditional on the nontechnology shocks stays around -0.8 in the total sample period. However, it ranges between -0.5 and -0.6 in the mid-1970s and the late 2000s, which is the same period for which the nontechnology shocks explain the output volatility more than the technology shocks.

Fig. 13 is inserted here.

There are many regions of negative correlations conditional on the technology shocks, which reflects the negative response of the labor input to the technology shocks in the short run. However, this negative relationship under the technology shocks does 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. In contrast, the employment share of the agricultural sector in the 1950s and 1960s declined rapidly. This reflects the huge sectoral movement of workers from the agricultural to non-agricultural sectors. The quarterly data are not available for the aggregate labor input in the 1950s and 1960s, but we find that the correlations of the labor input with productivity between the 1950s and 1960s are negative in both the non-agricultural and aggregate sectors.

Because of the quarterly data limitation, we re-estimate the model using the aggregate data starting from 1970Q1. Fig. 14 displays the results based on the aggregate labor input. The technology-shock contribution to the output volatility is consistent with the benchmark case. The contribution of the labor input volatility is roughly consistent except for during the recent crisis period. The conditional correlation between the labor input and labor productivity is also consistent.

Fig. 14 is inserted here.

6 Understanding two structural shocks

As discussed above, two structural shocks were estimated to determine whether they affect the labor productivity in the long run. We refer to a shock as a technology shock if it influences the labor productivity permanently, and as a nontechnology shock if its effect is temporary. In this section, we ask two additional questions: (i) Are the estimated technology shocks purely exogenous? (ii) What is the source of the nontechnology shocks?

[14]This means that the labor inputs are difference stationary.

To answer these questions, we conduct a standard multivariate analysis of ε and other potential explanatory variables in the spirit of Evans (1992).

$$\varepsilon_t^j = \mathbf{M}(L)\varepsilon_{t-1}^j + \mathbf{N}(L)z_{t-1} + \nu_t, \quad \text{for } j \in \{T, NT\}, \tag{19}$$

where ν_t is a mean zero, i.i.d. random variable, $\mathbf{M}(L)$ and $\mathbf{N}(L)$ are polynomials in the lag operator L, and z is a list of potential explanatory variables for the structural shocks.

6.1 Are the technology shocks exogenous?

If the technology shocks are purely exogenous, no additional explanatory variable should Granger-cause the innovations to labor productivity. Showing $\mathbf{N}(L) \neq 0$ is sufficient to refute the assumption that ε_t^T is strictly exogenous.

Following Evans (1992), we include the following nominal variables in vector x: M2 + CD ($M2 + CD$), the consumer price index (CPI), and the uncollateralized call rate (i). The data is quarterly and seasonally adjusted. The money and the consumer price index are measured as log first differences.[15]

Table 3 is inserted here.

As reported in Table 3, we find no evidence that $M2 + CD$, CPI, and the call rate individually Granger-cause ε^T over the sample period. Therefore, at least for these nominal variables, the technology shocks, ε^T, are exogenous.

6.2 What is the source of the nontechnology shocks?

One of our main results is that the labor movements are attributed to the nontechnology shocks, while the variance in the output is not explained by the nontechnology shocks. Thus, we examine a list of potential explanatory variables can explain the nontechnology shocks. Our estimated nontechnology shocks have broad implications. The typical determinants of the nontechnology shocks in the existing literature include household preference shocks, monetary policy shocks, and other shocks that could capture the labor market dynamics that are not related to the pure technology shocks.

Because of data limitations, we focus on the variables that reflect the labor market phenomenon. We include the followings variables in vector x: the nonscheduled hours worked index (NH), the labor turnover ratio ($Turnover$), and new firm openings ($Opening$). The labor input is composed of working hours and employment rate. The first variable is related to working hours and the other variables have close relationships with the employment rate. The data is quarterly and seasonally adjusted. Four lags of all variables are included in the autoregression (19).

Table 4 is inserted here.

Table 4 shows that NH Granger-causes ε^{NT} over the sample period, but there is no evidence that $Turnover$ and $Opening$ Granger-cause ε^{NT}. This implies that the nontechnology shocks are more related to working hours than to the employment rate.

[15] Other variables can be included in vector x. However, it is difficult to obtain variables with quarterly bases.

7 Discussion

In this section, we first assess two stylized facts about the U.S. business cycles for comparison with our benchmark case. Second, we link the Japanese labor market dynamics to the output volatility.

7.1 Sign change in the U.S. labor market

The persistence of acyclical behavior of labor productivity concerning nontechnology shocks in the Japanese economy is an unusual phenomenon. For the U.S. case, a number of studies including Stiroh (2009), Galí and Gambetti (2009), and Galí and Rens (2010) have the common finding that the sign of the correlation between labor input and productivity changed from positive to negative. Barnichon (2010) shows similar results wherein the correlation between the unemployment rate and labor productivity changed from negative to positive. Focusing on the sign change in the correlation between the labor input and productivity, they argue that the acyclicality of the labor productivity conditional on the nontechnology shocks is the actual cause of the moderation. They argue that the acyclical behavior of labor productivity in the Great Moderation period reflects 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. This may be indicative of the unique characteristics of the Japanese labor market. The structural changes in the labor market may have occurred several times, but the impact of the changing dynamics of the labor market on the volatility of the output growth has not changed substantially.

Barnichon (2010) and Galí and Rens (2010) investigate the potential sources in the decline of correlation between the labor input and labor productivity using a dynamic general-equilibrium labor-search model. Galí and Rens (2010) show that the 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 rather than the employment level, fluctuates more. This unobservable effort is included in productivity, which makes the measured labor productivity more procyclical and volatile. A reduction in the frictions decreases the volatility of effort, and therefore the degree of procyclicality of productivity decreases. Barnichon (2010) suggests that an increase in the elasticity of hours worked is another factor for the vanishing procyclicality of labor productivity. The fluctuations in hours worked generate countercyclical productivity movement, whereas the fluctuations in effort generate procyclical productivity movements; in the end, productivity becomes less procyclical. As a result, the decline in labor effort volatility can be a driving force in explaining the sign shift in the correlation between the labor input and labor productivity in the U.S.

7.2 No sign change in the Japanese labor market

How can we interpret our results using the abovementioned structural labor market models? To see more details in the labor input movements, we decompose labor input and hence can determine which factor of labor input drives negative correlation with labor productivity. In the first panel of Fig. 15, we decompose labor input into working hours and employment rate and plot the correlation between each one of these components and productivity. Both working hours and employment rate show a negative relationship with labor productivity throughout the sample period. However, the correlation between working hours and labor productivity closely traces that between labor input and productivity. This finding is consistent with that in Braun, Esteban, Okada, and Sudo (2006), who find that most of the variation in labor input is due to variations in working hours per worker. Our new finding is that the contribution of working hours in explaining the movements of labor input is time-invariantly dominant.[16]

The second panel shows the correlations of the total, male, and female employment rates with labor productivity. The correlation of female employment rate with labor productivity closely traces that of the total employment rate. On the other hand, the correlation between the male employment rate and labor productivity is positive in almost half the total periods. Therefore, we can conclude that the female employment rate is an important source of the negative correlations.

The third panel displays the correlation of the employment rate with its components. By definition, the variability of the employment rate is explained by the variability of employment and working population and their comovements.[17] Even when employment is volatile, there is a possibility that the employment rate is not volatile when the volatility of the working population cancels out that of employment. We can observe that employment almost has unit correlation with the employment rate, implying that most of the volatility of the employment rate can be explained only by the volatility of employment.

Fig. 15 is inserted here.

Compared to the U.S., employment volatility has been low throughout the total sample period. Therefore, the increase in employment volatility due to the decline in labor market frictions may be not the case with Japan. Moreover, the labor input volatility is explained mostly by the volatility in the hours. This may be indicative of the elasticity of hours being higher than that of the labor effort. Therefore, the labor adjustments do not seem to have switched from efforts to hours because we cannot find any sign shift or contribution change of the major components of labor input. The adjustment mechanism of the labor input seems not to have changed at least in the aggregate level data. Rather, a simple RBC model with time-varying productivity is consistent with our results in explaining the output volatility, while alternative explanations are needed to explain the labor market dynamics.

7.3 Sector level evidence

In this subsection, we ask whether the negative correlation between labor input and productivity holds in the sectoral level. For the Japanese case, for the three-digit level, we use the *Japanese Industrial Production* (JIP) database, which includes annual data for 92 sectors for 1973 to 2007. Data for the two-digit level is taken from Ko and Kwon (2012). For labor input, we use man-hour data. For the U.S. case, we use industry data from the NBER-CES Manufacturing Industry Database, which includes only manufacturing data

[16] They also document that the correlation between working hours and the employment rate is negative, but our data reveal that it is rather positive in the 1960s, 1970s, and 2000s.

[17] The standard deviation of the employment-rate growth can be decomposed into three parts: $Var(\Delta\text{employment rate}_t) = Var(\Delta\text{employment}_t) + Var(\Delta\text{working population}_t) - 2Cov(\Delta\text{employment rate}_t, \Delta\text{working population}_t)$.

for 458 four-digit industries for 1958-1996. Following Chang and Hong (2006), we use total hours employed in the industry, measured by the sum of hours of production and nonproduction workers. Output and labor input measures are seasonally adjusted but not normalized because the size of the sectoral working population is not available.

Table 5 reports the sector-level correlations between labor input and productivity in Japan. The correlations for the total sample period are calculated because of the limited number of annual data. Over half of the sector have negative correlations: 19 out of 28 sectors in the two-digit level and 62 out of 92 sectors in the three-digit level.

In Table 6, for the U.S. case, the pattern is less pronounced. In the two-digit level, only 9 out of 20 sectors exhibit negative correlations, while in 89 out of 140 sectors the patterns are observed in the three-digit level. Furthermore, if we divide the sample into pre- and post-1984 periods, the pattern is obvious in the latter period: it increases from 85 to 92 entering the Great Moderation period.

Tables 5 and 6 are inserted here.

8 Concluding remarks

We document two important issues relating to the postwar Japanese business cycles. First, we obtain the timing of the Great Moderation and its changing pattern. The Great Moderation phenomenon occurred in Japan beginning in the mid-1970s and was accompanied by a dramatic decline in the macroeconomic volatility. Unlike in the U.S., however, Japan's Great Moderation has not been persistent, with some volatile movements in the late 1980s and the late 2000s. Second, we find a persistently negative correlation between the labor input and labor productivity throughout the total sample period.

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

The correlations among these variables change 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 productivity is continuously negative, especially under the nontechnology shocks. Moreover, we find no sign shift in the correlation of each component of labor input with productivity, and hence we might need a different model to analyze the Japanese labor market dynamics.

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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.

Table 3
The predictability of technology shocks

Case	Variable			F value	p value
1	$\Delta\ CPI$			1.585	0.181
2	$\Delta M2+CD$			1.371	0.246
3	call rate			0.426	0.789
4	$\Delta M2+CD$,	call rate		0.896	0.521
5	$\Delta\ CPI$,	call rate		1.072	0.385
6	$\Delta\ CPI$,	$\Delta M2+CD$		1.379	0.209
7	$\Delta\ CPI$,	$\Delta M2+CD$,	call rate	1.090	0.372

Notes: (a) H null: variables do not Granger-cause technology shocks. (b) Four lags of ε_t^T and x_t were chosen. (c) All variables are seasonally adjusted.

Table 4
The predictability of nontechnology shocks

Case	Variable			F value	p value
1	NH			5.658	0.000
2	$Turnover$			1.194	0.316
3	*Openning*			2.018	0.095
4	$Turnover$	*Openning*		1.677	0.109
5	NH	*Openning*		5.506	0.000
6	NH	$Turnover$		3.617	0.001
7	NH	$Turnover$	*Openning*	3.954	0.000

Notes: (a) H null: variables do not Granger-cause nontechnology shocks. (b) Four lags of ε_t^{NT} and x_t were chosen. (c) All variables are seasonally adjusted. (d) NH denotes nonscheduled hours worked index, $Turnover$ denotes labor turnover ratio, and *Openning* deontes new opennings.

Table 5
Correations in the sectoral level

Data	Negative	Positive
2-digit	19	9
Manufacturing	9	6
Nonmanufacturing	10	3
3-digit	62	30
Manufacturing	31	21
Nonmanufacturing	31	9

Notes: The number of sectors with a negative or positive correlations between labor productivity and labor input is listed. 28 2-digit data are taken from Ko and Kwon (2012). 92 3-digit data are taken from JIP and the sample period is 1974-2007.

Table 6
Correations in the U.S. manufacturing sector

	Total		Pre-1984		Post-1984	
Data	Negative	Positive	Negative	Positive	Negative	Positive
2-digit	9	11	9	11	10	10
3-digit	89	51	85	55	92	48

Notes: The number of sectors with a negative or positive correlations between labor productivity and labor input are listed. Data are taken from the NBER-CES Manufacturing Industry Database by Erice Bartelsman et al. (2000). They include 458 4-digit manufacturing industries for 1958-1996.

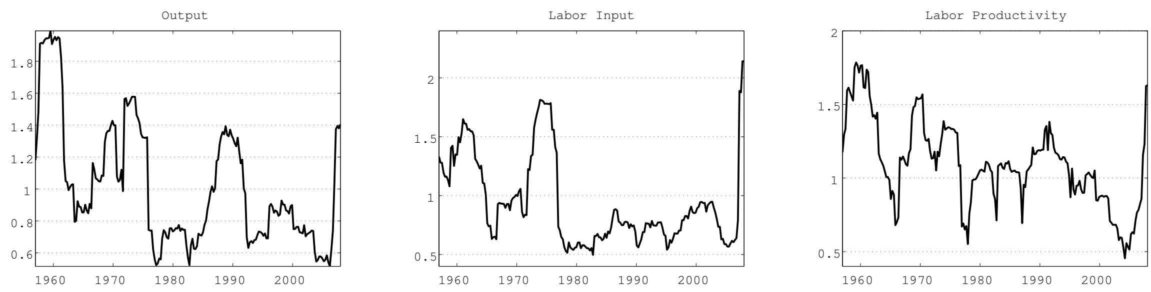

Fig. 1. Rolling standard deviations of output, labor input, and labor productivity.

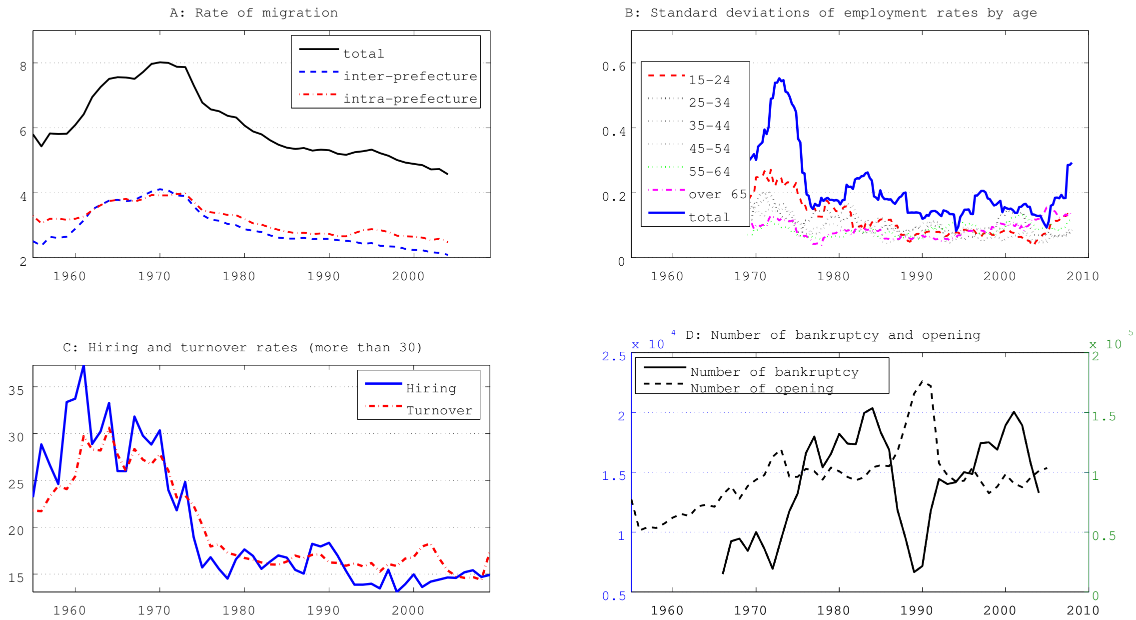

Fig. 2. Post-war Japanese Economy.

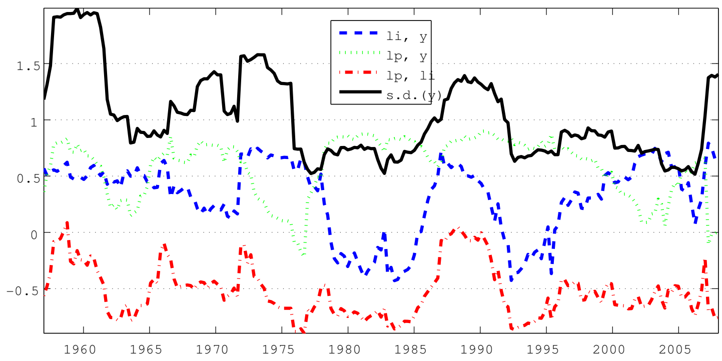

Fig. 3. Rolling correlations. *li*, *y*, and *lp* denote labor input, output, and labor productivity, respectively. The black solid line is standard deviation of output. Blue dashed, green dotted, and red dash-dotted lines are respectively correlations between labor input and output, labor productivity and output, and labor input and labor productivity.

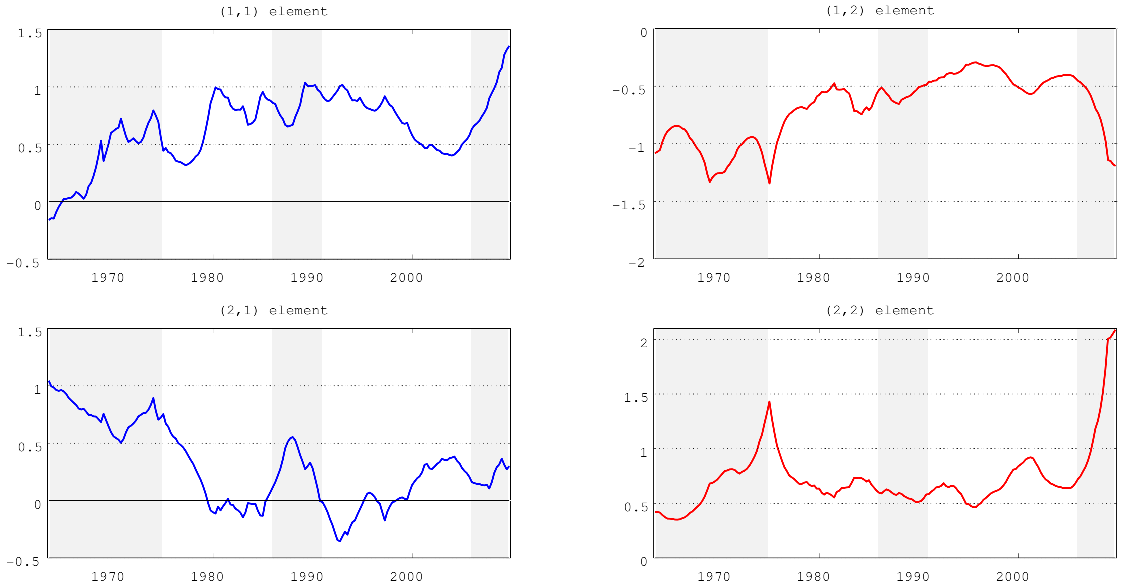

Fig. 4. Historical impact size of estimated structural shocks on labor productivity and input.

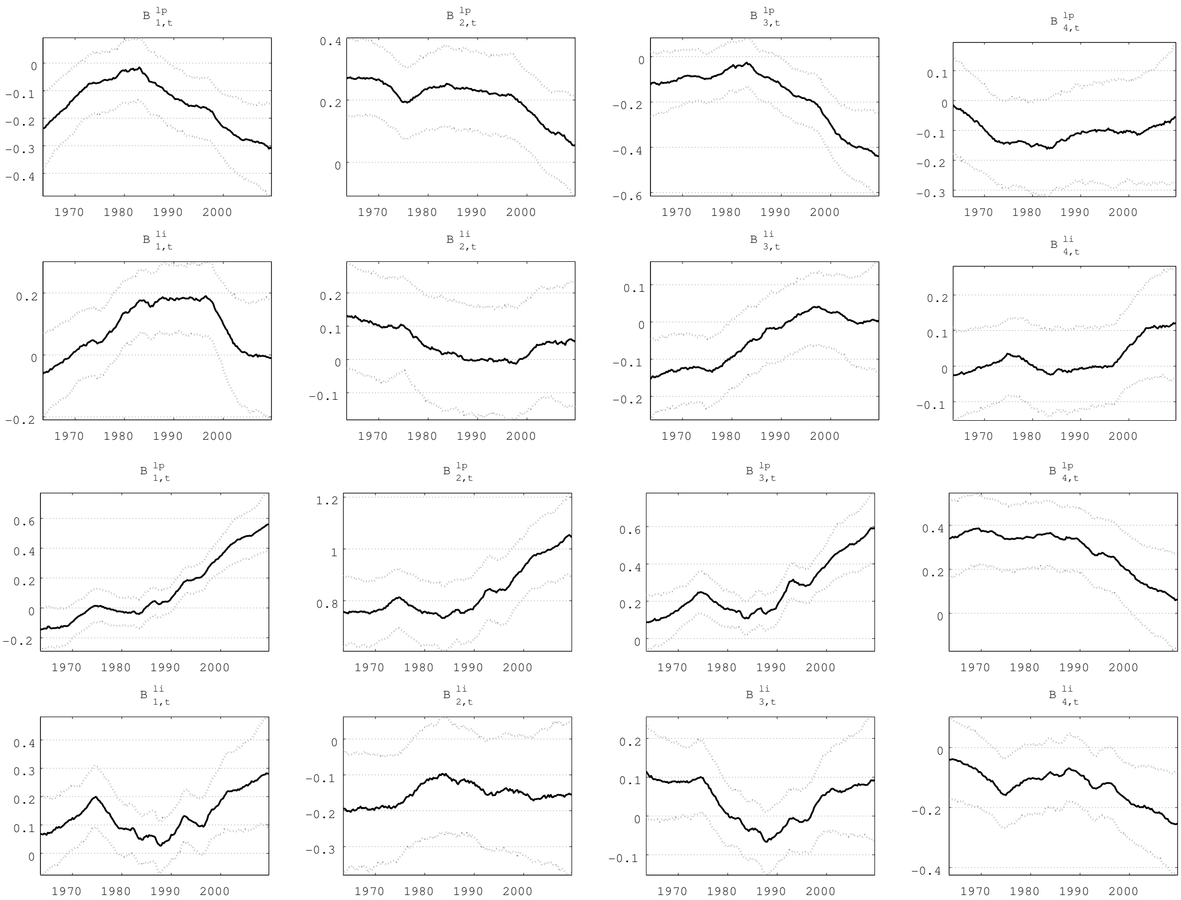

Fig. 5. Coefficients under the benchmark case. Coefficients on labor productivity (labor input) lags to explain the current labor productivity are listed from the left to the right panels in the first (second) row, and those to explain the current labor in the third (fourth) row. The number in the subscript indicates how past the date is from the current period. The superscript indicates the independent variables: *lp* and *li* respectively denote labor productivity and labor input. The black solid line indicates the posterior mean values. The dashed lines present the bounds of credible intervals with the 16-th and 84-th percentiles.

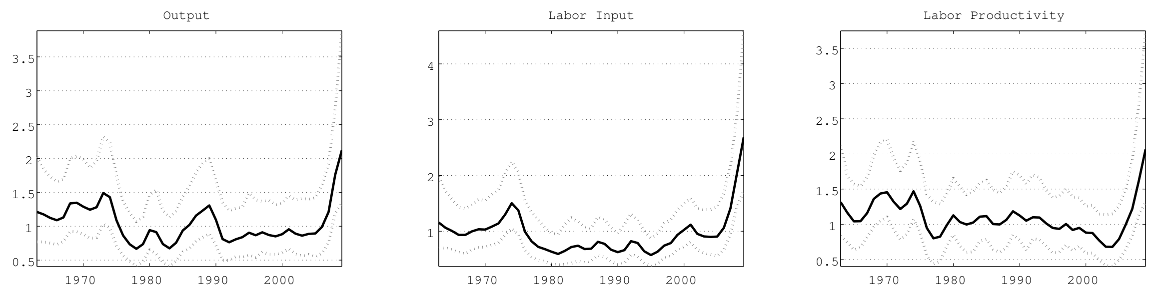

Fig. 6. Unconditional standard deviations of output, labor input, and labor productivity. The dashed lines present the 16-th and 84-th percentiles of the time varying standard deviation of coefficients.

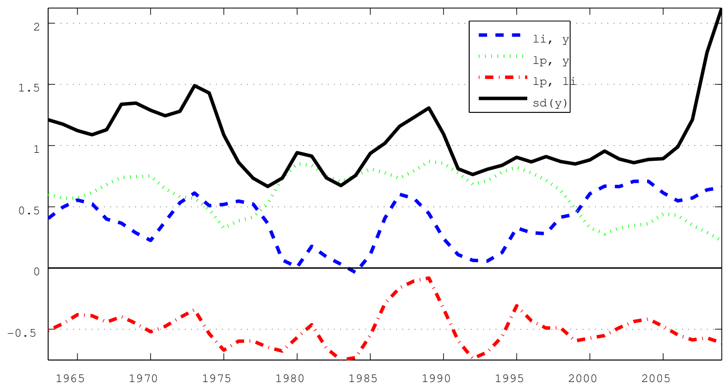

Fig. 7. Unconditional correlations

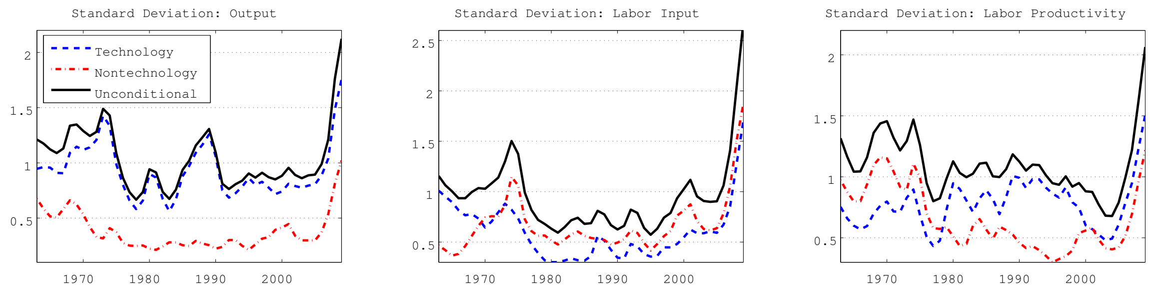

Fig. 8. Conditional standard deviations under the benchmark case. Unconditional and conditional standard deviations of output, labor input, and labor productivity are listed from the left to the right panels. The black solid line is the unconditional volatility of each variable. The blue dashed line is the contribution of technology shocks while the red dotted line is the contribution of nontechnology shocks.

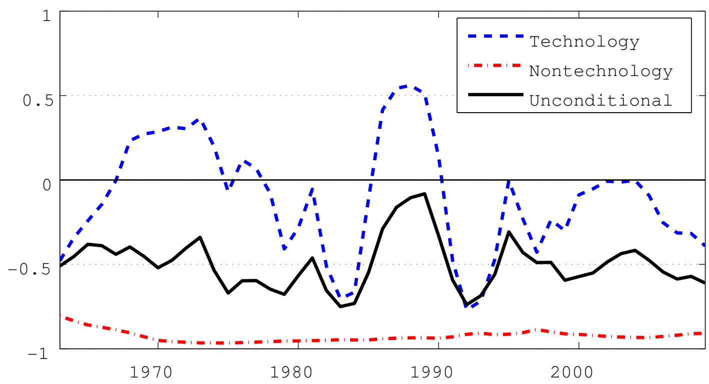

Fig. 9. Conditional correlation between labor input and labor productivity. The black solid line is the unconditional correlation between labor input and productivity. The blue dashed line is the contribution of technology shocks while the red dotted line is the contribution of nontechnology shocks.

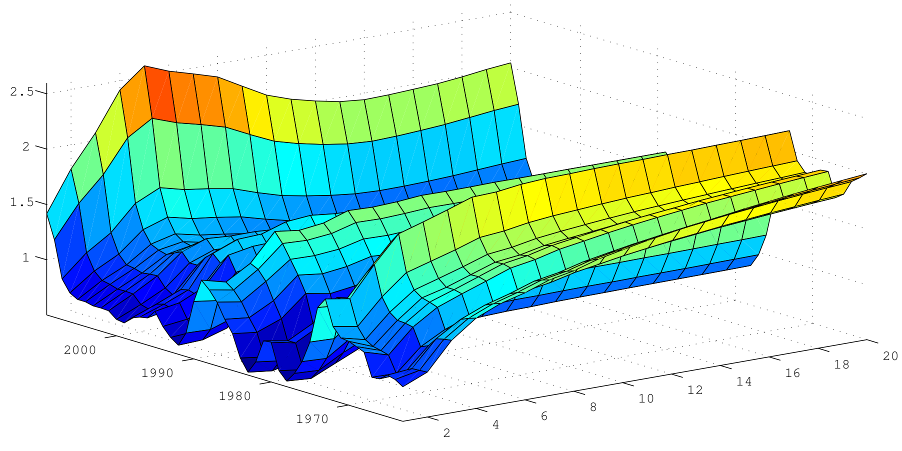

Fig. 10. Impulse response of output to technology shocks.

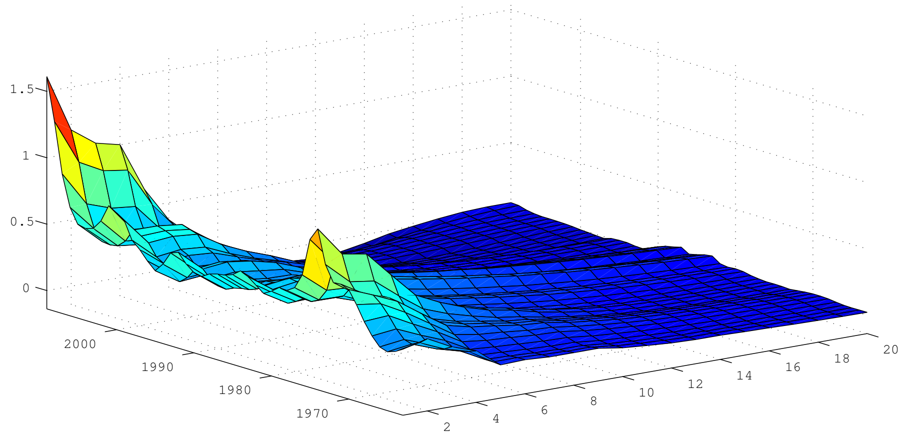

Fig. 11A. Impulse response of labor input to nontechnology shocks

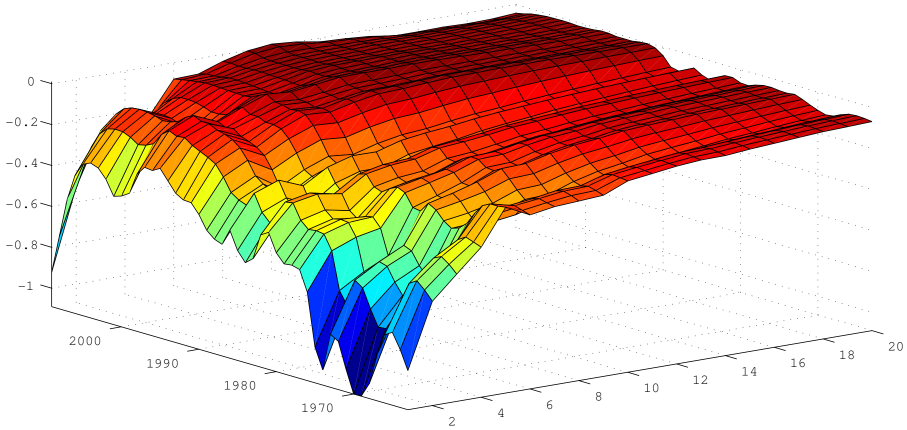

Fig. 11B. Impulse response of labor productivity to nontechnology shocks

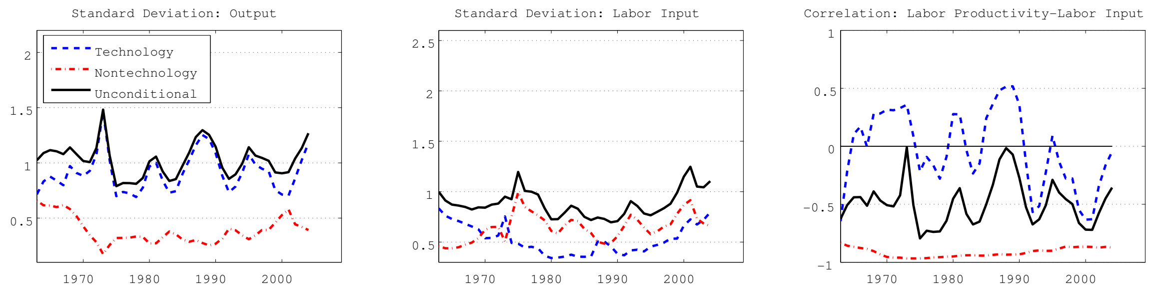

Fig. 12A. Conditional standard deviations and correlations with sample period 1955q2 to 2004q4. Standard deviations of output and labor input are listed in the left and the middle panels, respectively. The unconditional and conditional correlation between labor input and productivity is listed in the right panel.

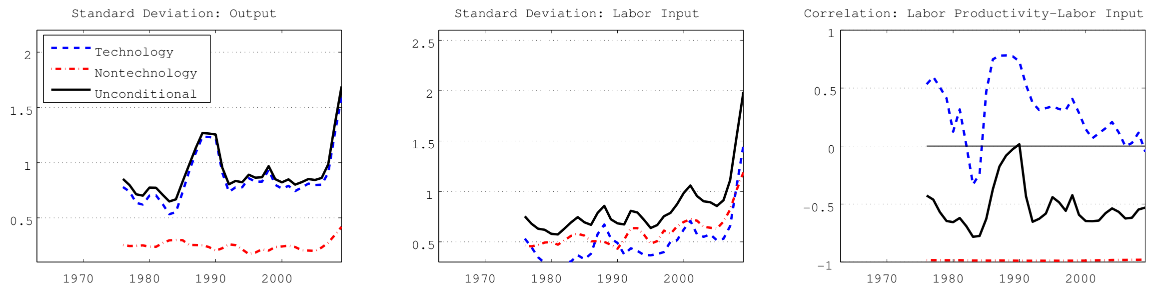

Fig. 12B. Conditional standard deviations and correlations with sample period 1968q1 to 2009q4. Standard deviations of output and labor input are listed in the left and the middle panels, respectively. The unconditional and conditional correlation between labor input and productivity is listed in the right panel.

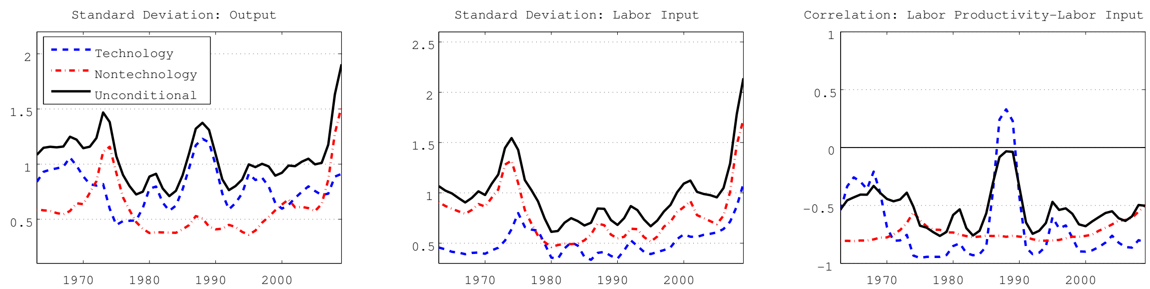

Fig. 13. Conditional standard deviations and correlation under the difference and difference scheme

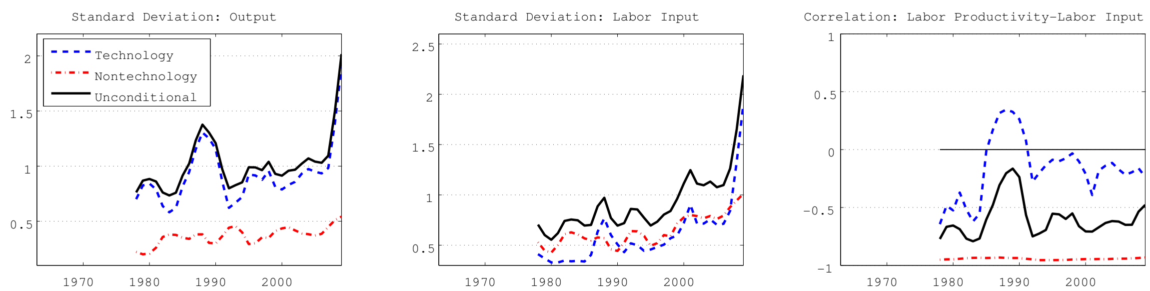

Fig. 14. Conditional standard deviations and correlation with aggregate labor input data

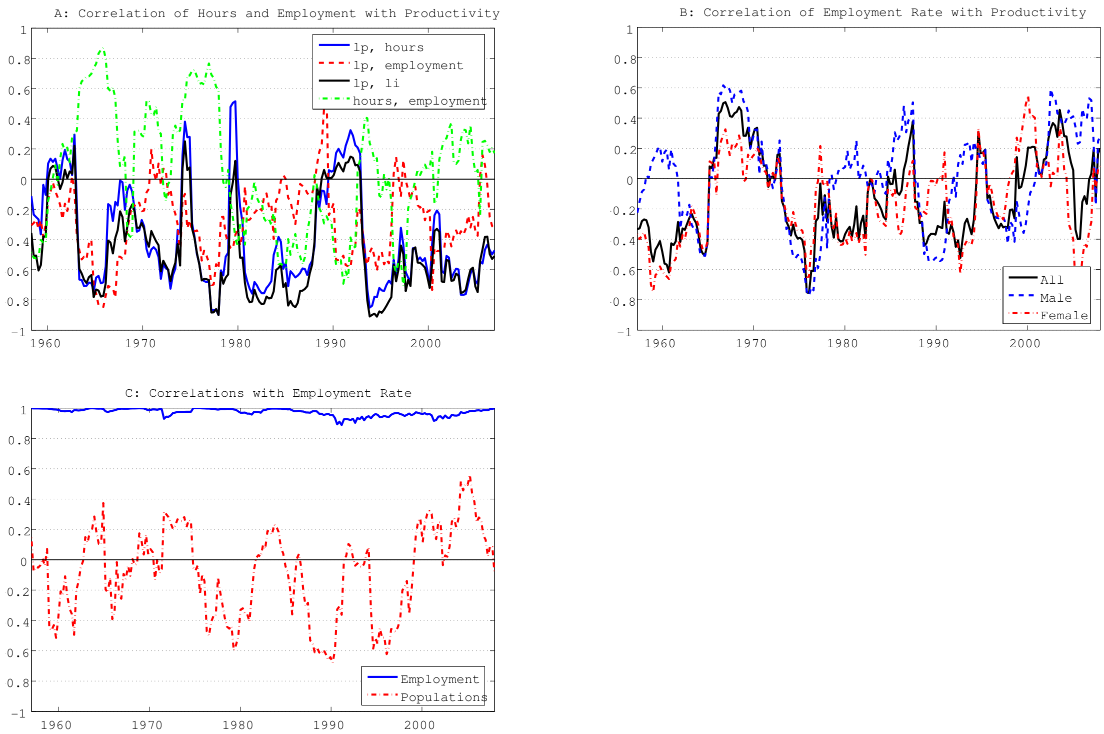

Fig. 15. Sources of the negative correlation between labor input and productivity. Panel A displays the contribution of hours and employment. The black line is the correlation between labor input and productivity. Blue, red dashed, green dotted lines are respectively the correlations between hours and productivity, employment and labor productivity, and hours and employment. Panel B displays the decomposition of employment rates into males and females. The black line is the correlation between the employment rate and productivity. Blue and red lines are respectively the correlation of male and female employment rates with productivity. Panel C displays the decomposition of employment rates into employed persons and working populations. The blue and red lines are respectively the correlation of the employment rate with employment and working population.

Appendix

Data

Fig. 1A presents the evolutions of key variables during the sample period: output, labor productivity, labor input, and working hours. Output and labor input are in per capita.

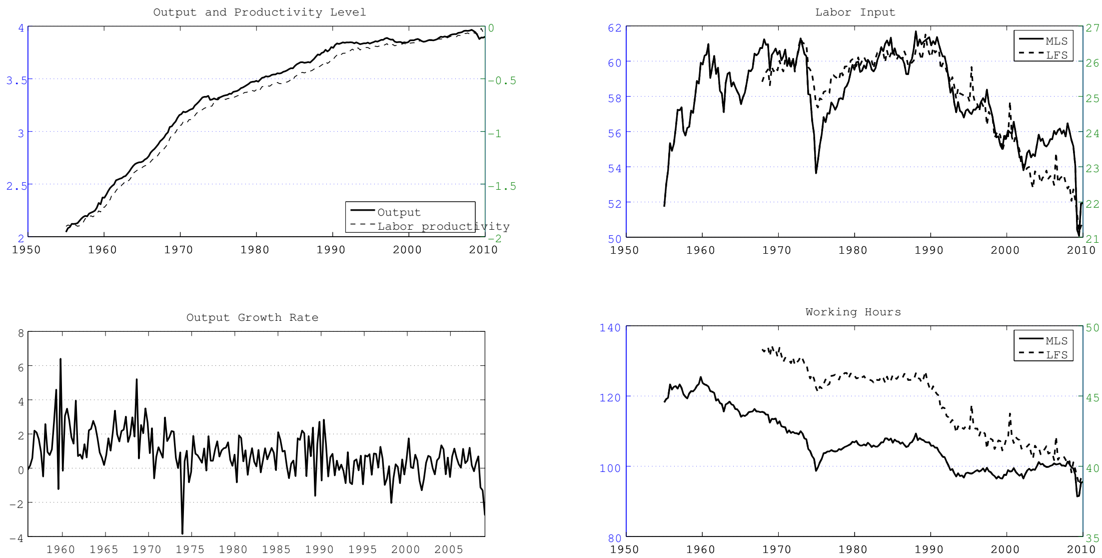

Fig. 1A. Data.

Priors

The TVP-VAR model is estimated using Bayesian methods. Data from 1955Q1 to 1962Q4 is used to calibrate the priors and data from 1963Q1 to 2009Q4 to estimate the model.

- Following Cogley and Sargent (2005) and Galí and Gambetti (2009), we make following assumptions prior distributions and its hyperparameters:

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

- $\hat{\theta}_{OLS}$ 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 $\hat{A}$.
- $\bar{Q} = k_Q \times \hat{V}(\hat{\theta}_{OLS})$.
- T_0 is the number of observations in the initial sample.
- $\bar{\Xi} = k_\Xi$.
- $\bar{\Psi} = k_\Psi \times |\hat{\alpha}_{OLS}|$.
- In the benchmark case, we set $k_Q = 0.005$, $k_\Xi = 0.0001$, and $k_\Psi = 0.001$.
- Including the robustness check, we estimated 18 models with all possible combinations of $k_Q = \{0.1, 0.001, 0.005\}$, $k_\Xi = \{0.001, 0.0001\}$, and $k_\Psi = \{1, 0.1, 0.001\}$.

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 joint posterior density, $p(\theta^T|x^T, \alpha^T, h^T, Q, \Psi, \Xi)$ can be expressed as

$$p(\theta^T|x^T, \alpha^T, h^T, Q, \Psi, \Xi) = p(\theta_T|x^T, \alpha^T, h^T, Q, \Psi, \Xi)\Pi_{t=1}^{T-1} p(\theta_t|\theta_{t+1}, x^t, \alpha^T, h^T, Q, \Psi, \Xi). \quad (20)$$

- To draw from the conditional posterior, we employ the algorithm of Carter and Kohn (1994).
- The conditional mean and variance of the terminal state θ_T is computed using standard Kalman filter recursions.
- For all the other states the following backward recursions are employed:

$$\theta_{t|t+1} = \theta_{t|t} + P_{t|t}P_{t|t+1}^{-1}(\theta_{t+1} - \theta_{t|t}), \quad (21)$$
$$P_{t|t+1} = P_{t|t} - P_{t|t}P_{t+1|t}^{-1}P_{t|t}, \quad (22)$$

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.

Fig.s A2 to A5 give sample paths and densities of some parameters.

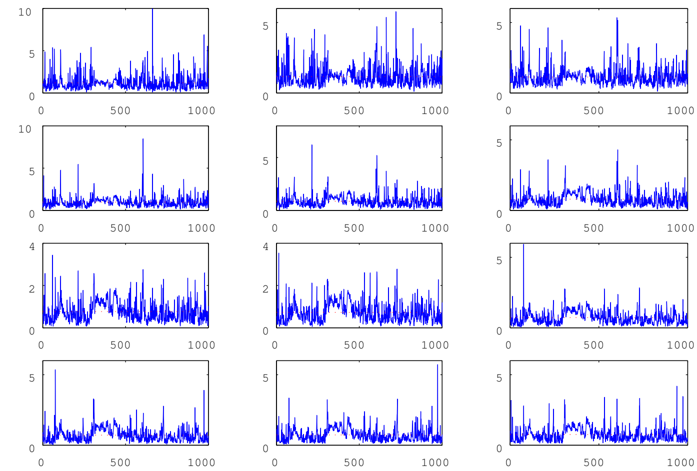

Fig. A2. Sample paths of posterior $\log h_t$. Blue lines indicate 1000 remained draws and the red dashed lines indicate the mean values of these draws.

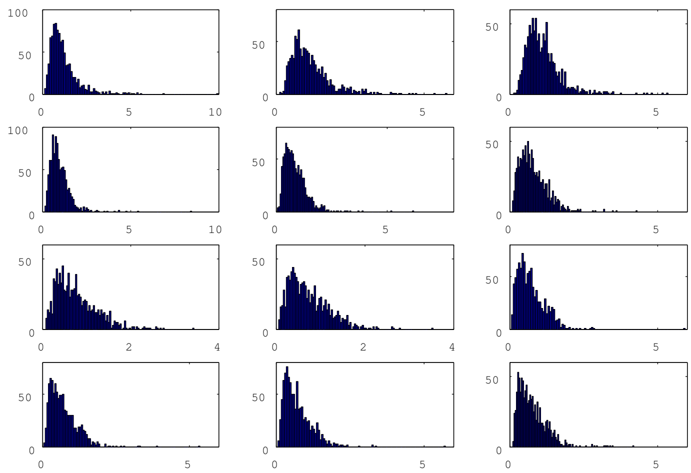

Fig. A3. Density of posterior $\log h_t$.

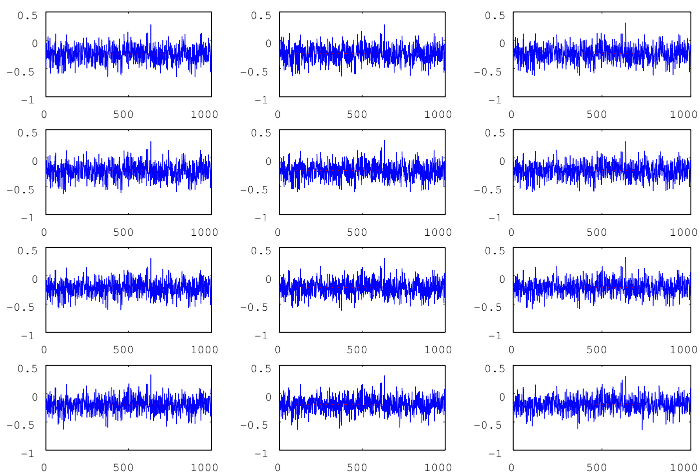

Fig. A4. Sample paths of posterior $\beta_{1,t}$. Blue lines indicate 1000 remained draws and the red dashed lines indicate the mean values of these draws.

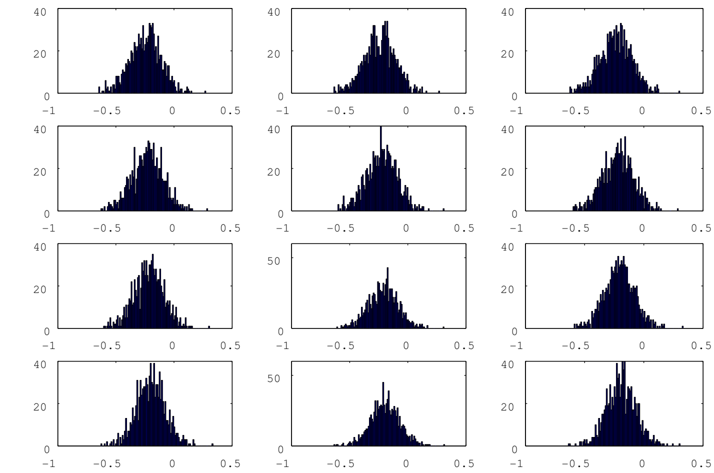

Fig. A5. Density of posterior $\beta_{1,t}$.

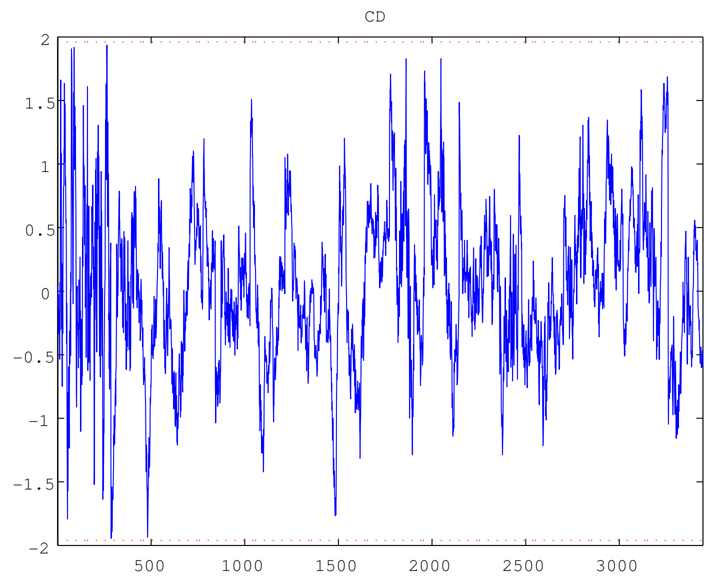

Fig. A6. CD statistics. The estimates for the convergence diagnostics (CD) of Geweke (1992), the 95 % credible intervals, We cannot reject the null hypothesis based on the CD statistics.