Technology Shocks and Work Hours in Japan:

Evidence from a New VAR approach

By
R. Anton Braun
University of Tokyo

and

Etsuro Shioji
Yokohama National University

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Abstract

This paper studies if technology shocks raise or lower work hours in Japan. Influential studies of the US data, such as Galí (1999), find that, in response to a positive technology shock, work hours *decline*. We claim that there is a limitation to the VAR approach most commonly used by previous authors in this literature. To overcome such a shortcoming, we propose a new VAR approach which is an extension of Uhlig (2001)'s VAR with sign restrictions. Our method has an advantage in that it allows us to introduce any variable into the VAR in its levels or first differences. Using this approach, we find that work hours *increase* in response to a positive technology shock, when all the variables are entered in the VAR in their levels. Hence, compared to the previous studies, our results are more consistent with the view that technology shocks are an important driving force of business cycles fluctuations.

1 Introduction

This paper uses the VAR methodology to study if technology shocks raise or lower work hours in Japan. Using the US data, Galí (1999) and other influential studies show that, in response to a positive technology shock, work hours *decline*. We develop a new identification scheme which is more flexible than the one employed by Galí and others. We find that work hours *increase* in response to a positive technology shock, when all the variables are entered in the VAR model in their levels rather than first differences. Hence, our results are more consistent with the view that technology shocks are an important driving force of business cycles fluctuations.

The effect of technology shocks on work hours has been a subject of a heated debate among macroeconomists in the past few years. This is because it has a direct consequence on how we model business cycles. According to the basic real business cycle theory, technology shocks are an important source of output fluctuations over business cycles. On the other hand, other theories emphasize roles of other types of shocks such as aggregate demand shocks. A distinguishing feature of business cycles in the data is that labor productivity and total work hours are strongly positively correlated[1]. If technology shocks were to be a dominant source of fluctuations in output and hours, as the basic real

[1] For the US, the correlation between labor productivity and work hours, both detrended by the approximate Band-Pass Filter of Baxter and King (1999) is 0.89. The sample period is 1964Q1-2001Q4. For the Japanese data that we use here, the correlation is lower

business cycle model claims, they ought to be able to reproduce this positive correlation. In other words, those shocks would have to move both variables in the same direction. Using the US data, Galí (1999) shows that, in fact, work hours decline in response to a positive technology shock. As labor productivity tends to increase in response to the same shock, this would create a negative correlation between the two variables. It then follows that those shocks cannot be important for explaining business cycles. Galí (2004) used data from the Euro area to obtain a similar conclusion. Francis and Ramey (2002) perform robustness checks on the nature of technology shocks identified by Galí (1999), and conclude that they cannot reject his conclusion. For a good survey on this literature, see Galí and Rabanal (2004).

Galí employs the VAR with long run restrictions, developed by Blanchard and Quah (1989). His model consists of two variables, labor productivity and aggregate work hours (divided by adult population for normalization). Those two variables are assumed to be driven by two types of shocks, technology shocks and non-technology shocks. Identification of those two types of shocks are achieved by assuming that only the former type of shocks can alter the level of labor productivity in the long run. Justification for such a restriction comes from the neoclassical growth model. That is, if the economy converges to the balanced growth path in the long run, according to this model, labor

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but is still respectable 0.53. The sample period for this case is 1955Q2-2001Q1.

productivity should be determined by the technology level[2]. There is, however, a limitation to this method: it requires researchers to introduce the variable that is subject to a long run zero restriction, labor productivity in this case, in their first differences, rather than in their levels. As Sims, Stock and Watson (1990) and Doan (2000) emphasize, taking first differences in a VAR analysis may throw away important information contained in the data. That could happen when, for example, the original series is stationary or when there is a cointegrating relationship between the variables. On the other hand, estimating VARs in levels does not yield such a problem. Thus, the fact that the Blanchard-Quah approach allows us to incorporate labor productivity only in first difference means a serious limitation.

To overcome this problem, we develop a new identification scheme which is qualitatively similar to that of Galí and others but allows us to employ more flexible specifications. It is an extension of the VAR developed by Uhlig (2001): the original approach imposes restrictions on the signs of the impulse responses. We generalize this approach and assume that, in the long run, the response of labor productivity to a non-technology shock must be very close to zero. This method has an advantage in that it allows us to incorporate any variable either in its levels or in first differences. Using this approach, we

[2] To derive this conclusion, it is required that the production function exhibits constant returns to scale, and that technology enters in the production function in the labor augmenting manner.

estimate bivariate VARs with labor productivity and work hours, experimenting with differences and levels specifications. We find that the empirical results are sensitive to the use of first differences vs. levels. When both variables are in first differences, we obtain results that are consistent with Galí's claim. However, we find that work hours *increase* in response to a positive technology shock, when all the variables are entered in the VAR model in their levels. As we consider estimation in levels as more reliable, we conclude that our results are more consistent with the basic real business cycles type view.

The remainder of the paper is organized as follows. Section 2 describes the empirical methodology. Section 3 describes the data and estimation details. Section 4 reports the results and Section 5 contains our concluding remarks.

2 Empirical Methodology

In this paper, we try to follow the approach taken by Galí (1999) as closely as possible, except for the issue of the estimation technique (and the issue of levels vs. first differences). Hence, we consider bivariate VAR models with labor productivity and work hours per capita. Three cases will be considered. In the (D,D) case, the two variables are both entered in the model in first differences. In the (D,L) case, labor productivity is in first differences but work hours are in levels. In the (L,L) case, both are in levels. In any of those three cases, we assume that the movements of the two variables are driven by two types of structural shocks, technology shocks and non-technology shocks. The two are mutually uncorrelated. Since innovations in labor productivity and work hours are generally correlated, recovering the relationship between the innovations and the structural shocks requires an identification restriction.

Let x_t be a (2×1) vector of macroeconomic variables. The first variable is labor productivity (in log), either in levels (denoted y_t) or in first differences (denoted Δy_t). The second variable is work hours per capita (in log), either in levels (denoted h_t) or in first differences (denoted Δh_t). In all three identification schemes, this vector is assumed to follow the following dynamics:

$$x_{t+1} = C_0 + C(L)x_t + u_{t+1}, \quad u_t \sim IID(0, \Sigma) \tag{1}$$

where, L is a lag operator, and $C(L)$ is a lag polynomial and u_t is a (2x1) vector of disturbances. On the other hand, denote a (2x1) vector of structural shocks as ε_t where the first element is a technology shock ($\varepsilon_{TECH,t}$) and the second element is a non-technology shock ($\varepsilon_{NON-TECH,t}$). To identify those structural shocks, we posit a linear relationship between the disturbances to the VAR and the structural shocks $\varepsilon_t = Pu_t$. That is we select a (2x2) matrix P such that:

$$Px_{t+1} = PC_0 + PC(L)x_t + Pu_{t+1}, \quad E(Pu_t u_t' P') = I \tag{2}$$

The three methodologies differ in the type of restrictions that serve to pin down P and thereby *identify* the particular rotation of the VAR disturbances that can be interpreted as structural shocks.

2-1 VAR with Long Run Restrictions

Galí (1999), among many others in this literature, employs the VAR with long run restrictions, a methodology proposed by Blanchard and Quah (1989). They impose a restriction that, in the long run, a non-technology shock has no effect on labor productivity. Consider a VAR model in which both labor productivity and work hours are in first differences: that is, $x_t = (\Delta y_t \quad \Delta h_t)$. Assuming invertibility, (2) can be written as

$$\hat{x}_{t+1} = \widetilde{C}(L) \cdot \varepsilon_{t+1} = \begin{pmatrix} \widetilde{C}^{11}(L) & \widetilde{C}^{12}(L) \\ \widetilde{C}^{21}(L) & \widetilde{C}^{22}(L) \end{pmatrix} \cdot \varepsilon_{t+1} \tag{3}$$

where $\hat{x}_{t+1}$ is the vector x_{t+1} suitably demeaned, and $\widetilde{C}(L) \equiv [P(I - C(L))]^{-1}$. The long run restriction employed by Galí and others implies $\widetilde{C}^{12}(1) = 0$: that is, the cumulative effect of a non-technology shock to labor productivity is zero (i.e., it has no effect on the *level* of labor productivity). It is important to note that the nature of this methodology requires labor productivity to enter into the model in first differences. As for work hours, it is not necessarily required to use their first differences.

The use of a differences specification can be problematic: in our case, for example, if hours are stationary and one estimates the model in first differences, or if labor productivity and hours are cointegrated, estimation with first differences becomes inconsistent. However, if one estimates in levels we always obtain consistent estimates regardless of the integration/cointegration properties of hours. Christiano, Eichenbaum and Vigfusson (2003) recognize this point and use the level of work hours instead of its first differences, in the same methodological framework. They obtain a drastically different result: using the US data, they find that work hours increase, rather than decrease, in response to a positive technology shock.

However, note that even Christiano et. al. (2003) employ a differences specification for labor productivity. This is because, as discussed above, that is what is required by the nature of the methodology. However, this would render the estimates to be inconsistent if, say, the two variables are cointegrated. If switching one variable from first differences to levels yields a drastically different outcome, researchers might want to try using both variables in their levels. But it is impossible with the methodology considered here. This is a serious limitation of the Blanchard-Quah approach.

2-2 VAR with Sign Restrictions

Uhlig (2001) proposes a method based on restrictions on the signs of impulse response functions[3]. It involves a rejection based quasi-Bayesian monte-carlo procedure. The procedure consists of two steps, or “outer-loop draws” and “inner-loop draws”. After estimating a reduced form VAR model, in the first step, we randomly draw from the posterior distributions of the matrix of reduced form VAR coefficients, the variance covariance matrix of the error term, Σ (Uhlig (2001) shows that, under a diffuse prior,

[3] Braun and Shioji (2003a, b, 2004a) apply this technique to the Japanese data.

the former is normally distributed and the latter is Wishart distributed). For each set of the first-step random draws, in the second step, we randomly draw the free elements of P^{-1}. If a particular monte-carlo draw satisfies the sign restrictions we tabulate it, otherwise it is discarded[4]. This way, we obtain a range of impulse responses that are compatible with the sign restrictions.

Francis, Owyang and Thedorou (2003) were the first to employ this methodology in the context of the effects of technology shocks on work hours. They assume that technology shocks have positive effects on productivity "in the long run" (say ten years after the shock). Using the differences specifications for both labor productivity and hours, they find that, in the US data, the response of hours to a technology shock is

[4] Denote a random draw for Σ as $\hat{\Sigma}$, and its eigenvalues as μ_1 and μ_2, and the corresponding eigenvectors as v_1 and v_2. Uhlig (2001) shows that the first column of P^{-1}, which we denote by *a*, has to take the following form: $a = \sum_{m=1}^{2} \alpha_m \cdot \sqrt{\mu_m} \cdot v_m$, where the α 's are weights attached to each of the two eigenvalues. We impose the following normalization: $\sum_{m=1}^{2} \alpha_m^2 = 1$. This leaves us with one degree of freedom to determine the weights. We draw α 's randomly from a uniform distribution, and then normalize them to satisfy the above normalization restriction.

insignificantly different from zero. It is important to note the conceptual difference between the Galí-type restriction and the restriction that those authors consider. The Galí-type restriction says that non-technology shocks have no effects on productivity in the long run, leaving the response of productivity to technology shocks unrestricted. Those authors say that technology shocks have positive long run effects on productivity, leaving the response of productivity to non-technology shocks unrestricted.

2-3 VAR with Range restrictions

We propose a way to extend Uhlig's approach to consider a type of restriction similar to that of Galí (1999). Its idea is the following. Generally speaking, Uhlig's Monte Carlo procedure allows researchers to impose a restriction that a certain impulse response should fall into a certain range of values. Imposing signs on impulse responses is a special case of such restrictions. Hence, to be true to the spirit of Galí's restriction, rather than imposing restrictions on the signs of impulse responses, we can assume that the response of labor productivity to a non-technology shock has to fall within a certain range of values that are sufficiently close to zero, in the long run.

A major advantage of this approach over Galí's long run restrictions is that it does not force researchers to adopt the differences specification even for the variables that are subject to the restrictions (labor productivity in this case). If, as Christiano et. al. (2003) show, the results are sensitive to whether the variables enter in their levels or their first differences, researchers would not wish to commit to a certain specification because the nature of the methodology requires them to do so. Moreover, for reasons discussed in the introduction, using levels specifications is becoming the standard practice in the VAR literature. Considering this, the advantage of this approach could be large.

3 Data and details of estimation

We use quarterly Japanese data for the period 1955Q2-2003Q4. We take the index of work hours published in *Monthly Labor Survey* of the Ministry of Health, Labour and Welfare as an index for the average work hours per worker. We take the index of employment published from the same source as an index of the number of workers. Those indices cover establishments with over 30 employees and exclude agriculture. Until 1970 they also exclude the service industry. They are both seasonally adjusted. By taking the product of the two we obtain an index of total hours worked. By dividing this by the estimated population aged 15 and over published by the Statistics Bureau of Japan, we get our index for work hours per capita. On the other hand, our index for output is real GDP (seasonally adjusted) published by the Economic and Social Research Institute. We divide this by total work hours to obtain our index of labor productivity[5].

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[5] Thus, data on output includes agriculture but hours data excludes it. To see if this difference influences the result, we tried estimating the quarterly share of agriculture in GDP (actual share is available only annually) and subtracting it from output data. When

In what follows, we always use VARs with four lags, which means that our sample period of estimation is 1956Q2-2003Q4. We do not include any deterministic terms other than the constant term. As for the "range restriction", we assume that the response of labor productivity to a non-technology shock has to fall between -0.01 and 0.01 in all of the 80th, 100th, and 120th periods. The signs of the shocks are normalized so that a "positive" technology shock increases labor productivity at the impact, while a "positive" non-technology shock increases work hours at the impact. However, as will be discussed later, there was a case in which this normalization turned out to be problematic, in which case a different assumption was employed. The numbers of random draws were 100 for the "outer loop" draws and 1,000 for the "inner loop" draws. However, in the (D,L) case, the fraction of draws that was deemed "valid" was relatively low, so, to produce enough number of valid draws, the number of outer loop draws was increased to 300.

4 Estimation Results

This section reports and discusses the estimation results. As was discussed earlier, we employ three different specifications, (D,D) case, (D,L) case, and (L,L) case. Our discussion below will focus on impulse responses and variance decomposition. Figures 1-3 report impulse responses in each of the three cases (solid lines), together with the 66

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we re-estimated the model with this data, the results were practically unchanged.

percentile error bands (dotted lines). All the figures concern the responses of the levels of the variables: that is, when a variable is entered into the VAR in first differences, the impulse responses in the figure are its cumulative responses. Table 1 and 2 report results of variance decomposition for the contemporaneous forecast error variance and the 20 steps ahead forecast error variance, respectively, by reporting percentage contribution of technology shocks. Table 3 reports the fraction of random draws that satisfy the restriction in percentages.

4-1 (D,D) case

First, consider the case in which both variables are in first differences, as in Galí (1999). Figure 1 shows that work hours decrease in response to a positive technology shock. This is consistent with Galí's claim. Thus, his results are not unique to the US and European data[6]. The variance decomposition result shown in the first rows of Table 1 and 2 indicate that technology shocks are a very important source of variations in labor productivity, and a reasonably important source of variations in work hours, but explains only about 12% of impact variations in aggregate output, which is the sum of the two (because of the logarithmic form). This is because this type of shock moves productivity and hours in opposite directions. This result is again consistent with the view that technology shocks

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[6] We also applied the Blanchard-Quah approach to the same data, and the resulting impulse responses were virtually identical to those in Figure 1. Thus, our result is not driven by the specific identification technique we used.

are not important for output fluctuations. Finally, from the fourth row of Table 3, we see that the percentage of valid draws is 1.9%.

4-2 (D,L) case

Figure 2 presents the impulse responses for the (D, L) specification, in which only labor productivity is in first differences. In constructing the error bands, we first used the standard normalization restriction that a "positive" technology shock increases labor productivity at the impact. However, we obtained very wide bands that were almost symmetric around the zero axis. This was presumably due to the problem of an inappropriate normalization, which is discussed extensively in Waggoner and Zha (1997)[7]. To deal with this problem, for this case only, we change the normalization restriction and assume that, in response to a "positive" technology shock, the response of labor productivity has to be positive at the 40th period rather than the 1st period. The dotted lines in Figure 2 are the resulting error bands.

Note that, contrary to Figure 1, the response of work hours to a technology shock turns positive. Thus, this result supports the claim made by Christiano et. al. (2003) that Gali's results are sensitive to the use of levels vs. differences for work hours. The second rows of Table 1 and 2 present the contribution of technology shocks to forecast error variances. It can be seen that this type of shocks explain less than 10% of the variations in productivity

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[7] We thank Christopher A. Sims for point out this problem for us.

at the impact, and less than 50% of those in hours. This is a big reduction from the (D,D) case. They are, however, the dominant source of fluctuations in aggregate output. This is because technology shocks, in this case, tend to move both labor productivity and work hours in the same direction. On the other hand, non-technology shocks, as can be seen in Figure 2, tend to produce a negative correlation between the two, which explains why its contribution to output variations is very small. Finally, Table 3 shows that the fraction of valid draws in overall draws is very small, only 0.1%.

4-3 (L,L) case

Figure 3 presents the impulse responses for the case where both variables enter in their levels, which we consider most reliable. Note that the response of work hours to a technology shock is again significantly positive, which is the opposite from the result in Figure 1. From the variance decomposition result in the last rows of Table 1 and 2, we see that technology shocks explain only 20-30% of variations in labor productivity and work hours, but are a dominant source of fluctuations in aggregate output. Finally, from the last row of Table 3, we see that valid draws were 1.2% of overall draws.

It is interesting to note that the (D, L) case yields a set of impulse responses that are quite similar to the one in the (L, L) case, at least in terms of point estimates. The (D, D) case, on the other hand, is very different. This may suggest that the possible bias with the differences specification comes mainly from taking differences of work hours. Taking first differences of labor productivity, on the other hand, seems less consequential.

5 Conclusions

In this paper, we have estimated the VAR with range restrictions, which allows us to impose restrictions that are qualitatively similar to those of Galí (1999) and others, but at the same time allows us to choose between the differences specification and the levels specification. We find that the results are very sensitive to the specification of the variables. In the (L, L) case which we consider most reliable, the result is the opposite to that of Galí: a positive technology shock raises labor productivity. Our results are thus more consistent with the basic real business cycle model's view of the world.

As this paper imposes restrictions that are qualitatively similar to that of Galí and others, most of the criticisms aimed at their work apply here as well. Most importantly, if there is another type of shock that have long run effects on labor productivity, our methodology may not identify technology shocks correctly. A typical example of such a shock that is often referred to in the literature is a permanent change in the capital income tax rate. In future work, we plan to explore ways to improve the current identification scheme by incorporating other important variables, such as capital income tax rate.

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Table 1 Variance decomposition: Fraction of Variance Explained by Technology Shocks (in percentage), within one peirod

case	Productivity	Hours	Output
D,D	89.4	61.1	11.9
D,L	6.6	49.3	83.5
L,L	21.1	27.3	93.3

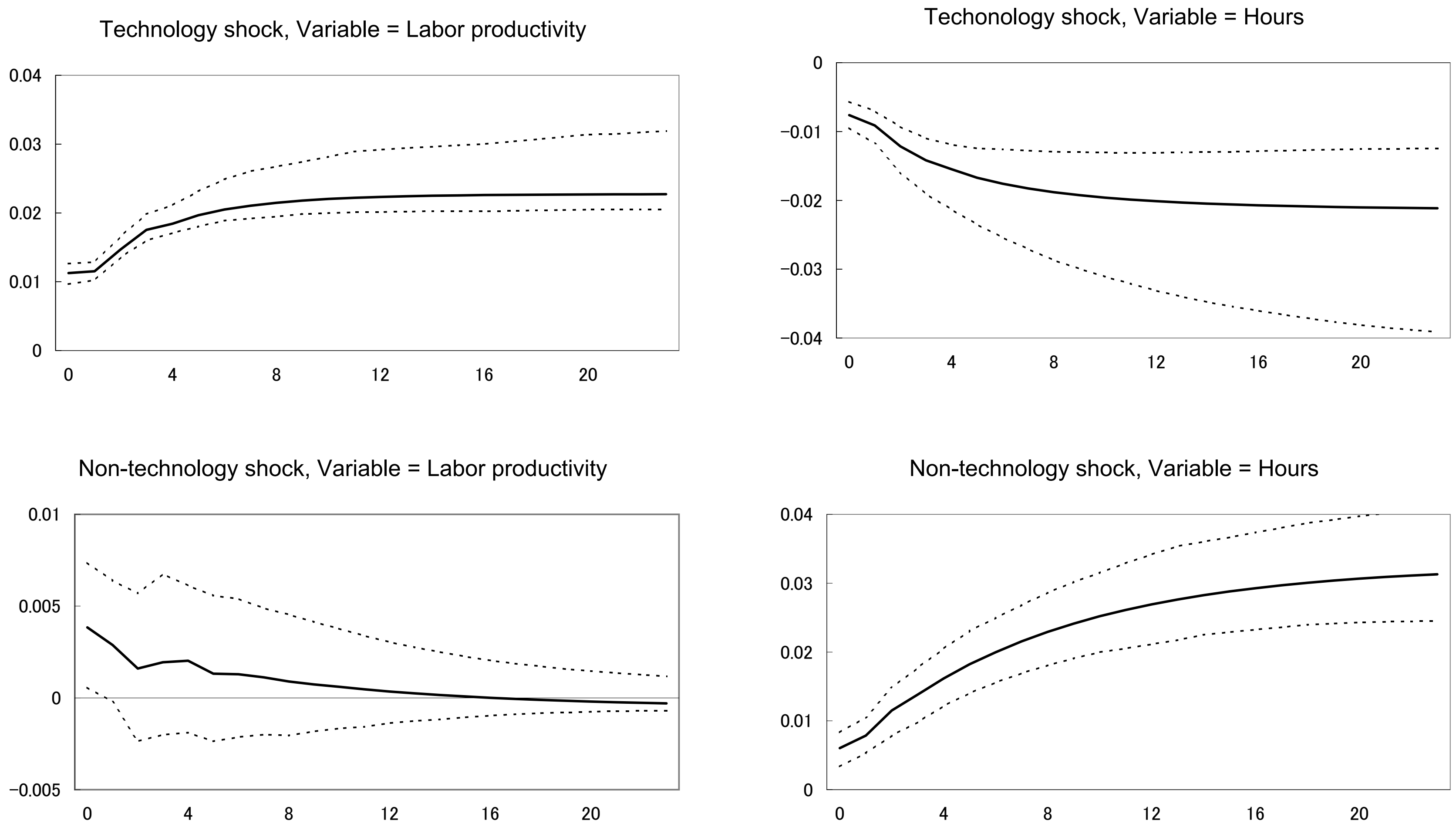
Table 2 Variance decomposition: Fraction of Variance Explained by Technology Shocks (in percentage), twenty periods ahead

case	Productivity	Hours	Output
D,D	100.0	31.9	0.3
D,L	0.9	88.7	99.9
L,L	47.9	38.5	99.8

Table 3 Fraction of random draws that satisfy the range restriction (in percentage)

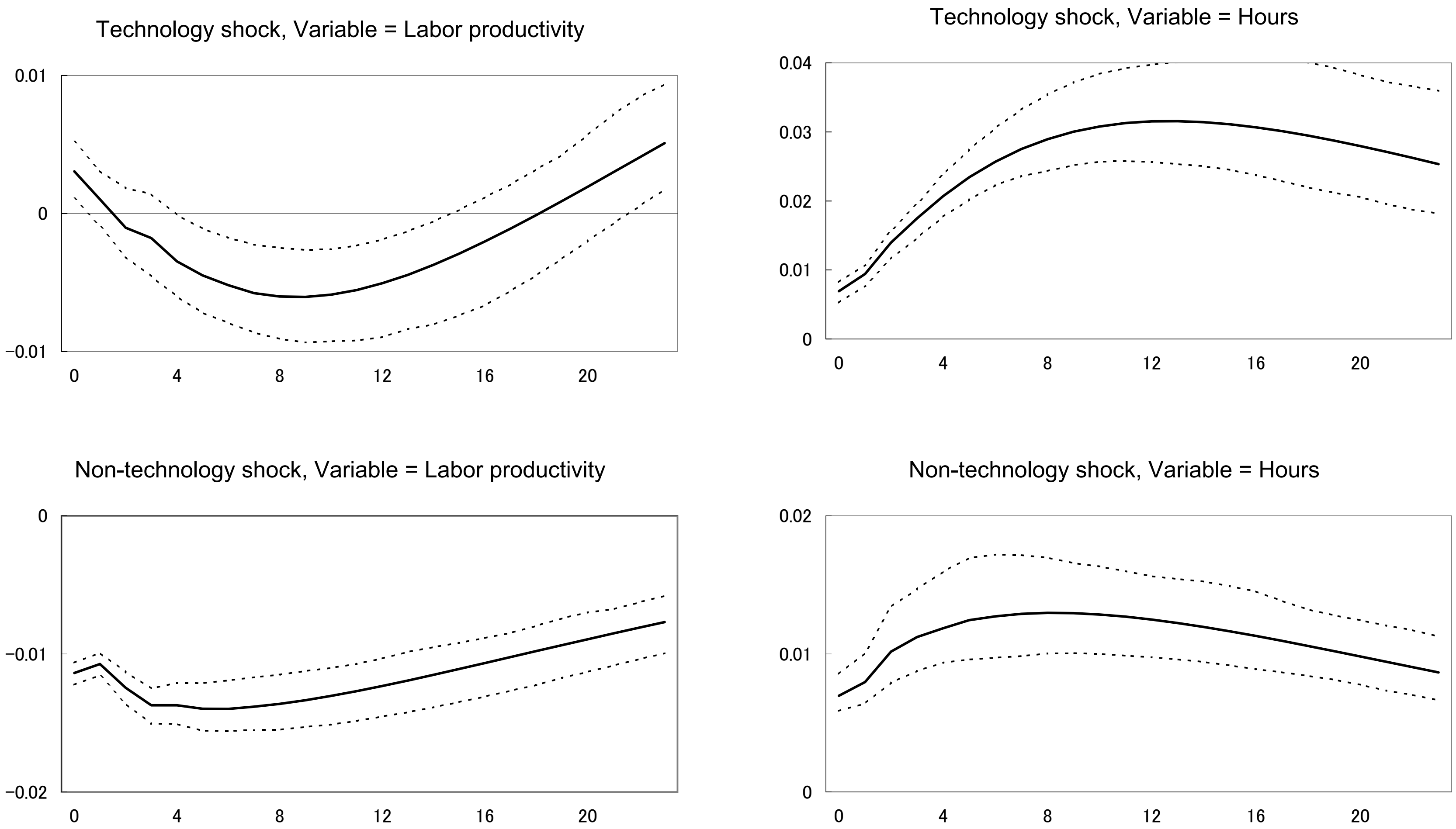
Case	Fraction of valid draws	Fraction of outer loop draws for which at least one valid inner loop draw was found
D,D	1.9	99
D,L	0.1	17
L,L	1.2	75

Figure 1 Impulse responses, (D,D) case



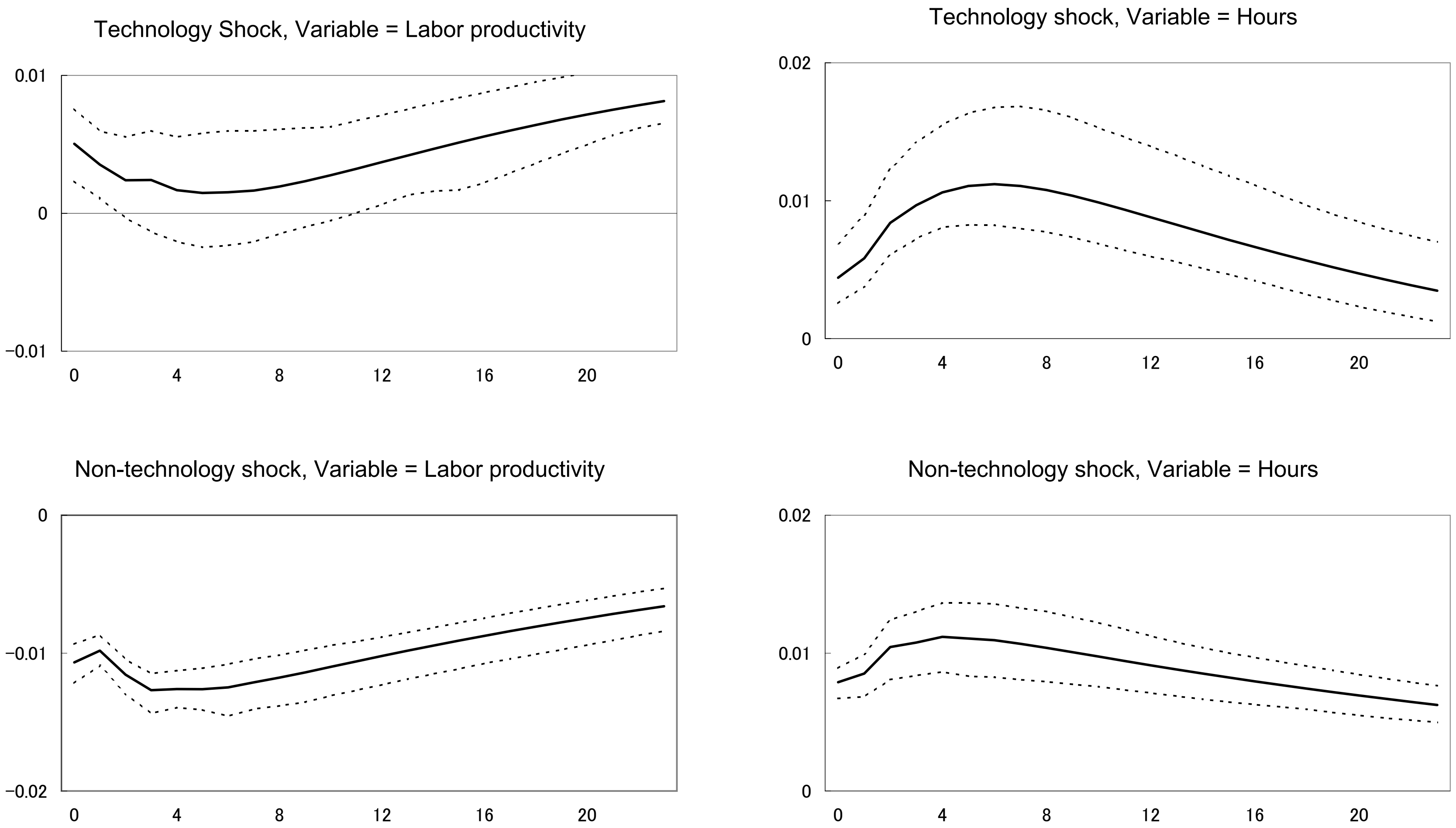
Note: Solid lines are impulse responses generated from the averages of the randomly generated parameters that satisfy the range restrictions.
Dotted lines are the 66% error bands around the median of the randomly generated impulse responses that are deemed valid.

Figure 2 Impulse responses, (D,L) case



Note: Solid lines are impulse responses generated from the averages of the randomly generated parameters that satisfy the range restrictions. Dotted lines are the 66% error bands around the median of the randomly generated impulse responses that are deemed valid.

Figure 3 Impulse responses, (L,L) case



Note: Solid lines are impulse responses generated from the averages of the randomly generated parameters that satisfy the range restrictions.
Dotted lines are the 66% error bands around the median of the randomly generated impulse responses that are deemed valid.