U.S. R&D and Japanese Medium Cycles

R. Anton Braun
University of Tokyo

Toshihiro Okada
Kwansei Gakuin University

Nao Sudou
Bank of Japan and Boston University

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Abstract

In the thirty year period between 1960 and 1990 Japan saw labor productivity rise from a level of 27 percent of the U.S. to 87 percent of the U.S. This development miracle can be explained by an initial low capital stock and measured variations in TFP. These facts motivate our investigation into the sources of Japanese TFP variations. We consider Japanese and U.S. data that is filtered to retain medium cycle events such as the productivity slow down in the 1970's. An investigation of Japanese medium cycles reveals an important role for the diffusion of usable ideas from the U.S. to Japan. U.S. R&D leads Japanese TFP by four years and accounts for as much as 60% of the variation in medium term cycle Japanese TFP. Japanese R&D, in contrast, is coincident with Japanese TFP. Simulations designed to isolate the roles of Japanese and U.S. R&D finds that the diffusion of knowledge from the U.S. is a key driver of Japanese medium cycles.

1 Introduction

In the thirty year period between 1960 and 1990 Japan experienced very rapid gains in productivity. Labor productivity increased from a level of 27 percent of the US in 1960 to 87 percent of the U.S. in 1990. Productivity gains of this magnitude over such a short period are unusual and have led Parente and Prescott (1994) to refer to Japan's experience as a development miracle. What explains Japan's development miracle? Recent research has focused on two factors: technology diffusion and capital deepening.

A firm's knowledge about the best technique for combining capital and labor to produce a good is now widely thought to be an international public good. Over time this proprietary knowledge diffuses to a firm's competitors within the same country as well as producers in other countries. Recent research by Eaton and Kortum (1999), Howitt (2000), Klenow and Rodriguez (2004) and Parente and Prescott (2004) posit models in which country incomes eventually grow at the same rate. A country's relative income level is determined by factors such as government policies, investment and human capital. From the perspective of these models Japan's development miracle occurred because it was successful in adopting and/or creating frontier production technologies.

Formal hypotheses for Japan's development miracle have been offered by Parente and Prescott (1994) and Eaton and Kortum (1997). Parente and Prescott (1994) emphasize the role of barriers that limit firms' incentives to adopt technology and Japan's development miracle is attributed to a lowering of the barriers of adoption after the end of World War II. Eaton and Kortum (1997) focus instead on the processes of innovation and diffusion of ideas. They assume that the U.S. at the end of the World War II has a large stock of ideas relative to Japan and other countries and use patent data and country productivity data to parameterize their model in a way that reproduces the rate of convergence of relative income levels and the size of the remaining differences at the end of their sample.

Both models have the property that convergence is monotonic and smooth. In pratice, convergence has not been smooth. Japanese TFP grew at an annualize rate of 7.2% between 1960-1973, then fell to 2.2% between 1973-1983 before picking to 3.6% between 1973-1991 and finally fell again to 0.5% between 1991-2000. It is our contention that analyzing these variations in TFP growth and the comovements in other macroeconomic variables contains valuable information for identifying the sources of Japan's development miracle.

Our work builds on recent work by Hayashi and Prescott (2002) and Chen, Imrohoroglu and Imrohoroglu (2005). Hayashi and Prescott (2002) find that a neoclassical growth model with changes in the work week and slower growth in TFP accounts for Japan's lost decade. Chen et al. (2005) show that one can account for the variations in savings rates in Japan between 1960 and 2000 using the neoclassical growth model with exogenous labor, an initially low capital stock and measured variation in Solow's residual. We consider a similar model with endogenous labor supply and show that the same two factors account for the principal movements in GNP, investment, consumption, hours and the capital output ratio.

We next turn to analyze the source of variations in Japanese TFP over the 1960 - 2002 sample period. Comin and Gertler (2003) suggest that the medium cycle component of filtered data offers useful information for understanding the diffusion of ideas within the United States. This filter removes the trend but retains medium cycle information such as the productivity slow down in the 1970's.[1] When we filter Japanese data to remove all fluctuations with duration of more than 40 years, the resulting medium cycle components exhibit a distinctive pattern of co-movements that show strong evidence of technology diffusion from the US to Japan. Empirical evidence based on cross-correlations indicates that US R&D leads Japanese TFP by four years whereas Japanese R&D is coincident with Japanese TFP. Granger Causality tests indicate that US R&D Granger Causes Japanese TFP even after controlling for the effects of Japanese R&D. And a decomposition of the variance of medium cycle Japanese TFP suggests that US R&D accounts for a much larger fraction of the variance in Japanese TFP than Japanese R&D.

We also investigate whether patterns in other medium cycle filtered data are consistent with our hypothesis that diffusion of usable knowledge from the U.S. to Japan is an important determinant of Japanese TFP. In particular research by Eaton and Kortum (1999) posits a temporal relationship between the arrival of ideas, the patenting decision and the embodiment of these ideas in technology at home and abroad. We find that domestic R&D Granger Causes patent applications in both Japan and the United States. Moreover, as one would expect under our diffusion hypothesis, U.S. R&D Granger Causes Japanese patents.

Finally, we use the model to assess the quantitative role of technology diffusion from the US to Japan for other variables. If technology diffusion from the U.S. is an important determinant of Japanese TFP and Japanese TFP is an important determinant of Japanese economic activity, then current values of US R&D should predict future movements in Japanese economic activity. We use model simulations to assess this hypothesis versus an alternative hypothesis that assigns a primary role to the diffusion of Japanese R&D. The simulation results confirm the key role played by the diffusion of knowledge from the U.S. Current values of US R&D are important determinants of future Japanese medium cycle output, consumption, the capital output ratio and investment. The simulations are also consistent with the hypothesis that the focus of Japanese R&D has been on activities that require shorter gestation lags such as imitation or development as emphasized in Rosenberg and Steinmueller (1988). Specifications that assume that Japanese R&D gets reflected TFP in one or two years can also account for important aspects of medium cycle data. However, as the lag of diffusion is increased the explanatory power of Japanese R&D for Japanese medium cycle deteriorates.

Our finding that the diffusion of technology from the U.S. to Japan is an

[1] Klenow and Rodriguez (2004) present evidence that the productivity slowdown in the 1970's was a global phenomenon and use this fact to argue that there are important knowledge spillovers across countries.

important determinant of Japanese TFP is consistent with other results in the literature. Eaton and Kortum (1996) decompose Japanese growth in labor productivity into domestic and foreign R&D components and find that 27% of Japanese productivity growth is due to domestic R&D and 62% is due to U.S. R&D. Bernstein and Mohnen (1998), estimate R&D spillovers between the U.S. and Japan using growth accounting methods applied to R&D intensive industries. They find no evidence of spillovers from Japan to the U.S. but find that 46% of Japanese TFP growth is due to spillovers from U.S. R&D capital. Finally, Branstetter and Ug (2004) in an analysis of microeconomic firm level data find evidence of spillovers from scientific ideas that orginate in U.S. universities to Japanese R&D. Our results are also broadly consistent Keller (2002), Okada(1999) and Branstetter and Ug (2004). Keller (2002) considers a partial equilibrium model and finds that international R&D from the G5 countries accounts for 90% of R&D's total contribution to TFP growth in 9 other OECD countries. Okada(1999) performs an empirical analysis that decomposes growth for a panel of countries into two components capital deepening and technology transfer and finds that technology diffusion from the leader has a large effect on middle income countries. Our results suggest that knowledge spillovers from the U.S. are very important for high income countries too.

The remainder of the paper is as follows. Section 2 describes our model. Section 3 documents the important role of variations in TFP in accounting for Japanese GNP, investment and the capital output ratio. Section 4 conducts an empirical analysis and establishes that the important role of US R&D account for Japanese TFP medium cycle fluctuations. Section 5 uses the model to measure the contribution of US R&D in accounting for Japanese medium cycle facts. Section 6 contains our concluding remarks.

2 The Model

The representative household maximizes:

$$U = \sum_{t=0}^{\infty} \beta^t N_t \left(\ln \frac{C_t}{N_t} + \alpha \ln(T - \frac{H_t}{N_t}) \right) \ , \tag{1}$$

where β is a discount factor, N_t is the number of working-age members of the household , C_t is total consumption of the household , T is time endowment per working-age person, H_t is total hours worked by all working-age members of the household.

The period budget constraint of the representative household is given by:

$$(1+\tau_c)C_t + X_t = (1-\tau_w)w_t H_t + r_t K_t - \tau_k(r_t - \delta)K_t \tag{2}$$

where

$$K_{t+1} = (1-\delta)K_t + X_t \ . \tag{3}$$

Here, K_t is capital stock, X_t is investment, w_t is a wage rate, r_t is the return on capital, τ_c is the tax rate of consumption, τ_w is the tax rate of labor income, τ_k is the tax rate of capital income, and δ is the depreciation rate of capital.

The aggregate resource constraint is given by:

$$C_t + X_t + G_t = Y_t \ , \tag{4}$$

where

$$G_t = \psi_t Y_t \ . \tag{5}$$

Here, G_t is government purchases, Y_t is output, and ψ_t is the output share of government purchases.

The production technology is given by:

$$Y_t = A_t K_t^{\theta} H_t^{1-\theta} \ , \tag{6}$$

where A_t is TFP.

2.1 Household Optimization

The household's optimization problem is to maximize U in Eq.(1), subject to the budget constraint in Eq.(2). We assume no uncertainty. Since all working-age members of the household know that the number of working-age members increases at the exogenous rate $\gamma_{n,t} = \frac{N_t}{N_{t-1}}$, the maximization problem can be written as follows (by normalizing N_0 as $N_0 = 1$) :

$$Max \sum_{t=0}^{\infty} \left[\beta^t (\prod_{s=0}^{t} \gamma_{n,s}) \left(\ln c_t + \alpha \ln (T - h_t) \right) \right]$$

subject to

$$(1+\tau_c)c_t + \gamma_{n,t+1} k_{t+1} - k_t = (1-\tau_w) w_t h_t + (1-\tau_k)(r_t - \delta) k_t \ \ , \tag{7}$$

where $c_t = \frac{C_t}{N_t}$, $k_t = \frac{K_t}{N_t}$, $h_t = \frac{H_t}{N_t}$ and $\gamma_{n,0} = 1$. The present value Hamiltonian can be set up as:

$$\begin{aligned} H \ &= \ \beta^t (\prod_{s=0}^{t} \gamma_{n,s}) \left(\ln c_t + \alpha \ln (T - h_t) \right) \\ &\quad + \lambda_{t+1} \left[\frac{(1-\tau_w) w_t h_t + (1-\tau_k)(r_t - \delta) k_t - (1+\tau_c) c_t + k_t}{\gamma_{n,t+1}} - k_t \right] \end{aligned} \tag{8}$$

where the expression in [ ] equals $k_{t+1} - k_t$ and λ_{t+1} is Hamiltonian multiplier.

The first order conditions are given by:

$$\frac{\partial H}{\partial c_t} = \beta^t (\prod_{s=0}^{t} \gamma_{n,s}) \frac{1}{c_t} - \frac{\lambda_{t+1}(1+\tau_c)}{\gamma_{n,t+1}} = 0 \ , \tag{9}$$

$$\frac{\partial H}{\partial h_t} = -\frac{\alpha \beta^t \prod_{s=0}^{t} \gamma_{n,s}}{T - h_t} + \frac{\lambda_{t+1}(1-\tau_w) w_t}{\gamma_{n,t+1}} = 0 \ , \tag{10}$$

$$\frac{\partial H}{\partial k_t} = \frac{\lambda_{t+1}}{\gamma_{n,t+1}} \left[1 + (1-\tau_k)(r_t - \delta)\right] - \lambda_{t+1} = -(\lambda_{t+1} - \lambda_t) \ . \tag{11}$$

From Eq.(9), we can get

$$\beta^{t-1} (\prod_{s=0}^{t-1} \gamma_{n,s}) \frac{1}{c_{t-1}} - \frac{\lambda_t (1+\tau_c)}{\gamma_{n,t}} = 0 \ . \tag{9'}$$

Substituting Eq.(9') into Eq.(11) for λ_t and Eq.(9) into Eq.(11) for λ_{t+1} yields:

$$\frac{\beta^{t-1} (\prod_{s=0}^{t-1} \gamma_{n,s}) \ \gamma_{n,t}}{c_{t-1}(1+\tau_c)} = \frac{\beta^t (\prod_{s=0}^{t} \gamma_{n,s})}{c_t (1+\tau_c)} \left[1 + (1-\tau_k)(r_t - \delta)\right] \ .$$

Simplifying the above expression yields:

$$\frac{c_t}{c_{t-1}} = \beta \left[1 + (1-\tau_k)(r_t - \delta)\right] \ . \tag{12}$$

Next, substituting Eq.(10) into Eq.(9) for $\frac{\lambda_{t+1}}{\gamma_{n,t+1}}$ yields:

$$\frac{\alpha (1+\tau_c)}{T - h_t} c_t = (1-\tau_w) w_t \ . \tag{13}$$

2.2 Firm Optimization

Firms are perfectly competitive and rent capital and labor in competitive factor markets. Assuming no adjustment cost, the representative firm's profit optimization problem becomes a static one and the usual equation between a marginal product and a factor price gives:

$$r_t = \theta A_t k_t^{\theta-1} h_t^{1-\theta} \ , \tag{14}$$

$$w_t = (1-\theta) A_t k_t^{\theta} h_t^{-\theta} \ . \tag{15}$$

2.3 Equilibrium Conditions for the Economy

Above all, the equilibrium conditions for the economy are given by the following equations:

$$\frac{c_t}{c_{t-1}} = \beta \left[1 + (1-\tau_k)(r_t - \delta)\right] \ , \tag{12}$$

$$\frac{\alpha(1+\tau_c)}{T-h_t} c_t = (1-\tau_w) w_t \ , \tag{13}$$

$$(1+\tau_c)c_t + \gamma_{n,t+1} k_{t+1} - k_t = (1-\tau_w) w_t h_t + (1-\tau_k)(r_t - \delta) k_t \ , \tag{7}$$

$$r_t = \theta A_t k_t^{\theta-1} h_t^{1-\theta} \ , \tag{14}$$

$$w_t = (1-\theta) A_t k_t^{\theta} h_t^{-\theta} \ , \tag{15}$$

$$c_t + \gamma_{n,t+1} k_{t+1} - (1-\delta) k_t + \psi_t y_t = y_t \ . \tag{16}$$

Next, by letting $Z_t = A_t^{\frac{1}{1-\theta}}$, we transform variables in the following way:$\widetilde{c}_t = c_t/Z_t$, $\widetilde{k}_t = k_t/Z_t$, $\widetilde{y}_t = y_y/Z_t$, $\widetilde{w}_t = w_t/Z_t$. Then, by letting $\gamma_{z,t} = \frac{Z_t}{Z_{t-1}}$, the above equilibrium conditions can be rewritten as:

$$\frac{\widetilde{c}_t}{\widetilde{c}_{t-1}} \gamma_{z,t} = \beta \left[1 + (1-\tau_k)(r_t - \delta)\right] \tag{17}$$

$$\frac{\alpha(1+\tau_c)}{T-h_t} \widetilde{c}_t = (1-\tau_w) \widetilde{w}_t \tag{18}$$

$$(1+\tau_c)\widetilde{c}_t + \gamma_{n,t+1}\gamma_{z,t+1} \widetilde{k}_{t+1} - \widetilde{k}_t = (1-\tau_w) \widetilde{w}_t h_t + (1-\tau_k)(r_t - \delta) \widetilde{k}_t \tag{19}$$

$$r_t = \theta \widetilde{k}_t^{\theta-1} h_t^{1-\theta} \tag{20}$$

$$\widetilde{w}_t = (1-\theta) \widetilde{k}_t^{\theta} h_t^{-\theta} \tag{21}$$

$$\widetilde{c}_t + \gamma_{n,t+1}\gamma_{z,t+1} \widetilde{k}_{t+1} - (1-\delta) \widetilde{k}_t + \psi_t \widetilde{y}_t = \widetilde{y}_t \ . \tag{22}$$

2.4 Steady State

Using Eqs.(17)-(22), and letting $\widetilde{c}_t = \widetilde{c}_{t+1} = \widetilde{c}$, $\widetilde{k}_t = \widetilde{k}_{t+1} = \widetilde{k}$, $\widetilde{r}_t = \widetilde{r}_{t+1} = \widetilde{r}$, $\widetilde{w}_t = \widetilde{w}_{t+1} = \widetilde{w}$, $\widetilde{y}_t = \widetilde{y}_{t+1} = \widetilde{y}$, $\widetilde{\gamma}_{n,t} = \widetilde{\gamma}_{n,t+1} = \widetilde{\gamma}_n$ and $\widetilde{\gamma}_{z,t} = \widetilde{\gamma}_{z,t+1} = \widetilde{\gamma}_z$, we can get the following set of equations:

$$\gamma_z = \beta \left[1 + (1-\tau_k)(\theta \widetilde{k}^{\theta-1} h^{1-\theta} - \delta) \right] \quad , \tag{23}$$

$$\frac{\alpha(1+\tau_c)}{T-h} \widetilde{c} = (1-\tau_w)(1-\theta)\widetilde{k}^{\theta} h^{-\theta} \ , \tag{24}$$

$$\widetilde{c} + [\gamma_n \gamma_z - (1-\delta)]\widetilde{k} = (1-\psi)\widetilde{k}^{\theta} h^{1-\theta} \ . \tag{25}$$

Eqs.(23)-(25) show the restrictions applied in the steady state.

3 Calibration and Baseline Simulation Results

The calibration of our model is reported in Table 1. Most of the parameters are calibrated in the same way as Hayashi and Prescott (2002) using data from 1984-2001. This includes β, the preference discount parameter, the capital share parameter, θ, the depreciation rate on capital, δ, and the capital tax rate, τ. Our preference specification, however, is different from Hayashi and Prescott (2002). So the leisure weight in preferences is calibrated using equation (13). We use Japanese data on consumption, capital and hours running from 1984-2001 that is constructed using the same methodology as Hayashi and Prescott (2002).[2] We solve the model using a shooting algorithm. This algorithm requires one to posit the time paths of all exogenous variables. In our case this includes, the growth rate of TFP, the population growth rate and the share of government purchases in output. We make the following assumptions about these variables. The population growth rate is assumed to be zero after 2001 and TFP is assumed to grow at its average rate for the 1990-2000 in future years. The share of government purchases is also set at the average of its 1990-2000 values for all periods beyond 2001.

Chen et al. (2005) conduct perfect foresight simulations using a similar model except that labor input is exogenous. They condition on actual Japanese TFP data and assume a low initial value of the capital stock. Under these assumptions their model does a good job of accounting for movements in the Japanese Saving rate between 1960 and 2000. Consider Figure 1, which reports results for our model with endogenous labor and Japanese data for the 1961 -2001 sample period. The initial capital stock is set to 21% of its steady-state value. This choice reproduces the investment share of output in Japanese data in 1961. Our model also does a very good job of matching the Japanese national saving rate data. Notice also that the model reproduces the patterns

[2] The wage rate is measured using the marginal product pricing relationship with a capital share of 0.363.

on GNP, consumption, investment and the capital output ratio. The biggest gap between the model's predictions and Japanese data lie in its implications for labor input. Most notably the model does not produce the increase in (mostly female) participation that we see in Japanese data. The model also does not reproduce the steady increase in consumption's share of output from 0.57 in 1990 to nearly 0.64 in 2001. The conclusion that we draw from Figure 1 is that one can account for the principal economic events in Japan between 1961-2001 using standard economy theory. As emphasized in Chen et. al. (2005) both a low initial capital stock and measured variations in TFP are both important in producing this result.

It is useful to compare these results with those of Parente and Prescott (1994) and Eaton and Kortum (1997). Both Parente and Prescott (1994) and Eaton and Kortum (1997) consider models where the growth rate of productivity in the U.S. and Japan are eventually equal. To account for their different experiences in the post WWII period they posit big initial differerences in the level of productivity between the U.S. and Japan. Parente and Prescott (1994) combine a low initial capital stock with three other ingredients, an endogenous decision by firms on whether to update technology, a capital share of 0.55 and time variation in the barriers to adoption. The barriers to adoption are low in the 1960-1973 sub-sample and then increase for the 1975-1988 sub-sample. Increasing the tax barries to adoption after 1973 slows the rate at which firms choose to update their technology and thus accounts for the productivity slowdown in Japan that occurs in the post 1973 sub-sample. With this specification Parente and Prescott (1994) account for the speed of convergence of Japan's output to the U.S. and also the relative levels of output in Japan and the U.S. at the end of their sample. Eaton and Kortum (1997) ssume that the U.S. had a relatively big stock of usable knowledge at the end of WWII. They then parameterize rates of arrival and diffusion of ideas for different countries to data on patents and productivity and find that their theory can reproduce the timing of convergence of labor productivity in Japan, France, Germany and the U.K. and also the relative levels at country labor productivities at the end of the sample.

Our results demonstrate that standard theory in conjunction with a low initial capital stock plus the measured variation in *exogenous* TFP can also account for the speed of convergence and the output levels facts in Japan. Moreover, standard theory also reproduces other implications absent from this other research. In both Parente and Prescott (1994) and Eaton and Kortum (1997) Japan's relative income converges in a smooth monotonic way towards the level of the U.S. Figure 1 shows that there are some significant bumps in TFP along the way. During our sample period TFP has shown two periods of rapid growth and two periods of slow growth. Our simulations also reproduce the comovements among consumption, output, investment and the capital output ratio to these bumps. We think that a fruitful way to search for explanations of Japan's growth miracle is to ask what is producing the bumps in Japanese TFP?

We now turn to undertake an empirical investigation into the sources of variation in Japanese TFP.

4 Data facts

The basic data source for our Japanese annual dataset is Hayashi and Prescott (2002). The data are updated to 2002 based on the corresponding series in Annual report on National Account 2004, obtainable from the web-site of Economic and Social Research Institute. For the data set of Hayashi and Prescott (2002) are 68SNA base series and current SNA series released from the institute are of 93 SNA base, we extend the former series using the annual changes of the latter.

Our decision about what data facts to analyze is motivated by the fact that although Japanese TFP growth rates have declined over time, these declines have not been monotonic. During the 1960s TFP growth was high, but TFP growth slowed in the 1970s and early 1980s .Then TFP growth picked up again in the 1980s before slowing again in the 1990s (see e.g. Hayashi and Prescott (2002)). These swings in TFP growth have also been associated with movements in other macroeconomic variables as documented above in a way that accords well with standard theory. We think that by analzying these swings in TFP we can uncover information that is useful in understanding Japan's growth miracle. For this reason we choose to follow the example of Comin and Gertler (2003) and filter the data in a way that retains medium cycle content. The medium cycle filter retains cycles with duration of 40 years or less. This filter thus removes a trend component but retains the ups and downs in Japanese TFP that we think is valuable for understanding the sources of Japanese TFP variation. In an analysis of U.S. data Comin and Gertler (2003) have found that medium term cycles are large and exhibit a distinctive pattern of co-movements. We next demonstrate that Japanese data filtered in this way also exhibits a distinctive pattern of co-movements and that these co-movements provide valuable information about the sources of variation in Japanese TFP.

We decompose Japanese data into a trend and cycle component. The medium term cycle component includes all frequencies 40 years or less and the trend component includes frequencies longer than 40 years. In some of the analysis below we will further decompose the medium term cycle data into two further components a medium *frequency* component and a *high* frequency component. The medium frequency component includes frequencies between 8 and 40 years while the high frequency component includes frequencies between 2 and 8 years. The high frequency component corresponds to the conventional definition of business cycle frequencies.

When filtering the data we first take natural logaritms of the data and then use the Christiano-Fitzgerald (2003) band pass filter to decompose the data. To construct an optimal band pass filter one needs to know the time series representation of the raw data. Christiano and Fitzgerald (2003) argue that a random walk filter approximation, which assumes that the data generating process is a random walk, is nearly optimal for most US macroeconomic time-series. Since the focus of this paper is on medium cycle we don't report information on the trend components of Japanese data. However, it may be helpful to the reader to briefly describe what is retained in the trend component for Japanese GNP.

The trend component for Japanese GNP closely resembles a deterministic trend line with a break in the mid 1970s.

We will focus on lead/lag relationships as measured by cross-correlations and Granger Causality tests in our empirical analysis of medium cycle data. Theories of technology diffusion imply a particular pattern of dynamic relationships between variables that measure resources devoted to producing ideas and variables that measure their application in production. This simple approach provides considerable discrminatory power among alternative theories in medium cycle data.

4.1 Facts about the Japanese medium cycle

Japanese data exhibit large and distinctive medium cycle fluctuations. Table 2 shows that the standard deviation of the medium term cycle component of Japanese GNP is 4.5 times as large as the standard deviation of its high frequency component. Much of this variation is concentrated at medium term frequencies as illustrated by the fact that the medium term frequency component of GNP is 4.4 times as large as the high frequency component. Consumption, capital, TFP and investment exhibit similar patterns.

It is well known that GNP and TFP have a similar pattern at business cycle frequencies. This is also true for medium term cycle data. Consider Figure 2 which shows a plot of Japanese medium term cycle GNP and TFP. Both time series exhibit fluctuations of the same magnitude. The peaks and troughs of both variables coincide and their overall pattern is remarkably similar with the exception of the period between 1960 to 1962. Notice also that the peaks and troughs are also readily associated with important economic events like the oil price shocks in 1973 and 1978, the Japanese bubble period from 1984 to 1990 and the lost decade. In fact, the co-movements between GNP and TFP are even stronger in medium term cycle data than in high frequency data. Table 3 reports that the correlation between the medium term cycle component of these two variables is 0.95 and the correlation between the high frequency component is 0.88.

One variable that figures prominently in models with endogenous TFP is R&D (see e.g.Jones (1995) or Klenow and Rodriguez (2004)) Comin and Gertler (2003) find that US medium term cycle R&D leads U.S. GNP. This fact motivates their endogenous growth model. In their model demand shocks induce investment in R&D which over time produces ideas that improve TFP and thus raise GNP. In Japanese data GNP and R&D are highly correlated but coincident. Consider Figure 3 which shows the cross-correlation functions of R&D with GNP and TFP using medium cycle filtered and high frequency filtered Japanese data. The cross-correlation function of medium cycle R&D and GNP reaches its peak of 0.71 at zero and then falls sharply as one moves in either direction away from zero. The cross-correlation function of medium cycle R&D and TFP exhibits the same pattern. On the basis of cross-correlations there is no evidence that R&D leads either GNP or TFP in medium term cycle Japanese data. In Japanese high frequency data the peak cross-correlations of

R&D with GNP and TFP are much lower but there is again no evidence that Japanese R&D leads either GNP or TFP.

Another way to assess the temporal relationship between Japanese R&D and GNP and TFP is to conduct Granger Causality tests. These tests provide information on whether Japanese R&D provides any additional predictive content beyond that in the own lags of GNP or TFP. We regressed respectively Japanese medium term cycle GNP and TFP its own lags and lags of Japanese R&D using alternatively one, two, three or four lags and test the null hypothesis that the coefficients on R&D are jointly zero. Table 4 shows, that there is no evidence that Japanese medium term R&D Granger causes (GC) Japanese medium term GNP. Similarly, tests of Granger Causality based on bivariate VAR's with and Japanese R&D and TFP also show no evidence that Japanese R&D Granger causes Japanese TFP when the number of lags ranges from one to four.

R&D may still be an important source of fluctuations in medium term cycle GNP and/ or TFP even though R&D does not lead or Granger Cause either of these two variables. We explore this possibility be calculating variance decompositions of the two VAR's described above. In the case of the VAR using one lag with R&D and GNP (see Table 4), if GNP is ordered first R&D accounts for only 9% of the variance in GNP at a 10 year horizon. If R&D is ordered first it accounts for 72% of the variance in GNP at the same horizon. For the VAR using one lag with TFP and R&D (see Table 6) when TFP is ordered first R&D accounts for 0.3% of the variance in TFP. With the other ordering R&D accounts for 44% of the variance in TFP.

A number of theories of diffusion start from the premise that investment in R&D produces a flow of usable ideas and that usable ideas get patented and embedded in technology. It is interesting to see how Japanese patents are related to Japanese R&D and TFP. Patents are an alternative indicator of the flow of ideas and one would expect on a priori grounds that patents would lag R&D in a closed economy. Our measure of Japanese patents consists of applications for patents, utility models and designs. One distinctive feature of Japanese patent law is that all information related to the patent application is released to the public within 18 months after the patent application is filed. Over much of our sample companies were given a formal opportunity to submit an objection before the patent is granted. In addition, in Japan the patent is awarded to the first to apply for the patent. During our sample period there have been two major changes in Japanese patent law. In 1988 Japanese patent law was changed to in response to foreign pressure limit patent flooding a practice in which local companies would file patents for small derivative ideas around major innovations. Prior to 1988 one patent was awarded for each idea after this change it became easier to patent a process. Then in 1993-4 Japan negotiated trade agreements with the U.S. and other countries that harmonized patent regulations.

Figure 4 reports plots of medium cycle Japanese patent along with Japanese R&D and TFP. From this figure we can see that each of these two changes were followed by declines in medium cycle patents. Another interesting feature of this chart is that medium cycle Japanese patents show a recovery from 1995 on.

This is about the same time that U.S. patents started to rise (see e.g. Kortum and Lerner (1988)). The last thing to note about Figure 4 is that while, on the one hand, movements in Japanese TFP and R&D are coincident and track each other very closely patents look quite different. On the basis of a visual inspection it is difficult to tell whether patents lead or lag these other two variables and patents exhibit fluctuations that are indepenent of movements in TFP and/or R&D.

A formal statistical analysis also reveals contradictory evidence about the dynamic relationship between Japanese patents and R&D and TFP. Cross-correlations of Japanese R&D with Japanese patents reported in Figure 3 are s-shaped but show a peak positive correlation of 0.5 between current R&D and the fifth lag of patent applications. Granger Causality tests reported in Table 4, though indicate that Japanese R&D leads Japanese patents when the number of lags is one or two. However, Japanese Patents Granger Cause Japanese R&D at the 10% level when the number of lags is increased to three or four. Results for TFP and Japanese patents is also mixed. On the one hand, cross-correlations suggest that Japanese patents lead Japanese TFP by 5 periods. On the other hand, Granger Causality tests indicate that TFP Granger Causes Japanese patents when the number of lags is one, two or three. Finally, Japanese patents also Granger Cause Japanese TFP at the 10% significance level when the number of lags is 3 or 4. We interpert these emprical results as suggesting that the dynamic relation between Japanese patents and R&D and TFP is consistent with two distinct theories. On the one hand, the evidence supports the notion that Japanese patents are indeed the product of Japanese R&D.and thus lag the medium cycle. The results though do not rule out the possibility that Japanese patents lead both Japanese R&D and TFP. In this later scenario though one is left to wonder what resources are used to produce patents. We present evidence below that suggests Japanese Patent applications, at least partially, reflect the results of U.S. R&D.

4.2 Comparison of Japanese and U.S. medium term TFP

Consider Figure 5 which plots the medium term cycle component of Japanese and U.S. TFP. Details on the calculation of TFP for each country is reported in the Data Appendix. There are two noteworthy features about Figure 4. First, the general patterns of medium term cycle Japanese TFP and U.S. TFP are remarkably similar. TFP in both countries increases in the 1960's, declines during the 1970's and increases again in the 1980's. Second, TFP in Japan appears to lag US TFP.

More concrete evidence about this second point is found by inspecting the cross-correlation function of Japanese and US TFP reported in Figure 6-1. The peak cross-correlation occurs when current period Japanese TFP is correlated with period t-1 US TFP and the value of the correlation is 0.83. The cross-correlations then fall monotonically as one moves in either direction. Figure 6-2 also reports the cross-correlation function of US R&D with US TFP. US R&D leads US TFP by three years and the peak correlation is 0.59. Next consider the cross-correlation function of US R&D and Japanese TFP. This figure shows that US R&D leads Japanese TFP by 4 years. Surprisingly, Japanese medium term cycle TFP is more highly correlated with US R&D than Japanese R&D with a peak correlation of 0.73. Finally, consider the cross-correlation of US R&D and Japanese R&D reported in Figure 6-4. US R&D also leads Japanese R&D by about four years and the peak correlation is 0.74. These results are consistent with other results reported in Coe and Helpman (1995), Eaton and Kortum (1999) and Keller (2004) who find a significant role of technology adopted from foreign countries in accounting for domestic TFP.

Next we consider evidence on the joint relationship between U.S. R&D, Japanese R&D and Japanese TFP. Table 7 reports Granger Causality tests in which Japanese TFP is regressed on its own lags and lagged values of Japanese and U.S. R&D. As Table 7 shows, the Ganger causality tests show lots of evidence that US R&D Granger causes Japanese TFP for VAR's at all lag lengths. However, we fail to reject the null hypothesis of that Japanese R&D does *not* Granger cause Japanese TFP with one, two, three and four lags.

Table 8 reports the results of variance decompositions of Japanese TFP. When Japanese TFP is ordered first, Japanese R&D is ordered second and US R&D is ordered third we find that US R&D explains substantially more of the variance of medium term cycle Japanese TFP than Japanese R&D. This choice of ordering is conservative in that it assigns less weight to US R&D than orderings in which it appears first or second. For a specification with one lag US R&D explains 31% of the variance of Japanese TFP whereas Japanese R&D only explains 10% at the 10 year horizon. If the number of lags in the VAR is increased to three the fraction of Japanese TFP explained by US R&D rises to 61% and the fraction explained by Japanese R&D is 9%. Taken together this evidence suggests that diffusion of U.S. R&D is much more important for understanding Japanese TFP than Japanese R&D.

We also investigated comovements of U.S. patent applications with U.S. and Japanese R&D and TFP. One objective is to ascertain whether U.S. patent applications lag U.S. R&D in medium cycle filtered data. One would expect this to be the case if the U.S. had a technological advantage relative to the rest of the world during most of our sample period as posited in e.g. Eaton and Kortum (1997). The data is very consistent with this view. U.S. patents lag U.S. R&D by five years and are Granger Caused by U.S. R&D when the number of lags is one, two three and four. U.S patent applications also lag U.S. TFP by 2-3 years and are Granger Caused by U.S. TFP. Moreover, there is no evidence that U.S. patents Granger Cause either U.S R&D or TFP. We find it noteworthy that U.S. patent applications lag the medium cycle. It suggests that the strategic incentive to delay the disclosure of innovations emphasized in e.g. Hopenhayn and Squintani (2005) is large in the U.S. According to our results companies are waiting to apply for patents until after the idea gets reflected in TFP.[3] We also investigated the dynamic relationship between U.S. patents and

[3] In the U.S. regulations restrict the right to apply for a patent for an ideas to a grace period of one year from the date that the invention has been sold or described in a publication.

Japanese TFP and found that U.S. patent applications lag Japanese TFP by one year. On the basis of this evidence we conclude that although U.S. patents are consistent with the view that they are produced primarily by U.S. R&D the gestation lags are sufficiently long that U.S. patents are not a good leading indicator of either the U.S. or Japanese medium cycle.

Above we described two distinct hypotheses for the empirical patterns in Japanese patents. One possibility that we pursue further here is that Japanese patents partially reflect ideas that are produced by U.S. R&D. Table 9 provides some further evidence in favor of this possibility. In this table we conduct Granger Causality tests using regressions with three variables , Japanese patents, Japanese TFP and US R&D. Observe that for all choices of lag length US R&D Granger Causes Japanese patents but that Japanese patents fail to Granger Cause U.S. R&D. This evidence suggests that Japanese patent data may partially reflect diffusion of usable knowledge from the U.S. to Japan. Notice finally that Japanese patents continue to Granger Cause Japanese TFP when the number of lags is three or four.

The results from this empirical analysis are provocative. On the one hand, Japanese R&D is highly correlated with Japanese TFP but does not lead Japanese TFP as one would expect if Japanese R&D was the principal source of usable knowledge in Japan and the diffusion time of domestic knowledge was three to five years. On the other hand, U.S. R&D does appear to diffuse domestically over a three to five year horizon as measured by comovements with U.S. GNP and patent applications. In addition U.S. R&D accounts for a substantial fraction of Japanese medium cycle TFP fluctuations and leads Japanese TFP by about 4 years. International diffusion of usable ideas at this rate is considerably faster than has been estimated in cross-sectional analyses such as Eaton and Kortum (1999) and appears to happen on average slightly before or perhaps at the same time that the producer of the idea applies for a patent The resource costs associated with acquiring U.S. knowledge also appear to be small. If they were large then presumably this would be reflected in the dynamics of Japanese R&D. This final finding resembles a previous finding by Klenow and Rodriguez (2004) who need a fraction of knowledge diffusion to be costless in order to account for cross-sectional differences in country incomes. If the diffusion of U.S. usable knowledge is a principal driver of the Japanese medium cycle then we would expect that lagged values of U.S. R&D would account for comovements between Japanese TFP and other macro aggregates. In the next section we investigate this hypothesis by conducting more simulations.

5 Assessing the roles of U.S. and Japanese R&D for Japanese Medium Cycles

In Section 3 we found that the growth model with a low initial capital stock and measured variations in Japanese TFP accounts for the principal movements in GNP, investment, consumption and the capital output ratio in Japanese data.

The results from Section 3 suggest two things. First, that there is a lot of information in medium term cycle data and second, that this information suggests that technology diffusion from the US to Japan accounts for a substantial fraction of Japanese TFP movements. We now use our model to assess the role of Japanese R&D and the diffusion of US R&D for medium cycle fluctuations in Japanese economic activity. If R&D is a significant determinant of Japanese TFP then we should find that a specification that isolates the role of R&D should account for medium term fluctuations in other Japanese macroeconomic variables too. In addition, if technology diffusion from US R&D is important then previous levels of US R&D should help account for contemporaneous movements in Japanese macroeconomic variables too. Investigating how the explanatory power of these two variables changes as the forecasting lags are increased provides further evidence about diffusion and also says something about the nature of the R&D activities. Presumably R&D investments that are focused on creating new inventions require longer gestation lags than R&D investments that are targetted more narrowly on imitation and/or development of more established business ideas.

In order to investigate the roles of Japanese and US R&D we need a way to isolate the effects of these variables on Japanese TFP. The effects of Japanese R&D and medium term fluctuations in economic activity are isolated and assessed in the following way. First, decompose Japanese TFP and Japanese R&D into trend and medium cycle components in the way described in Section 3. Next project the medium cycle component of Japanese TFP on four lags of Japanese medium cycle R&D and four lags of U.S. medium cycle R&D. To isolate the effects of Japanese R&D zero out the coefficients on U.S. R&D and predict Japanese TFP using only the information in Japanese R&D. To isolate the effects of U.S R&D zero out the coefficients on Japanese R&D and predict Japanese TFP using only U.S. R&D. Take the predicted values of TFP constructed in this fashion and add them back together with the trend component of TFP. This constructed measure of TFP can now be used to simulate the model using the methodology described in Section 2. Finally, the simulated time-series are filtered using the medium cycle filter and summary statistics are tabulated. Table 10 reports simulation results on relative variabilities using medium term cycle filtered data. Consider first the simulation results labeled "baseline." These results are computed by applying the medium term cycle filter to the simulated data reported in Figure 1. The baseline model reproduces some of the principal features of Japanese medium cycle data. Investment is about twice as variable as output and consumption and hours are less variable than output. However, the model predicts considerably more variation in output than we see in Japanese data and understates the relative variability of the capital output ratio. Figure 7 reports plots of the model predictions and the corresponding Japanese medium cycle filtered Japanese data. As we can see from the figure the model captures the principal movements in the data of all variables. Model consumption is a bit more variable than consumption in the data but overall the fit is quite good. Table 11 reports contemporaneous correlations between model predicted values and actual data values of each timeseries

The correlations between the model and data medium cycle filtered time-series are above 0.9 for all variables except consumption where the correlation is 0.89 and hours where the correlation is negative. Although we don't dwell on this point here it suggests that the dynamics of Japanese labor input at medium cycle frequencies are quite different from their dynamics at business cycle frequencies. Labor input at medium cycle frequencies is actually countercyclical. The contemporaneous correlation between medium cycle GNP and hours is -0.18. Griliches and Mairesse (1988) in a comparative analysis of firm level TFP and R&D in Japan the U.S. found that Japanese technological improvements were labor saving. This is showing up in medium cycle filtered aggregate data too.

Next consider the results for simulations that attempt to isolate the contribution of Japanese R&D in Japanese TFP at medium cycle frequencies. Looking first at the results for relative volatilities observe that the specification with lags 1 through 4 of Japanese R&D is similar and somewhat better than the baseline model. The correlations of the predicted with actual data are in virtually all cases lower than for the baseline specification with all correlations less than or equal to 0.7 with the exception of consumption, which has a correlation of 0.86 with actual consumption data. In order to get an idea of the importance of timing we also report results in which only lags of Japanese R&D of 2-4, 3-4 and 4 are used to predict Japanese TFP. The general picture that emerges from these other runs is that most of the predictive power is in the first lag of Japanese R&D. The correlations in the specification with lags 2-4 are quite a bit lower. The correlation of model investment with investment in the data is only 0.55 and the correlation between the model and data capital output ratio is 0.47. Omitting successively lags 2 and 3 further reduces the quality of the fit.

One peculiar feature of the results is that the correlations of actual TFP with predicted TFP is negative for the Japanese specifications with lags of 3-4 and lag 4. Yet the model still produces a positive correlation between e.g. model output and output in the data. The reason for this is that the correlations reported in Table 11 also reflect other features of the model. In particular, the initial capital stock and variations in government purchases and population are also affecting the correlations. To measure the role of these other factors we report in the bottom row of Table 10 and 11 results for a simulation in which only the trend component of TFP is used. A comparison of these results with the lag 4 Japan R&D specification shows that the correlations are very similar indicating that the contribution of the fourth lag of Japanese R&D to medium cycle fluctuations is about zero.

Next consider the results in which US R&D is used to predict Japanese TFP. The US R&D specification with lags 1-4 does a better job of reproducing the relative variabilities of investment, the capital output ratio, consumption and hours than the Japanese R&D specification with lags 1 -4. Moreover, as we successively move to the specification with only the fourth lag there is no discernible deterioration in fit. In fact, the US R&D specification with only lags 4 appears to have the best overall match in terms of relative volatilities and also does quite well in terms of correlations with actuals as reported in Table 11. Moreover, a comparison of the results for the lag 4 US R&D specification with the TFP trend component specification indicates that there is a lot of information content in the fourth lag of U.S. R&D. The correlation of predicted with actual investment is 0.66 as compared to -0.32 and the correlations of model and data investment and output are also much stronger.

In Section 3 we found some evidence that Japanese Patents may lead the Japanese medium cycle. To assess this hypothesis we replaced Japanese R&D with Japanese patents and repeated the same simulations. Figure 8 shows a plot of the specification with the 4th lag only. For purposes of comparison we report the results for the US R&D specification with the 4th lag only in Figure 9. It is very clear from these figures that the information content in lagged values of Japanese patents for Japanese medium cycles is very small. We have performed other exercises, that are not reported here due to space considerations, including plotting predicted and actual TFP for alternative lag lengths and combinations of forecasts and the same conclusion emerges: neither Japanese R&D nor Japan patents are reliable predictors of Japanese TFP at horizons beyond 2 years.

Given the success of US R&D in accounting for Japanese medium cycle facts it is also interesting to consider the 1990's. According to Figure 9 the 1990's is not a puzzle for our theory. The decline in medium cycle TFP growth during the 1990's is due to declining medium term US R&D between 1985 and 1994.Jorgenson and Nomura(2004) provide evidence of a slowing in the rate of relative price declines for memory chips during this period. They also argue that from 1995 on technological progress in the semi-conductor industry rapidly accelerated and that Japanese TFP in the late 1990's is higher once one accounts for this acceleration. It is interesting that the timing of these events lines up surprisingly well with our theory. In Figure 7 the trough in Japanese medium cycle TFP occurs in 1999 exactly four years after the acceleration in TFP in the semi-conductor industry started.

6 Conclusion

This paper has documented an important role of diffusion of U.S. business knowledge to Japan. One can account for Japan's growth miracle by standard theory with the two factors emphasized in Chen at al. (2005): a low initial capital stock and measured variation in Solow's residual. Motivated by previous research by Comin and Gertler (2003) and Klenow and Rodriguez (2004) we filtered Japanese data in a way that removes the trend but retains cycles of length 40 years or less. Our analysis of Japanese and U.S. medium cycle data isolates a large and significant role for US R&D. Our model simulations with diffusion of knowledge from the U.S. to Japan reproduce the major swings in economic activity including both the rapid growth Japan experienced during the 1980s and the slow growth during the 1990s. This suggests that the role of domestic demand disturbances or other domestic shocks was small. This does not rule out the possibility that demand shocks in the U.S. were important sources of variation in U.S. R&D as posited by e.g. Com and Gertler (2003) and thus in turn important sources of medium cycle variation in Japan.

We are currently looking further into the mechanism(s) whereby Japan adopts US technology by collecting by analyzing the role of domestic R&D and foreign domestic investment in disaggregated data. In addition we are also working on developing a formal theory of Japanese TFP. Based on our analysis here a successfuly theory of Japanese TFP will have to assign a prominant role to knowledge spillovers from the U.S. We are particularly interested in understanding the role of domestic R&D. Movements in Japanese R&D are contemporaneously highly correlated with Japanese TFP and GNP. Perhaps this reflects a focus on development rather than innovation during our sample period. In our future research we plan to produce a quantitative theory that makes a formal distinction between research focused on innovation and research focused on imitation as in Jovanovic and Mac Donald (1994) and use it to analyze the role of research and development in Japan.

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Table 1: Model Calibration

β	δ	θ	τ^k	α
0.977	0.085	0.363	0.45	2.79

Table 2: Standard Deviations of Japanese Filtered Data

	Percentage Standard Deviations		
	Medium Term Cycle	Medium Frequency	High Frequency
GNP	5.53	5.40	1.22
Consumption	2.94	2.78	0.97
Investment	13.04	12.55	3.41
Total Hours Worked	2.32	2.07	0.95
Capital	7.07	7.05	1.56
R&D	9.39	9.00	2.68
TFP	6.86	6.57	1.89

Table 3: Correlation Between Filtered Japanese GNP and TFP

Corr(GNP$^{\mathrm{JPN}}$, TFP$^{\mathrm{JPN}}$)		
Medium Term Cycle	Medium Frequency	High Frequency
0.95	0.96	0.86

Table 4: Granger Causality (G.C.) Tests on Japanese Data

H0:	R&D does not G.C. GNP	R&D does not G.C. TFP	R&D does not G.C. patents	Patents do not G.C. R&D	TFP does not G.C. patents	Patents do not G.C. TFP
Lags	p value	p value	p value	p value	p value	pvalue
1	0.282	0.881	0.619	0.383	0.011	0.339
2	0.857	0.974	0.411	0.210	0.041	0.590
3	0.930	0.899	0.005	0.052	0.048	0.061
4	0.867	0.270	0.082	0.012	0.511	0.011

1. The 1st column shows the number of lags.
2. For each Granger Causality test the second variable is regressed on its own lags and lags of the other variable.

Table 5: Variance Decomposition Percentage of 10 Year Error Variance of Japanese GNP by Bivariate VAR

	Ordering: $GNP^{JPN} \rightarrow R\&D^{JPN}$		Ordering: $R\&D^{JPN} \rightarrow GNP^{JPN}$	
Lags	$R\&D^{JPN}$	GNP^{JPN}	$R\&D^{JPN}$	GNP^{JPN}
1	9.31	90.69	72.42	27.58
2	1.56	98.44	51.43	48.57
3	2.43	97.58	56.51	43.49
4	2.36	97.64	45.29	55.71

Table 6: Variance Decomposition Percentage of 10 Year Error Variance of Japanese TFP by Bivariate VAR

	Ordering: $TFP^{JPN} \rightarrow R\&D^{JPN}$		Ordering: $R\&D^{JPN} \rightarrow TFP^{JPN}$	
Lags	$R\&D^{JPN}$	TFP^{JPN}	$R\&D^{JPN}$	TFP^{JPN}
1	0.26	99.76	44.43	55.57
2	0.44	99.56	49.89	50.11
3	1.50	98.50	46.92	53.08
4	7.07	92.93	35.23	64.77

Table 7: Granger Causality (G.C.) Tests for Japanese TFP

Null Hypothesis:	JPN R&D does not G.C. JPN TFP	US R&D does not G.C. JPN TFP
Lags	p value	p value
1	0.473	0.014
2	0.642	0.075
3	0.502	0.014
4	0.136	0.037

Note:

1. The 1st column shows the number of lags.
2. The 2nd (3rd) column shows the p-value of the test under the null hypothesis that Japanese (U.S.) R&D does not Granger Cause Japanese TFP.
3. For each G.C. tests, 'JPN TFP' is regressed on lags of 'JPN TFP', 'JPN R&D' and 'U.S. R&D'.

Table 8: Variance Decomposition Percentage of 10 Year Error Variance of Japanese TFP by Trivariate VAR

	Ordering: $TFP^{JPN} \rightarrow R\&D^{JPN} \rightarrow R\&D^{US}$		
Lags	TFP^{JPN}	$R\&D^{JPN}$	$R\&D^{US}$
1	58.67	10.24	31.09
2	63.10	6.30	30.60
3	29.87	8.84	61.30
4	26.02	10.64	63.35

Table 9: Granger Causality (G.C.) Tests for Japanese Patents

Null Hypothesis:	JPN Patents do not G.C. JPN TFP	U.S. R&D does not G.C. JPN patents	JPN patents do not G.C. U.S. R&D
Lags	p value	p value	p-value
1	0.73	0.003	0.12
2	0.72	0.010	0.69
3	0.02	0.014	0.72
4	0.01	0.079	0.37

Note:

1. The 1st column shows the number of lags.
2. The 2nd - 4th columns show the p-value of the test under the null hypothesis.
3. All of the Granger Causality Tests are based on regressions with three variables Japanese Patents, Japanese TFP and U.S. patents

Table 10: Relative Volatilities Japanese Data and Models (medium term cycle filtered data)

Specification	σ_Y	σ_Z/σ_Y	σ_C/σ_Y	σ_X/σ_Y	$\sigma_{\frac{k}{Y}}/\sigma_Y$	σ_H/σ_Y
Japanese data	0.055	1.15	0.64	2.36	1.87	0.39
Baseline	0.081	0.78	0.57	2.19	1.60	0.37
Japan R&D lags 1-4	0.044	0.64	0.81	1.69	0.90	0.23
US R&D lags 1-4	0.057	0.69	0.68	2.04	1.40	0.32
Japan R&D lags 2-4	0.039	0.64	0.85	1.66	0.95	0.25
US R&D lags 2-4	0.065	0.73	0.62	2.13	1.53	0.36
Japan R&D lags 3-4	0.037	0.67	0.89	1.56	0.99	0.24
US R&D lags 3-4	0.071	0.73	0.63	2.10	1.50	0.35
Japan R&D lag 4	0.037	0.67	0.92	1.51	0.95	0.24
US R&D lag 4	0.070	0.75	0.60	2.19	1.57	0.38
TFP Trend Component	0.062	0	0.51	0.78	0.35	0.13

Note:
σ_a denotes standard deviation of variable a. $Z, Y, X, \frac{K}{Y}, C$ and H denote TFP, GNP, Investment, K/Y, consumption and total hours worked.

Table 11: Correlation between Model Predicted Values and Actual Values in Japanese Data (medium term cycles filtered data)

Specification	ρ_{Z^m,Z^d}	ρ_{Y^m,Y^d}	ρ_{C^m,C^d}	ρ_{X^m,X^d}	$\rho_{\frac{K}{Y}^m,\frac{K}{Y}^d}$	ρ_{H^m,H^d}
Baseline	1	0.97	0.89	0.92	0.96	-0.26
JPN R&D lags 1-4	0.33	0.70	0.86	0.63	0.54	-0.25
US R&D lags 1-4	0.63	0.81	0.89	0.72	0.68	-0.17
JPN Patents 2-4	0.01	0.55	0.84	0.37	0.10	-0.10
US R&D lags 2-4	0.67	0.80	0.90	0.70	0.68	-0.23
JPN R&D lags 3-4	-0.22	0.43	0.81	0.17	-0.16	0.05
US R&D lags 3-4	0.68	0.80	0.90	0.68	0.67	-0.23
JPN R&D lags 4	-0.26	0.40	0.81	0.11	-0.23	0.02
US R&D lags 4	0.68	0.80	0.89	0.70	0.66	-0.20
TFP Trend component	–	0.41	0.82	0.13	-0.32	-0.29

Note:
$\rho_{a,b}$ denotes correlation between variables a and b. $Z^m, Y^m, X^m, \frac{K}{Y}^m$, C^m and H^m denote model predicted values of TFP, GNP, Investment, K/Y, consumption and total hours worked, respectively. Z^d, Y^d, X^d, $\frac{K}{Y}^d$, C^d and H^d denote actual values of TFP, GNP, Investment, K/Y, consumption and total hours worked, respectively.All data are medium term cycle filtered.

Figure 1: Simulation Results model and Japanese data

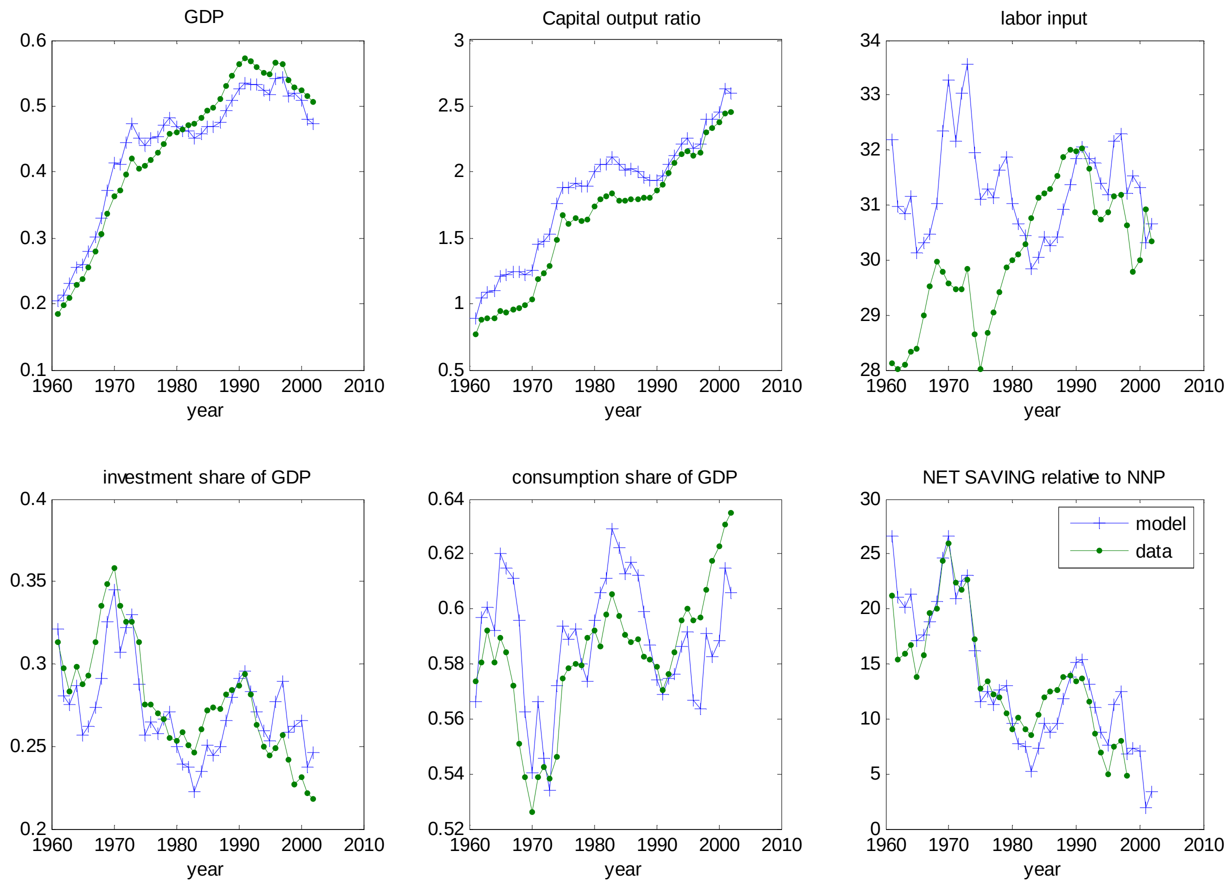

Figure 2: Japanese Medium Cycle GNP and TFP

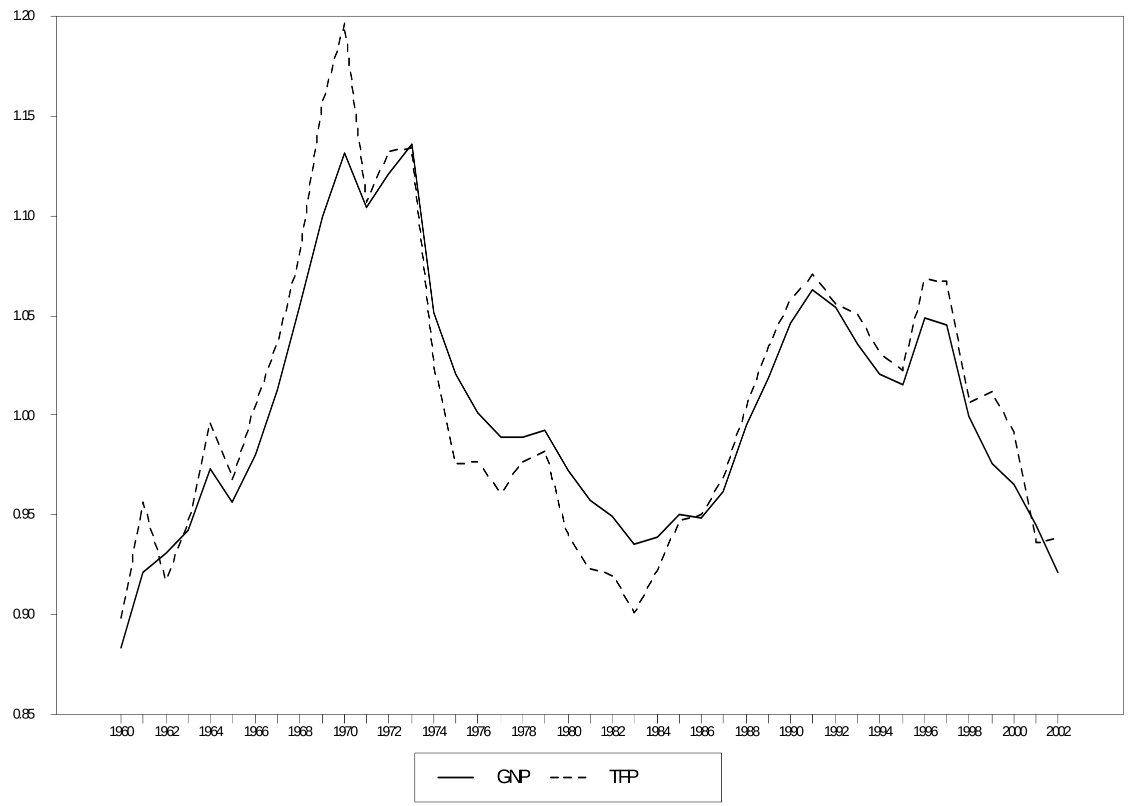

Figure 3: Cross-correlations of Japanese R&D with Japanese GNP and TFP

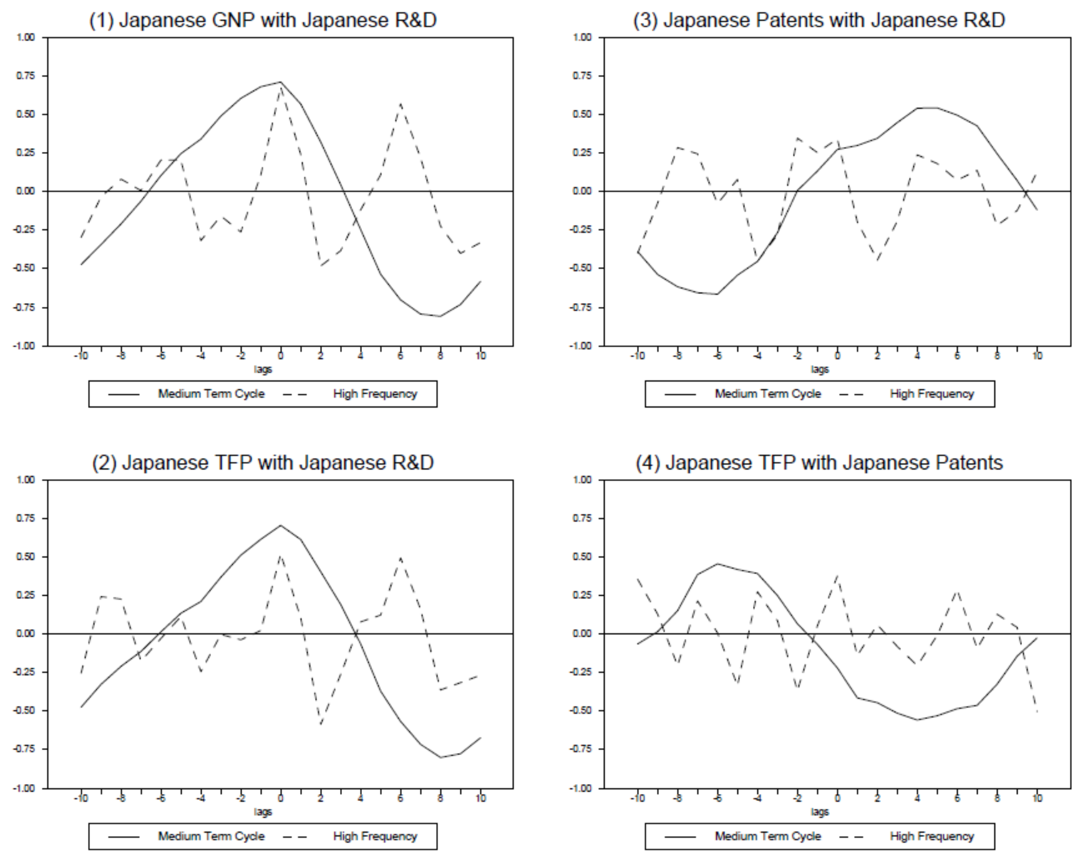

Figure 4: Medium Cycle Japanese Patents, TFP and R&D

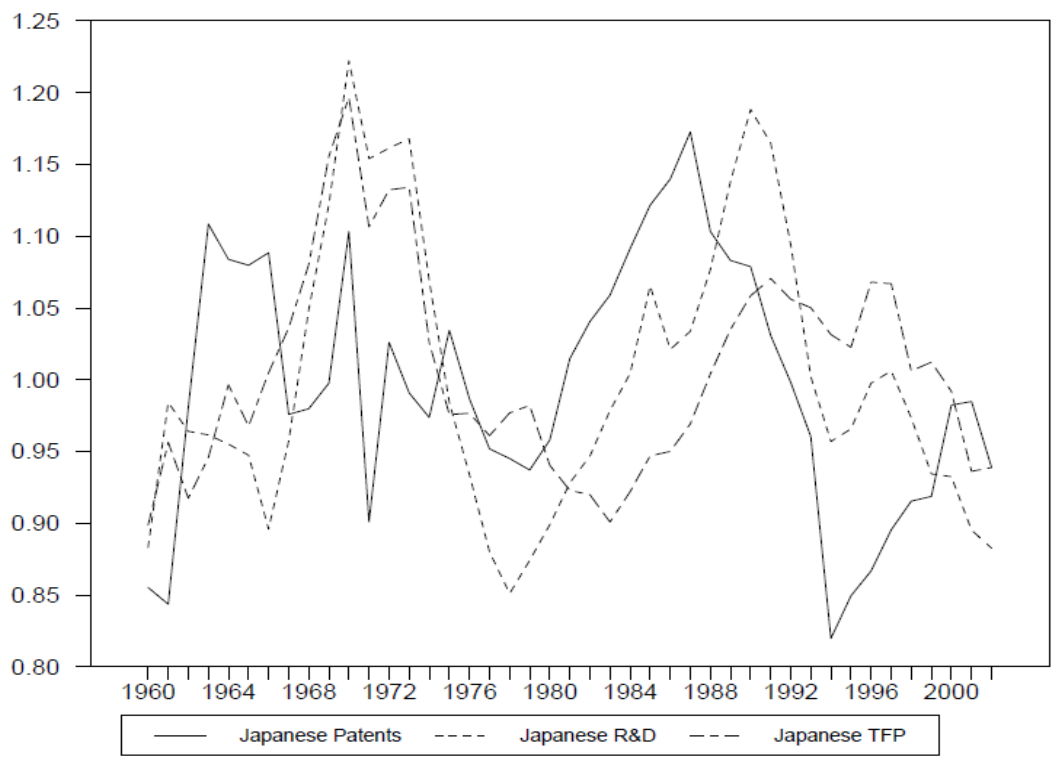

Figure 5: Japanese and U.S. Medium Cycle TFP

Figure 6 Cross-correlations Japanese and U.S. TFP, R&D

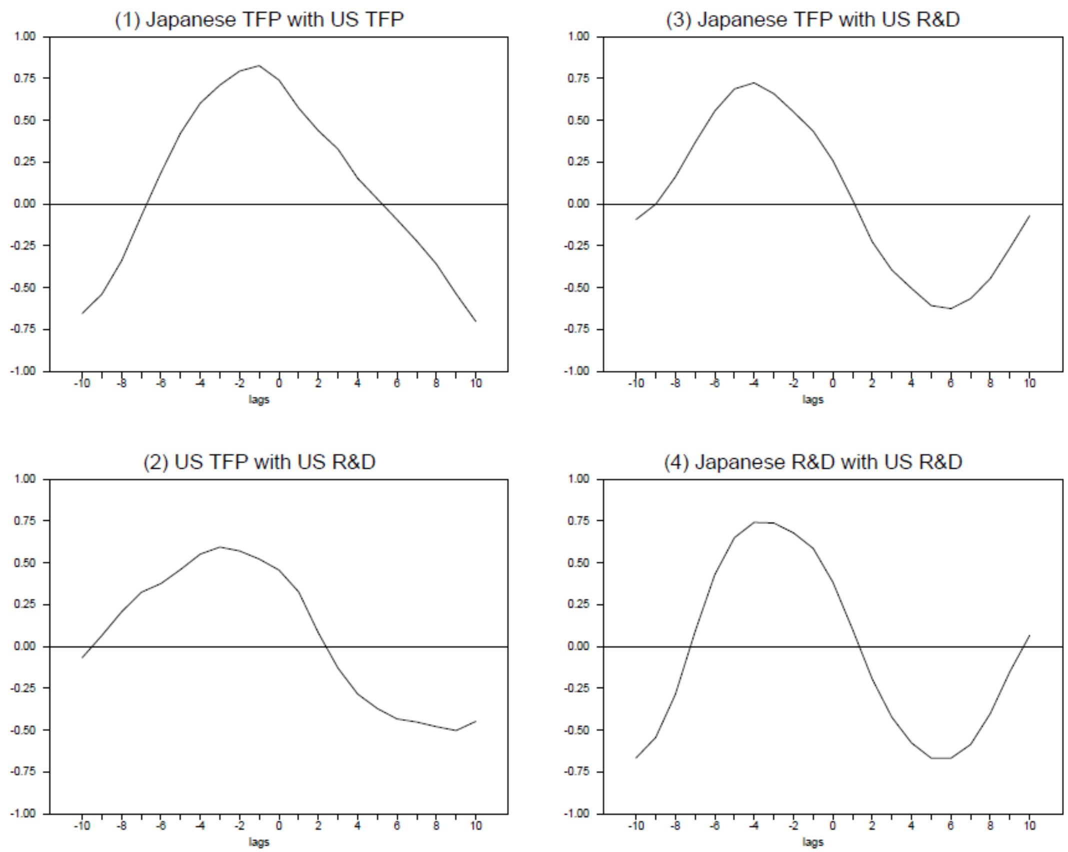

Figure 7 Model predicted medium term cycles and Japanese data

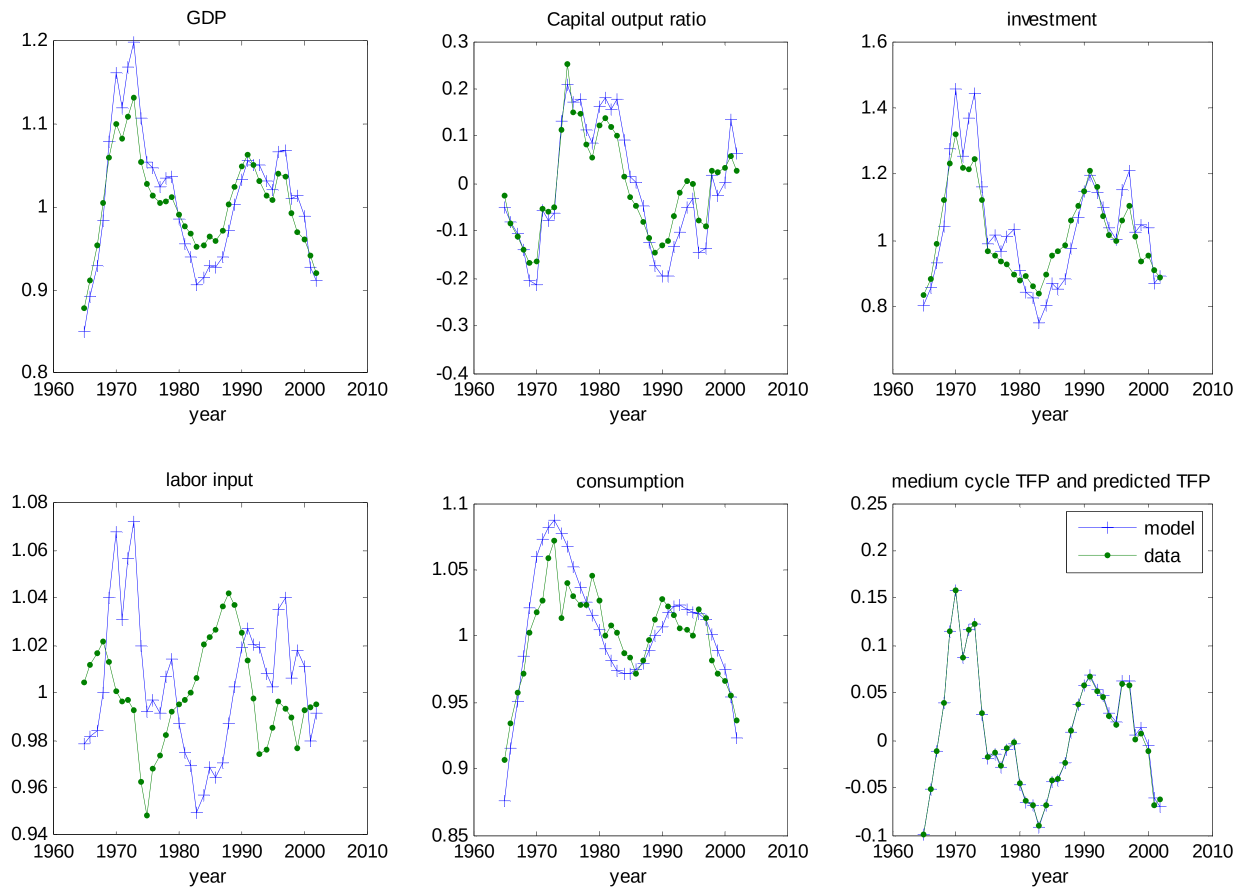

Figure 8 Simulation with 4th lag of Japanese patents used to predict Japanese TFP

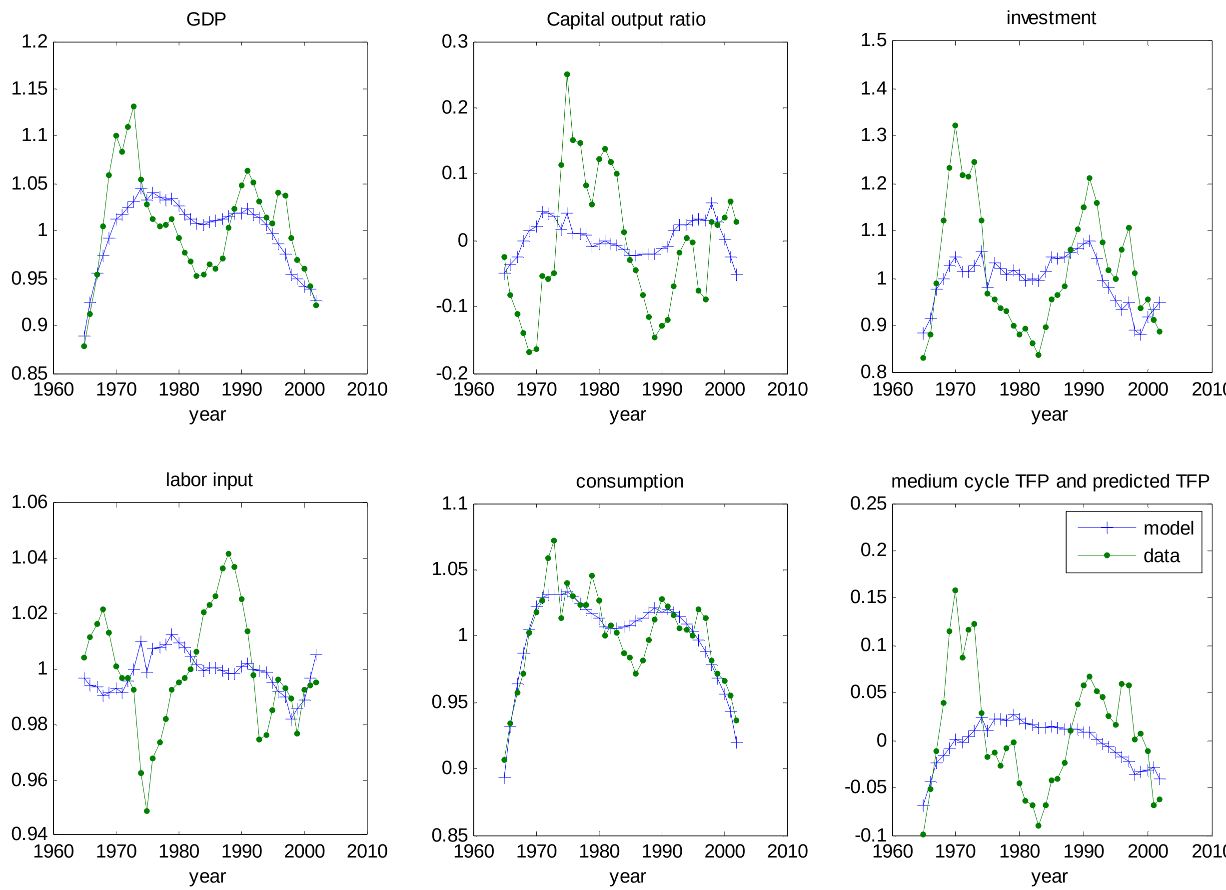

Figure 9 Simulation with 4th lag of U.S. R&D used to predict Japanese TFP