# U.S. R&D Made Japan's Development Miracle

R. Anton Braun
University of Tokyo

Toshihiro Okada
Kwansei Gakuin University

Nao Sudou
Bank of Japan

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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 and find that US R&D is the main determinant of medium cycle Japanese TFP. U.S. R&D leads Japanese R&D by about four years and accounts for as much as 60% of the variation in medium term cycle Japanese TFP. A simulations which assume that U.S. R&D is the sole driver of medium term cycle Japanese TFP do a better job of accounting for the medium term cycle data facts in Japan than other specifications that rely on domestic R&D.

# 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) posits a common world technology frontier. In their models economic growth rates are eventually the same in all countries and investment and TFP determine a country's relative income level. From the perspective of these models Japan's development miracle occurred because it was successful in adopting 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. They assume that the world frontier technology grows at an exogenous rate but that local institutions including work rules and other implicit taxes on investment affect the returns from investing in better technologies by local firms. Rules and institutions set up by the U.S. in Japan after World War II lowered the barriers and increased the return from investment. Firms then adopted better technologies and Japan rapidly developed. A calibrated model that formalizes this hypothesis can reproduce the timing and speed of Japan's development miracle if the capital share parameter is 0.5 - 0.55. Values in this range point to a significant role for organizational capital, which includes unmeasured human capital from learning by doing and managerial practices. Parente and Prescott (1994) estimate that stock of organizational capital is about 40% of output in Japan. The rapid rise in income in their model simulations is associated with large increases in measured TFP and the capital output ratio. In their model lower barriers promote capital deepening.

Eaton and Kortum (1997) focus instead on the processes of innovation and diffusion of ideas. TFP differs across countries due to country specific differences in rates of innovation and adoption of domestic and foreign ideas. They abstract entirely from capital deepening and link technology adoption to the rate of arrival of new ideas. The rate of arrival of domestic ideas increases with the size of the domestic R&D sector and other ideas diffuse from abroad. Rates of innovation and diffusion of ideas among countries are calibrated on a bilateral basis using patent application data. Eaton and Kortum's (1997) theory can also account for Japan's development miracle if there is a large initial knowledge gap between the U.S. and Japan. Under the same assumption their theory also accounts for convergence of TFP growth rates in the UK, France and Germany.

The goal of this paper is to provide some new facts about the magnitude and sources of technology diffusion to Japan between 1960 and 1990. Our analysis builds on recent work by Chen et al. (2005) who show that one can account for the pattern of savings rates in Japan between 1960 and 2000 using the neoclassical growth model with an initially low capital stock and measured variation in Solow's residual. We extend the model to allow for endogenous labor supply and show that the same two factors also account for the principal movements in GNP, investment and the capital output ratio between 1960 and 2002. If one conditions on the measured pattern in Solow's residual there is no need to appeal to organizational capital or changes in the size of the barriers to investment to produce Japan's development miracle.

We next turn to analyze the source of variations in Japanese TFP over the 1960 - 2002 sample period. Comin and Gertler (2003) have suggested that focusing on 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 component exhibits 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.

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 Japanese R&D. The simulation results confirm the diffusion hypothesis. Current values of US R&D are important determinants of future Japanese medium cycle output, the capital output ratio and investment. Current Japanese R&D, in contrast is much less important for understanding the future evolution of Japanese medium cycle output, investment and the capital output ratio.

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

[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.

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. Our results are also broadly consistent Keller (2002) and Okada(1999). 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 these spillover effects are also important in Japan.

Our findings also leave little role for domestic demand disturbances in accounting for medium term fluctuations in Japan. This does not necessarily rule out the possibility that demand disturbances influence R&D and thus TFP as posited by Comin and Gertler (2003). However, if demand disturbances are important for understanding the Japanese medium cycle than it must be demand shocks that have their origin in the US.

Finally, our results fail to find an important independent role for domestic R&D. This stands in contrast to work by Branstetter (1999) who finds that most knowledge spillovers in Japan are intranational and Comin (2002) who argues that the contribution of R&D to TFP is small. Our results suggest instead that the nature of technology diffusion from the U.S. to Japan did not require large amounts of domestic R&D to be adopted.

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 $\beta$ 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, $\tau_c$ is the tax rate of consumption, $\tau_w$ is the tax rate of labor income, $\tau_k$ is the tax rate of capital income, and $\delta$ 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 $\psi_t$ 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

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

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:

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

where the expression in [ ] equals $k_{t+1} - k_t$ and $\lambda_{t+1}$ 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 $\lambda_t$ and Eq.(9) into Eq.(11) for $\lambda_{t+1}$ 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:

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

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

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

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 $\beta$,the preference discount parameter, the capital share parameter, $\theta$, the depreciation rate on capital,$\delta$, and the capital tax rate, $\tau$. 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] This is the same sample period used by Hayashi and Prescott (2002) to calibrate their model.

Chen et al. (2005) conduct perfect foresight simulations using a model that is similar to ours 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 on GNP, investment and the capital output ratio. The biggest gap between the model's predictions and Japanese data lie in its implications for the consumption share of output. The model predicts less variability in the consumption share than we see in Japanese data and the model also fails to reproduce the steady increase in consumption's share of output between 1990 and 2000. In terms of the variability of consumption it should be pointed out that our measure of

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

consumption includes durables. Japanese NIPA data doesn't provide separate measures of durables, and other consumption categories. So there is no way to break durables out and treat them as part of investment which is common practice when working with US data. The conclusion that we draw from Figure 1 is that one can attribute the most important economic events in Japan between 1961-2000 to a low initial capital stock and measured variations in TFP.

It is useful to compare these results with those of Parente and Prescott (1994). Their theory combines an initial low capital stock with two other ingredients, a capital share of 0.55 and a tax on investment that is set to the level of 0.85 for the 1960-1973 sub-sample and to the value of 1.10 for the sample 1975-1988 sub-sample. For their theory to account for the facts they need to increase the barriers to change to account for the productivity slow-down. It is interesting to note that Klenow and Rodriguez (2004) have found that the productivity slow-down was a global phenomenon. Our model accounts for the productivity slow-down via slower growth in exogenous TFP. Whereas in their model the level of TFP is endogenous and depends on the size of the tax on investment.

We view our results as suggesting that it may not be necessary to resort to organizational capital and the high capital share it delivers to account for Japan's development miracle. Instead it may be sufficient to consider more carefully the sources of variations in TFP.

We now turn to document some facts that suggest that a good theory of Japanese TFP, is technology diffusion of technology from the United States.

# 4 Data facts

Our decision about what data facts to report is motivated by two things. First, 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. Second, it is our conviction that Japan's development miracle is a levels miracle. The variations in TFP that produce Japan's development miracle confound two effects. A levels effect that pins down Japan's relative position in the wealth of nations and a growth effect that is common to all countries. For these reasons 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 the 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 will demonstrate that filtering Japanese data also exhibits a distinctive pattern of co-movements and that these co-movements unmask some interesting information about the source of variations 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.

We 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. Before filtering the data first take natural logarithms.

## 4.1 Facts about the Japanese medium cycle

Japanese data also 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. 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.

It is also interesting to compare Japanese medium term cycle R&D with GNP. Comin and Gertler (2003) find that US medium term cycle R&D lead GNP. This fact motivates their endogenous growth model which attributes variation in TFP to variation in R&D. In Japanese data GNP and R&D are highly correlated but coincident. Consider Figure 3 which shows the cross-correlation function of GNP and R&D peaks at zero with a contemporaneous correlation of 0.71 and falls sharply as one moves in either direction away from zero. A comparison of medium term 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 and there is also no evidence that Japanese R&D leads either GNP or TFP.

In order to explore this issue further we estimated bivariate vector autoregressions or VAR's with Japanese medium term cycle R&D and Japanese GNP using alternatively one, two, three or four lags. As Table 4 shows, in no case did we find 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 showed 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 using variance decompositions of the two types of VAR's described above. In the case of the VAR using one lag with R&D and GNP (see Table 5), 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. These results suggest there are other and perhaps more important sources of variation in Japanese medium term TFP than Japanese R&D. The fact that Japanese R&D does not lead Japanese TFP and accounts for a relatively small share of the variance in Japanese TFP casts doubt on the relevance of Comin and Gertler's (2003) theory of TFP for Japan. If movements in R&D are driving economic growth then we would expect them to lead TFP and also account for a large fraction of the variance of TFP. We now turn to provide evidence on an alternative and more important source of variation in Japanese medium term TFP and output.

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

Consider Figure 4 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 of this Figure. 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 can be found by calculating the cross-correlation function of Japanese and US TFP. Figure 5-(1) reports the cross-correlation function for these two variables. Note that 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 5-(2) 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 as reported in Figure 5-(3). US R&D leads Japanese TFP by 4 years. Surprisingly, Japanese medium term cycle TFP is even 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. Figure 5-(4) reports that 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 some additional evidence based on tri-variate VAR's with Japanese TFP, Japanese R&D and U.S. R&D. As Table 7 shows, Ganger causality tests find that US R&D Granger causes Japanese TFP for VAR's with one, two, three and four lags. Japanese R&D, however, does not Granger cause Japanese TFP with one, two, three and four lags.

Table 8 reports the results of variance decompositions of Japanese TFP. Variance decompositions of Japanese TFP with Japanese TFP ordered first, Japanese R&D ordered second and US R&D ordered third show that US R&D explains substantially more of the variance of medium term cycle Japanese TFP than Japanese R&D. 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 TFP rises to 61% and the fraction explained by Japanese R&D is 9%.

The data analysis we have performed is provocative. If we take seriously the notion that our medium cycle measure of TFP represents the state of know-how in combining labor and capital then there is considerable evidence that US TFP and Japanese TFP are being driven by a common factor and that this common factor is US R&D. US R&D is an even more important determinant of Japanese TFP than US TFP. US R&D is also much more important for understanding medium term fluctuations in Japanese TFP than Japanese R&D. Next we use our model to assess the importance of US R&D for Japanese economic activity more generally.

# 5 Simulation Results

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.

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. Take the predicted values of TFP from this regression 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 model output is filtered using the medium cycle filter and summary statistics are tabulated. The same set of procedures is used to isolate the effects of US R&D. Table 9 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 6 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 10 summarizes the information in this figure in a Table. Note that the correlations between the model and data medium cycle filtered time-series is above 0.9 for all variables except consumption where the correlation is 0.89.

Next consider the results for simulations that attempt to isolate the contribution of Japanese R&D to 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 between 0.7 and 0.8 with the exception of consumption, which has a correlation of 0.86 with actual data. In order get an idea of the 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. Now the standard deviation of output in the model and the data are of about the same magnitude. 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.

Finally consider the results in which US R&D is used to predict Japanese TFP. Surprisingly, 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 either the Baseline or 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. The US R&D specification with only lags 3-4 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 10. But the specification with only the fourth lag of US R&D does nearly as well. The correlation of model predictions with the data are in excess of 0.8 for all variables but investment where the correlation is 0.71.

Given the success of US R&D in accounting for Japanese medium cycle facts it is interesting to consider the 1990's. Figure 7 reports the results for the US R&D specification with 3-4 lags. This figure shows that the 1990's is not a puzzle for our theory. According to 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 the important role for US R&D for Japanese TFP and Japanese economic activity more generally. We have shown that one can account for Japan's miracle by appealing to the same two factors emphasized in Chen at al. (2005), a low initial capital stock and measured variation in Solow's residual. To understand what made Japan's development miracle it is sufficient to understand what factors produced variations in measured TFP. 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 in significant role for US R&D. For Japan there is no role for domestic demand shocks in producing either the high growth of the 1980's or the low growth of the 1990's. Movements in US R&D are sufficient to explain the medium cycle facts for Japan.

There are many important questions left open by our analysis. For instance, the previous literature has assumed that there are substantial costs of adopting foreign technology and that domestic R&D is also an important determinant of

TFP. One interpretation of our results is that domestic R&D is not important for Japan. We explain the medium cycle facts from Japan very well with a specification that assigns no role to Japanese R&D. This suggests that the diffusion of technology to Japan from the U.S. was of a form that did not require large domestic R&D investments in order to be adopted.

In our future research we plan to look further into the mechanism(s) whereby Japan adopts US technology and try and quantify the role of domestic R&D and foreign domestic investment using Industry level data.

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Table 1: Model Calibration

| $\beta$ | $\delta$ | $\theta$ | $\tau^k$ | $\alpha$ |
|---|---|---|---|---|
| 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($GNP^{Japan}$, $TFP^{Japan}$) | | |
|---|---|---|
| Medium Term Cycle | Medium Frequency | High Frequency |
| 0.95 | 0.96 | 0.88 |

Table 4: Granger Causality Tests Based on Bivariate VAR

| Lags | p value$^{GNP}$ | AIC | SBC | p value$^{TFP}$ | AIC | SBC |
|---|---|---|---|---|---|---|
| 1 | 0.282 | -526.9 | -517.0 | 0.881 | -491.7 | -481.9 |
| 2 | 0.857 | -525.3 | -509.2 | 0.974 | -489.0 | -472.9 |
| 3 | 0.930 | -510.0 | -487.8 | 0.899 | -473.6 | -451.4 |
| 4 | 0.867 | -496.7 | -468.7 | 0.270 | -467.9 | -439.9 |

Note:
1. The 1st column shows the number of lags.
2. The 2nd (5th) column shows the p-value of the test under the null hypothesis that Japanese R&D does not Granger Cause Japanese GNP (TFP).
3. AIC and SBC show Akaike Information Criterion and Schwatz Bayesian Criterion for choosing lag length in each bivariate VAR (Japanese GNP and Japanese R&D, Japanese TFP and Japanese R&D). The one with the smallest value of AIC and/or SBC is the best specification.

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

| | Ordering: $GNP^{Japan} \rightarrow R\&D^{Japan}$ | | Ordering: $R\&D^{Japan} \rightarrow GNP^{Japan}$ | |
|---|---|---|---|---|
| Lags | $R\&D^{Japan}$ | $GNP^{Japan}$ | $R\&D^{Japan}$ | $GNP^{Japan}$ |
| 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: $TFP^{Japan} \rightarrow R\&D^{Japan}$ | | Ordering: $R\&D^{Japan} \rightarrow TFP^{Japan}$ | |
|---|---|---|---|---|
| Lags | $R\&D^{Japan}$ | $TFP^{Japan}$ | $R\&D^{Japan}$ | $TFP^{Japan}$ |
| 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 Tests Based on Trivariate VAR

| Lags | p $value^{Japan}$ | p $value^{US}$ | AIC | SBC |
|---|---|---|---|---|
| 1 | 0.473 | 0.014 | -769.6 | -750.0 |
| 2 | 0.642 | 0.075 | -757.2 | -723.4 |
| 3 | 0.502 | 0.014 | -744.5 | -697.0 |
| 4 | 0.136 | 0.037 | -730.2 | -669.6 |

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 (US) R&D does not Granger Cause Japanese TFP.
3. AIC and SBC show Akaike Information Criterion and Schwatz Bayesian Criterion for choosing lag length in trivariate VAR (Japanese TFP, Japanese R&D, and US R&D). The one with the smallest value of AIC and/or SBC is the best specification.

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

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

Table 9: Relative Volatilities Japanese Data and Models (Medium term cycle filtered data)

| Specification | $\sigma_Y$ | $\sigma_Z/\sigma_Y$ | $\sigma_I/\sigma_Y$ | $\sigma_{\frac{K}{Y}}/\sigma_Y$ | $\sigma_C/\sigma_Y$ | $\sigma_H/\sigma_Y$ |
|---|---|---|---|---|---|---|
| Japanese data | 0.061 | 1.15 | 2.23 | 1.61 | 0.59 | 0.33 |
| Baseline | 0.09 | 0.78 | 1.98 | 1.28 | 0.68 | 0.31 |
| Japan R&D lags 1-4 | 0.066 | 0.74 | 1.97 | 1.36 | 0.64 | 0.35 |
| US R&D lags 1-4 | 0.072 | 0.75 | 2.22 | 1.67 | 0.61 | 0.33 |
| Japan R&D lags 2-4 | 0.06 | 0.73 | 2.00 | 1.3 | 0.63 | 0.35 |
| US R&D lags 2-4 | 0.072 | 0.74 | 2.22 | 1.67 | 0.61 | 0.33 |
| Japan R&D lags 3-4 | 0.052 | 0.71 | 1.76 | 1.12 | 0.71 | 0.33 |
| US R&D lags 3-4 | 0.071 | 0.75 | 2.25 | 1.69 | 0.62 | 0.34 |
| Japan R&D lag 4 | 0.043 | 0.65 | 1.30 | 0.58 | 0.79 | 0.26 |
| US R&D lag 4 | 0.087 | 0.74 | 2.18 | 1.95 | 0.60 | 0.36 |

Table 10: Correlation between Model Predicted Values and Actual Values in Japanese Data (Medium term cycle filtered data)

| Specification | corr($Y^{\mathrm{m}}, Y^{\mathrm{d}}$) | corr($I^{\mathrm{m}}, I^{\mathrm{d}}$) | corr($\frac{K}{Y}^{\mathrm{m}}, \frac{K}{Y}^{\mathrm{d}}$) | corr($C^{\mathrm{m}}, C^{\mathrm{d}}$) |
|---|---|---|---|---|
| Baseline | 0.98 | 0.93 | 0.93 | 0.89 |
| Japan R&D lags 1-4 | 0.79 | 0.73 | 0.70 | 0.87 |
| US R&D lags 1-4 | 0.92 | 0.90 | 0.81 | 0.86 |
| Japan R&D lags 2-4 | 0.68 | 0.55 | 0.47 | 0.88 |
| US R&D lags 2-4 | 0.91 | 0.89 | 0.78 | 0.86 |
| Japan R&D lags 3-4 | 0.56 | 0.36 | 0.30 | 0.86 |
| US R&D lags 3-4 | 0.91 | 0.88 | 0.78 | 0.86 |
| Japan R&D lag 4 | 0.43 | 0.09 | -0.13 | 0.86 |
| US R&D lag 4 | 0.88 | 0.77 | 0.81 | 0.81 |

$Y^{\mathrm{m}}$,$I^{\mathrm{m}}$,$\frac{K}{Y}^{\mathrm{m}}$, and $C^{\mathrm{m}}$ denote model predicted values of GNP, Investment, K/Y, and consumption, respectively. $Y^{\mathrm{d}}$,$I^{\mathrm{d}}$,$\frac{K}{Y}^{\mathrm{d}}$, and $C^{\mathrm{d}}$ denote actual values of GNP, investment, K/Y, and consumption, respectively. All data are medium term cycle filtered.

Figure 1: Simulation Results for the Model

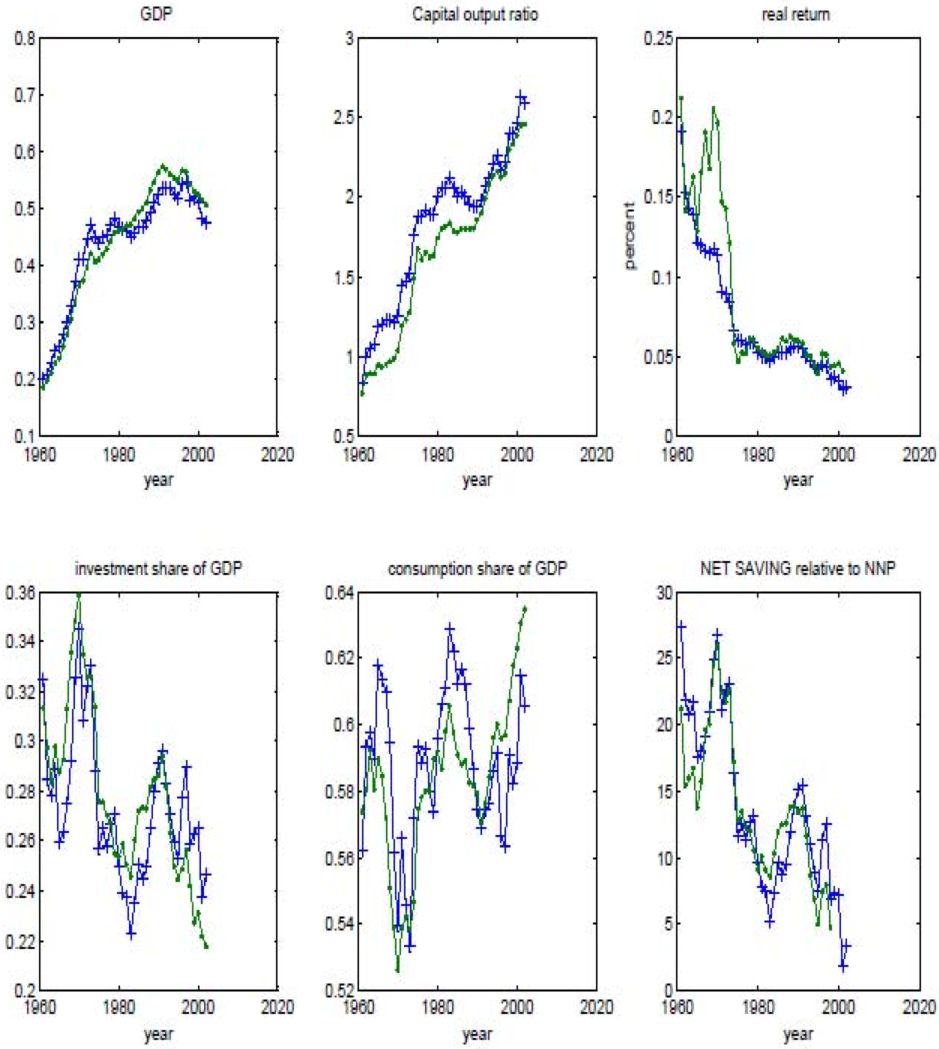

Figure 2: Japanese Medium Term Cycle GNP and TFP

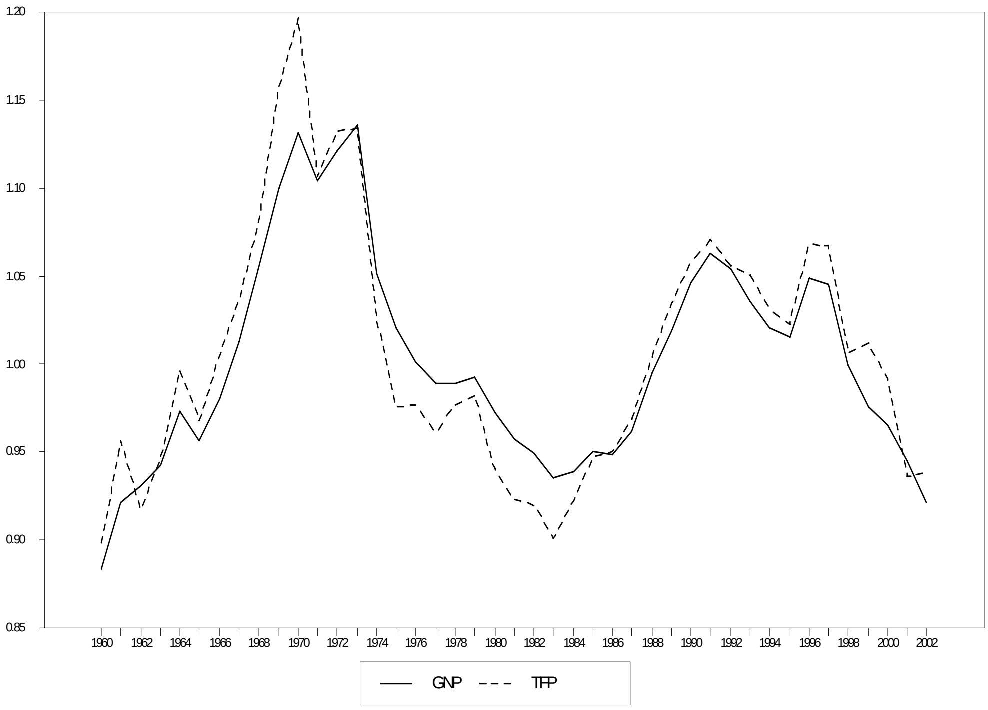

Figure 3: Cross-correlation of Japanese R&D with Japanese GNP and TFP

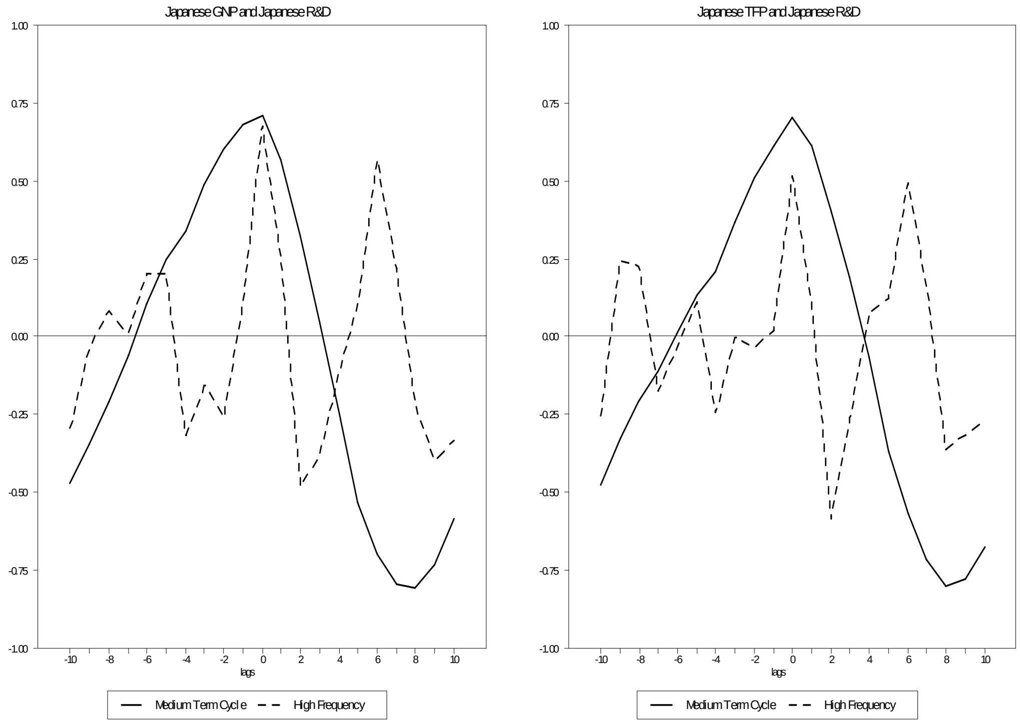

Figure 4: Japanese Medium Term Cycle TFP and U.S. Medium Term Cycle TFP

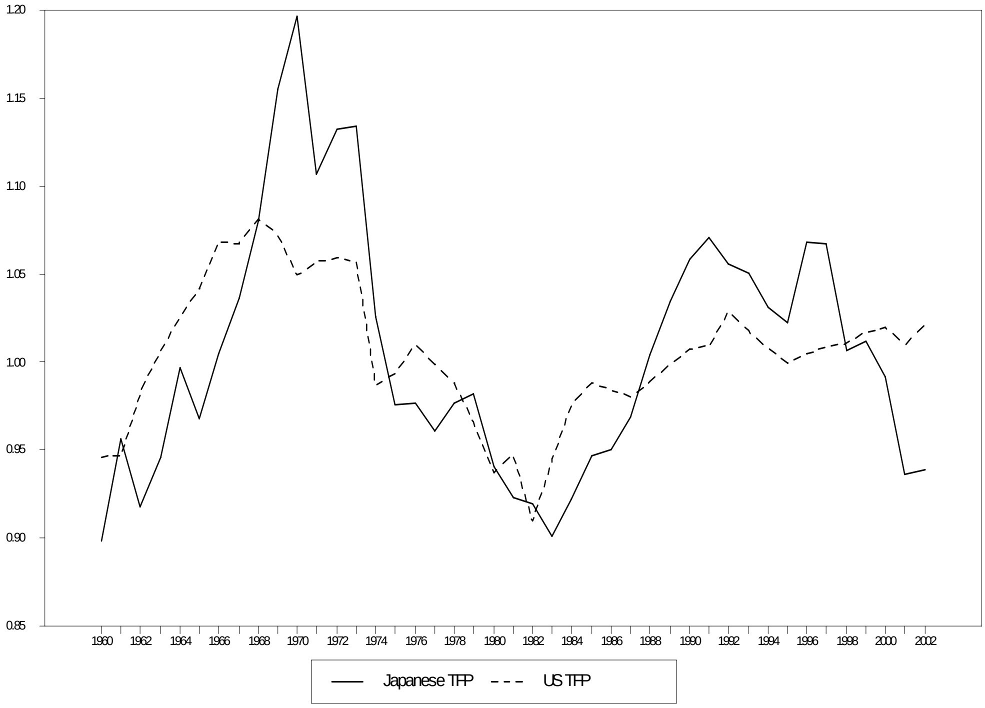

Figure 5: Cross-correlation Functions of TFP and R&D of Japan and the U.S.

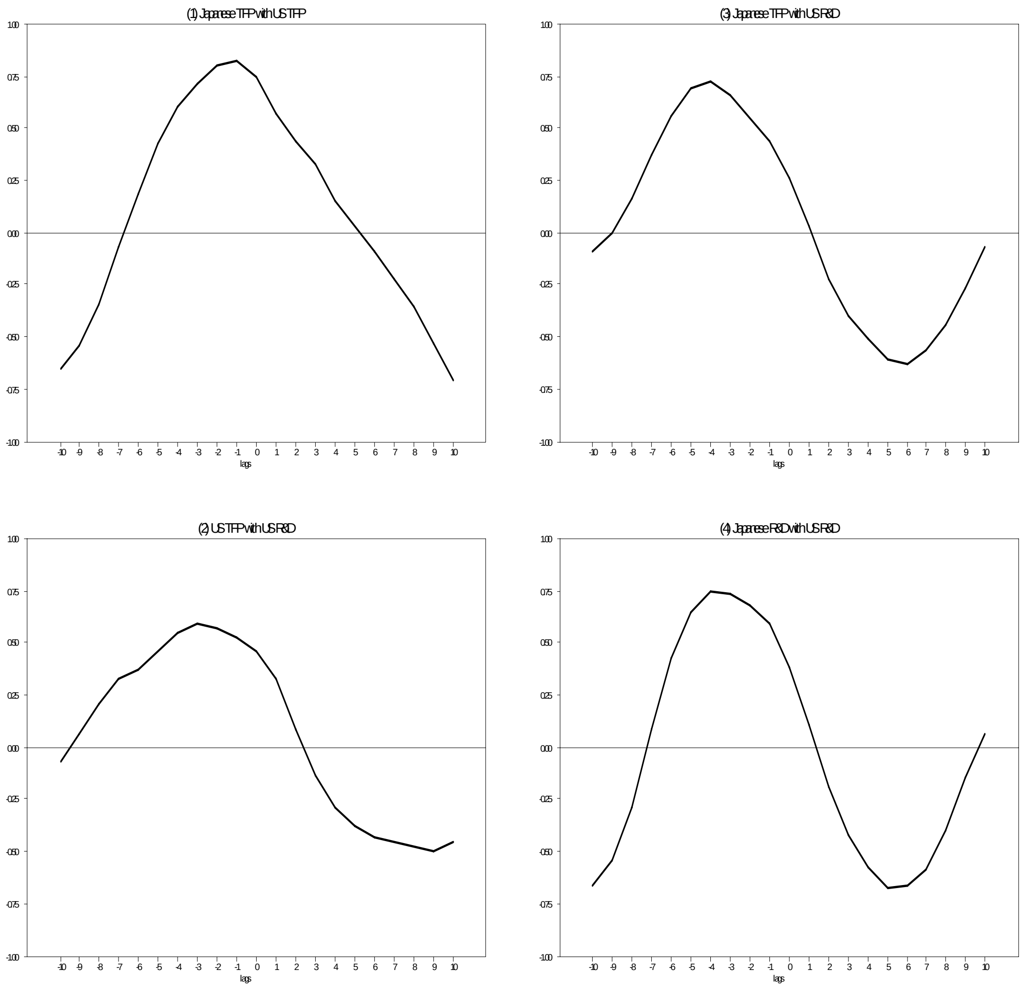

Figure 6: The Model Predictions and Medium Term Cycle Filtered Japanese Data

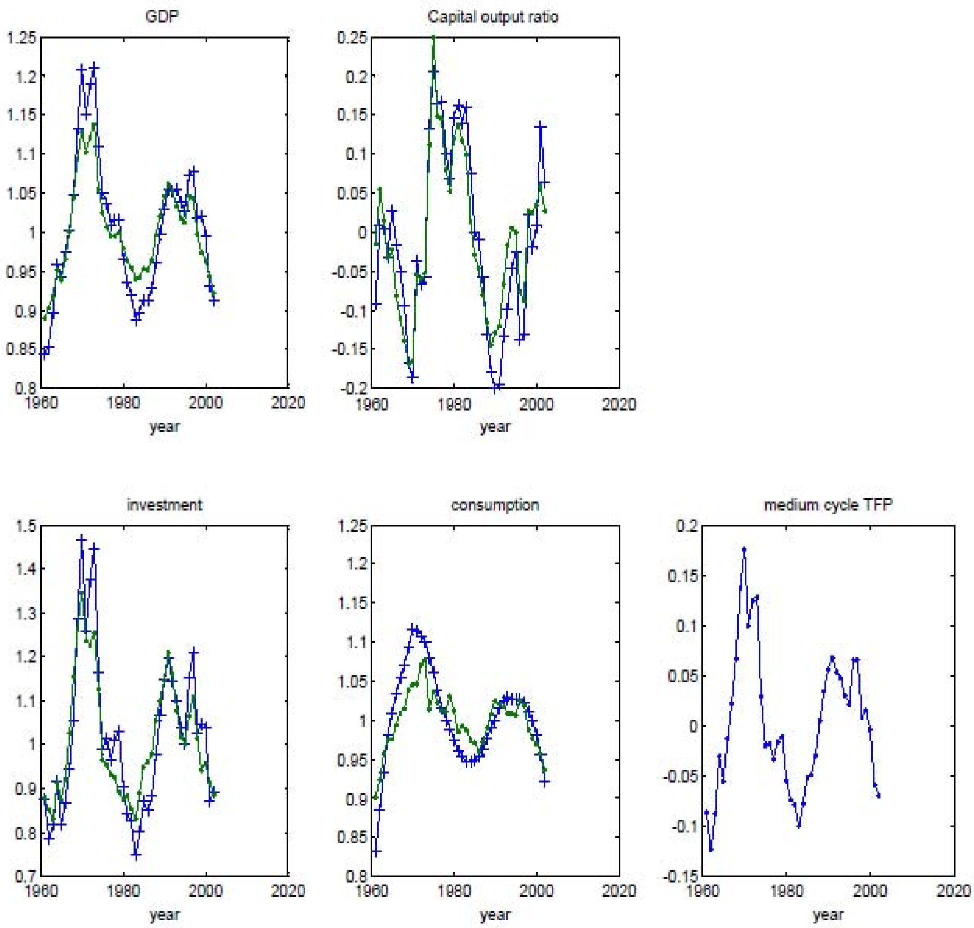

Figure 7: The Model Predictions with the US R&D Specification