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U.S. R&D and Japanese Medium Term Cycles

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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 business 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 suggest that the diffusion of knowledge from the U.S. is a key driver of Japanese medium cycles. Interestingly, our theory also accounts for Japan's experience in the 1990s. Slow growth during this period was preceded by a sharp and persistent decline in U.S. R&D.

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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 U.S. 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 annualized rate of 7.2% between 1960-1973, then fell to 2.2% between 1973-1983, increased to 3.6% between 1983-1991 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 term 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 term 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 term cycle components exhibit a distinctive pattern of co-movements that show strong evidence of technology diffusion from the U.S. to Japan. Empirical evidence based on cross-correlations indicates that U.S. R&D leads Japanese TFP by four years whereas Japanese R&D is coincident with Japanese TFP. Granger Causality tests indicate that U.S. R&D Granger Causes Japanese TFP even after controlling for the effects of Japanese R&D. And a decomposition of the variance of medium term cycle Japanese TFP suggests that U.S. 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 term 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.

Next, we use the model to assess the quantitative role of technology diffusion from the U.S. 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 U.S. 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 U.S. R&D are important determinants of future Japanese medium term 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 Japanese TFP in one or two years can also account for important aspects of medium term cycle data. However, as the lag of diffusion is increased the explanatory power of Japanese R&D for Japanese medium term cycle TFP deteriorates.

Finally, we investigate the role of U.S. R&D in accounting for Japan's ex-

[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.

perience since 1990. We find that this episode of slow growth was preceded by a sharp and persistent decline in medium term cycle U.S. R&D. A model that captures the effects of an exogenous decline in U.S. R&D on Japanese TFP does a good job of accounting for the magnitude of the declines in Japanese medium term GNP and investment between 1990 and 2002. The same model also predicts a rise in the capital output ratio during this same period.

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 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 originate in U.S. universities to Japanese R&D. Our results are also broadly consistent with Keller (2002), Branstetter and Ug (2004) and Okada(2006). 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(2006) 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 U.S. R&D account for Japanese TFP medium term cycle fluctuations. Section 5 uses the model to measure the contribution of U.S. R&D in accounting for Japanese medium term 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 and θ is a constant with $0 < \theta < 1$.

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:

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

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:$\widetilde{c}_t = c_t/Z_t$, $\widetilde{k}_t = k_t/Z_t$, $\widetilde{y}_t = y_t/Z_t$, $\widetilde{w}_t = w_t/Z_t$. 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 $\widetilde{c}_t = \widetilde{c}_{t+1} = \widetilde{c}$, $\widetilde{k}_t = \widetilde{k}_{t+1} = \widetilde{k}$, $r_t = r_{t+1} = r$, $\widetilde{w}_t = \widetilde{w}_{t+1} = \widetilde{w}$, $\widetilde{y}_t = \widetilde{y}_{t+1} = \widetilde{y}$, $\widetilde{\gamma}_{n,t} = \widetilde{\gamma}_{n,t+1} = \widetilde{\gamma}_n$ 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 -2002 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,

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

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 reproduce the secular decline in per capita labor input that we see in Japanese data. The model also does not reproduce the steady increase in consumption's share of output from 0.58 in 1990 to nearly 0.64 in 2002. The conclusion that we draw from Figure 1 is that one can account for the principal economic events in Japan between 1961-2002 using standard economic 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) assume 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. 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 68 SNA 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 term cycle content. The medium term 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 of the economic variables. 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 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 logarithms 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 U.S. macroeconomic time-series. Since the focus of this paper is on medium term 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 term 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 term cycle data.

4.1 Facts about the Japanese medium term cycle

Japanese data exhibit large and distinctive medium term 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 0.86.

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 U.S. 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 term cycle filtered and high frequency filtered Japanese data. The cross-correlation function of medium term 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 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-correlation of R&D with TFP is much lower but there is again no clear evidence that Japanese R&D leads either GNP or TFP.

Another way to assess the temporal relationship between Japanese R&D, 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 on 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 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 by 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 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.

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 in response to foreign pressure to 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, but 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 term 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 term cycle patents. Another interesting feature of this chart is that medium term 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 three or four. However, Japanese Patents Granger Cause Japanese R&D at the 10% level when the number of lags is three or four. Results for TFP and Japanese patents are also mixed. On the one hand, cross-correlations suggest that Japanese patents lead Japanese TFP by six years. 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 three or four. We interpret 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 term cycle. The results though do not rule out the possibility that Japanese patents lead both Japanese R&D and TFP. In this latter scenario though one is left to wonder what resources are used to produce patents. We now present evidence 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 5. First, the general patterns of medium term cycle Japanese TFP and U.S. TFP are remarkably similar. TFP in both countries increases in the 1960s, declines during the 1970s and increases again in the 1980s. Second, TFP in Japan appears to lag U.S. TFP.

More concrete evidence about this second point is found by inspecting the cross-correlation function of Japanese and U.S. TFP reported in Figure 6-(1). The peak cross-correlation occurs when current period Japanese TFP is correlated with period t-1 U.S. 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 U.S. R&D with U.S.

TFP. U.S. R&D leads U.S. TFP by three years and the peak correlation is 0.59. Next consider the cross-correlation function of U.S. R&D and Japanese TFP. This figure shows that U.S. R&D leads Japanese TFP by 4 years. Surprisingly, Japanese medium term cycle TFP is more highly correlated with U.S. R&D than Japanese R&D with a peak correlation of 0.73. Finally, consider the cross-correlation of U.S. R&D and Japanese R&D reported in Figure 6-(4). U.S. 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 U.S. 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 U.S. R&D is ordered third, we find that U.S. 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 U.S. R&D than orderings in which it appears first or second. For a specification with one lag U.S. 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 U.S. 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 term 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 term 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.

[3] In the U.S. regulations restrict the right to apply for a patent for an ideas to a grace period

patents and 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 term 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 U.S. R&D. Observe that for all choices of lag length U.S. 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. 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 term 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 term 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 Term 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 infor-

of one year from the date that the invention has been sold or described in a publication.

mation in medium term cycle data and second, that this information suggests that technology diffusion from the U.S. 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 U.S. R&D for medium term 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 U.S. R&D is important then previous levels of U.S. 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 U.S. R&D we need a way to isolate the effects of these variables on Japanese TFP. We do this in the following way. First, we decompose Japanese TFP and Japanese R&D into trend and medium term cycle components in the way described in Section 3. Next we project the medium term cycle component of Japanese TFP on four lags of Japanese medium term cycle R&D and four lags of U.S. medium term cycle R&D. To isolate the effects of Japanese R&D we 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 we zero out the coefficients on Japanese R&D and predict Japanese TFP using only U.S. R&D. Then we 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, we medium term cycle filter the simulated time-series and calculate summary statistics.

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 term 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 term cycle filtered 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 term 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 term cycle frequencies are quite different from their dynamics at business cycle frequencies. Labor input at medium term cycle frequencies is actually counter-cyclical. The contemporaneous correlation between medium term cycle GNP and hours is -0.18. Griliches and Mairesse (1990) in a comparative analysis of firm level TFP and R&D in Japan and the U.S. found that Japanese technological improvements were labor saving. This is showing up in medium term 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 term 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 0.37 and the correlation between the model and data capital output ratio is 0.10. 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 term cycle fluctuations is about zero.

Next consider the results in which U.S. R&D is used to predict Japanese TFP. The U.S. R&D specification with lags 1-4 does a better job of reproducing the relative variabilities of investment, the capital output ratio, 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 U.S. R&D specification with only lag 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 U.S. 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 capital output ratio is 0.66 as compared to -0.32 and the correlations of model and data investment and output are also much stronger.

In Section 4 we found some evidence that Japanese patents may lead the Japanese medium term 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 U.S. 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 Japanese patents are reliable predictors of Japanese TFP at horizons beyond 2 years.

6 The role of R&D since 1990

What was the role of a slowdown in R&D in accounting for Japan's experience since 1990? It has been known at least since Poole(1970) that it is hard to describe the appropriate policy response until one understands the source of the shock. Explanations in the literature vary. Some research associates the onset of the lost decade with a sudden tightening in monetary policy that led to a collapse of a speculative bubble (see e.g. Ito and Mishkin (2004)). Other research posits exogenous negative shocks to preference discount factors (Eggertsson and Woodford (2004)) or to firm profits (Caballero, Hoshi, and Kashyap (2005)). Hayashi and Prescott (2002) have shown that the Lost Decade is not a puzzle for standard theory if one treats measured variation in Solow's residual as reflecting changes in the state of technology. Their paper is silent though about what is driving the variations in technology. We have shown above that variations in Solow's residual in conjunction with a low initial stock account for other important episodes in Japanese post WWII data too. The Japanese savings puzzle, the slow growth following the oil price shock in the 1970s and the rapid growth Japan experienced in the last half of the 1980s are predicted by this theory. We have found, moreover, that U.S. R&D is a key determinant of Japanese TFP. Our results demonstrate that U.S. R&D has been a key leading indicator of these same episodes. To our knowledge, nobody in the literature has documented that the other hypotheses can quantitatively account for the facts from the 1990s in Japan or any other episodes in Japanese data.

Japan's experience of slow growth in the 1990s was preceded by a significant slowdown in medium term cycle U.S. private industry R&D expenditures. Figure 10 reports total medium term cycle filtered industrial R&D for the U.S. and Japan. Between 1986 and 1995 U.S. medium term cycle R&D fell by 22 percent. Japanese R&D, in contrast continues to rise until 1990 and doesn't start to decline until 1991.[4]

To provide a more concrete picture of the model's performance in the 1990's in Table 12 we report the percent change in GNP, consumption, investment, and the capital output ratio between 1990 and 2002 for both Japanese data and our model. The model results are based on the specification that uses the fourth lag of U.S. R&D to predict current Japanese TFP. This table shows that a theory that attributes all variation in these variables to variations in U.S. R&D matches the magnitude of changes in output, consumption, and investment. The only variable that this theory has some difficulty with is the capital output ratio. The model gets the sign right but does not reproduce the magnitude of the changes in this variable. Braun, Ikeda and Joines (2005) argue that changes in demographics are also important for understanding movements in the capital output ratio in the 1990s. We have abstracted from the effects of demographics here.

Based on these results it is not a stretch to speculate that variation in U.S. R&D in conjunction with some auxiliary assumptions about the role of money and the form of the monetary policy rule can also account for the nominal facts in Japan since 1990. Braun and Waki (2005) consider a specification of the real side of the economy that is similar to the one considered here. The model has two sources of variation: exogenous variation in TFP and exogenous variation in government purchases. The model is augmented with costly price adjustment, adjustment costs on capital, and a Taylor rule. This later features help deliver sensible price implications. Their model accounts for the real facts, the decline in nominal interest rates to zero, and the pattern of inflation rates in the 1990s. We suspect that if one were to repeat the simulations in Braun and Waki (2005) using instead the projection of U.S. R&D on Japanese TFP in place of actual Japanese TFP that model would continue to perform well.

We now turn to consider industry level data. Industry level data is interesting for several reasons. First, R&D expenditures in both the U.S. and Japan are concentrated in a relatively small number of industries: chemicals, transportation, and machinery and equipment. In Japan these three industries account for 76% of all industry private R&D and in the U.S. they account for 80% (see Table 13). If the diffusion of ideas from the U.S. to Japan is important, then we should expect to find evidence of diffusion in these particular industries. Second, some of these industries now have higher productivity than their American counterparts. Inklaar, Wu and van Ark (2003), for instance, report that Japanese productivity is higher than in the U.S. in machinery and equipment and electrical equipment but lower in chemicals and transportation. From the perspective of e.g. Parente and Prescott (1994) the Japanese machinery and equipment and electrical equipment industries are closer to the world techno-

[4] Jorgenson and Nomura (2004) provide evidence of a slowing in the rate of relative price declines for memory chips during the late 1980's and early 1990's. 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 the timing of the slowdown in model TFP in Figure 9.

logical frontier than their U.S. counterparts. It is interesting to see how these industries perform in the 1990s.

Table 14 summarizes the results of Granger Causality tests of medium term cycle Japanese R&D on industry and Table 15 reports Granger Causality tests of U.S. same industry R&D on output for each Japanese industry. These results are highlighted by three findings. First, there is very little evidence that Japanese R&D Granger Causes industry output. The only industry where Japanese R&D is consistently significant for alternative lag lenghts is pulp, paper and printing. Second, there is stronger evidence that U.S. R&D Granger Causes same industry Japanese output. U.S. R&D Granger Causes Japanese output for at least one choice of lag length in food, beverage and tobaccor, pulp, paper and printing, chemicals, machinery and equipment, electrical equipment (a sub-category of machinery and equipment) and transport equipment. Third, the pattern of results shows stronger evidence of Granger Causality in R&D intensive industries. Due to problems in collecting a consistent measure of the capital stock back to 1960 we do not currently have results for TFP.

If medium term cycle U.S. R&D is an important determinant of Japanese same industry medium term cycle output during the 1990s then we would expect to see sharp declines in U.S. R&D. This is in fact the case between 1987 and 1994, U.S. R&D falls by 37 percent in transportation, 50 percent in machinery and equipment and 32 percent in electricity. R&D in chemicals declines by 10 percent.

These declines are indeed associated with declines in medium term cycle industry level Japanese output. From Table 15 we see that a three lag specification works reasonably well for all of these industries. Using this as a reference we measure the change in medium term cycle output from 1990 to 1997. Machinery and equipment and transportation show the largest declines falling respectively by 26 percent and 19 percent. Chemical falls by 5 percent and electrical falls by 6 percent.

Japanese same industry R&D also experienced declines during the 1990s. Transport and electrical Japanese R&D experience protracted declines from respectively 1992 and 1991 on and Japanese chemical R&D starts declining in 1993. For all of these industries the declines in Japanese R&D are occurring at about the same time that industry output falls. There is no evidence here that the output declines are preceded by declines in Japanese same industry R&D. However, in all three industries, the output declines are preceded by declines in U.S. same industry R&D.[5]

The patterns in the Japanese machinery data are different. Recall that this is a high productivity industry that according to Inklaar et al. (2003) is closer to the world technological frontier than its counterpart in the U.S. Japanese machinery R&D starts to decline in 1986, the same year that same industry U.S. R&D starts to fall. Japanese medium term cycle machinery output also starts to fall in 1986. Machinery output in the U.S. is depressed between 1982

[5]U.S. R&D starts to fall in 1989 in transport, 1990 in chemical and 1986 in electrical. Japanese industry output starts to fall in 1992 in transport, 1994 in chemical, and 1992 in electrical.

and 1993. Then U.S. R&D and U.S. output pick up again in 1994. This is followed one year later by a pick up in Japanese R&D and Japanese output. Although the diffusion lags are shorter in the Japanese machinery industry, there is no evidence that the relatively high level of productivity in this industry is associated with an increased dependence on domestic R&D.

Overall, the disaggregated evidence is consistent with our results from the aggregate analysis. U.S. R&D is an important leading indicator of medium term cycles in Japanese industry data as well as Japanese aggregate data.

7 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 term cycle data isolates a large and significant role for U.S. 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. Comin and Gertler (2003) and thus in turn important sources of medium term cycle variation in Japan.

We are currently looking further into the mechanism(s) whereby Japan adopts U.S. technology by collecting and analyzing in more detail the role of domestic and foreign R&D and foreign domestic investment in industry level productivity data. In addition we are also working on the mechanisms of diffusion. We are developing a theory in which slower growth in the world technology frontier acts as a barrier that reduces the benefits to adoption. The work we have presented here suggests that there may be no need to appeal to barriers to adoption as posited by Parente and Prescott (2004) to account for both the timing and cycles underlying Japan's development miracle.

References

[1] Braun, Richard A., Daisuke Ikeda, and Douglas H. Joines (2005), "Saving and Interest Rates in Japan: Why They Have Fallen and Why They Will Remain Low," CIRJE Working Papers: CIRJE-F-328.

[2] Braun, Richard A. and Yuichiro Waki (2005), "Monetary Policy during Japan's lost decade," CIRJE Working Papers: CIRJE-F-343.

[3] Bernstein, Jeffrey and Pierre Mohnen (1998), "International R&D Spillovers between U.S. and Japanese R&D Intensive Sectors," *Journal of International Economics,* vol. 44, no. 2 pp. 315-38.

[4] Branstetter, Lee (1999), "Are Knowledge Spilloevers International or Intranational in Scope?" *Journal of International Economics,* vol. 53 pp.53-79.

[5] Branstetter, Lee and Kwon Heog Ug (2004), "The Restructuring of Japanese Research and Development: The Increasing Impact of Science on Japanese R&D," Unpublished manuscript.

[6] Caballero, Ricardo. J., Takeo Hoshi, and Anil K. Kashyap (2005), "Zombie Lending and Depressed Restructuring in Japan," Unpublished manuscript.

[7] Chen, Kaji, Ayse Imrohoruglu, and Selo Imrohoruglu (2005), "Japanese Saving Rate," Unpublished manuscript.

[8] Christiano, Lawrence and Terry Fitzgerald (2003), "The Band Pass Filter," *International Economic Review*, vol44, no.2, pp. 435-465.

[9] Coe, David and Elhanan Helpman (1995), "International R&D Spillovers," *European Economic Review*, vol. 39, pp. 859-887.

[10] Comin, Diego (2002), "R&D? A Small Contribution to Productivity Growth," Unpublished manuscript.

[11] Comin, Diego and Mark Gertler (2003), "Medium Term Business Cycles," NBER Working Paper No. 10003.

[12] Eaton, Jonathan and Samuel Kortum (1999), "International Patenting and Technology Diffusion: Theory and Measurement," *International Economic Review*, vol. 40, no. 3, pp. 537-570.

[13] ———————————— (1997), "Engines of Growth: Domestic and Foreign Sources of Innovation," *Japan and the World Economy,* vol. 91 no. 2 pp.235-259.

[14] ———————————— (1996), "Trade in Ideas: Patenting and Productivity in the OECD," *Journal of International Economics,* vol. 40, pp. 251-278.

[15] Eggertsson, Gauti B. and Michael Woodford (2004), "Optimal Monetary and Fiscal Policy in a Liquidity Trap," NBER Working Paper No. 10840.

[16] Griliches, Zvi and Jacque Mairess (1990), "R&D and Productivity Growth: Comparing Japanese and U.S. Manufacturing Firms," in C. Hulten (ed.) *Productivity Growth in Japan and the United States*, University of Chicago Press for NBER, pp. 317-340.

[17] Hayashi, Fumio and Edward Prescott (2002), "The 1990s in Japan: A Lost Decade," *The Review of Economic Dynamics,* vol. 5 pp. 206-235.

[18] Hopenhayn, Hugo and Francesco Squintani (2005), "Preemption Games with Private Information," Unpublished manuscript.

[19] Howitt, Peter (2000), "Endogenous Growth and Cross-Country Income Differences," *American Economic Review,* vol. 90, no. 4, pp. 829-46.

[20] Inklaar, Robert, Harry Wu, and Bart van Ark (2003), "Losing Ground-Japanese Labour Productivity and Unit Labour Costs in Manufacturing in Comparison to the U.S.," Research Memorandum GD-64.

[21] Ito, Takatoshi and Frederic S. Mishkin (2004), "Two Decades of Japanese Monetary Policy and the Deflation Problem," NBER Working Paper No. 10878.

[22] Jones, Charles (1995), " R&D-Based Models of Economic Growth," *Journal of Political Economy*, vol. 103, pp. 759-784.

[23] Jorgenson, Dale and Koji Nomura (2004), "Information Technology and the Japanese Growth Recovery," Unpublished manuscript.

[24] Jovanovic, Boyan and Glenn MacDonald (1994), "Competitive Diffusion," *Journal of Political Economy*, vol. 102, pp.24-52.

[25] Keller, Wolfgang (2004), "International Technology Diffusion," *Journal of Economic Literature,* vol. 42, no. 3, pp. 752-782.

[26] Keller, Wolfgang (2002), "Geographic Localization of International Technology Diffusion," *American Economic Review*, vol. 92, pp. 120-142.

[27] Klenow, Peter and Andres Rodriguez-Clare (2004), "Externalities and Growth," NBER Working Paper No. 11009.

[28] Kortum, Samuel and Joshua Lerner (1998), "Stronger Protection or Technological Revolution: Which is Behind the Recent Surge in Patenting?" Carnegie-Rochester Conference Series on Public Policy, 48, pp. 247-304.

[29] Okada, Toshihiro (2006), "What Does the Solow Model Tell Us about Economic Growth?," *Contributions to Macroeconomics*, vol. 6, no. 1, article 5.

[30] Parente, Stephen and Edward Prescott (2004), "A Unified Theory of the Evolution of International Income Levels," Unpublished manuscript.

[31] ———————————— (1994), "Barriers to Technology Adoption and Development," *Journal of Political Economy,* vol. 102, no. 2, pp. 298-321.

[32] Poole, William (1970), "Optimal Choice of Monetary Policy Instruments in a Simple Stochastic Macro Model," *Quarterly Journal of Economics,* vol. 84, no. 2, pp. 197-216.

[33] Rosenberg, Nathan and W. Edward Steinmueller (1988), "Why are Americans Such Poor Imitators?" *American Economic Review,* vol. 78, no. 2, pp. 228-234.

Data Appendix

Japanese data

The primary data source of the Japanese data set, is Economic and Social Research Institute, Cabinet Office, "National Accounts". Labor variables are taken from Ministry of Internal Affairs and Communications, "Labor Force Survey," and Ministry of Health, Labour and Welfare, "Monthly Labor Survey". The data are reclassified in order to be consistent with Hayashi and Prescott (2002). Total factor productivity (TFP) is constructed by using the "output" (Y), "capital" (K) and "total hours worked" (H) series in the following way: $TFP = \left(Y/(K^{0.363}H^{1-0.363})\right)^{\frac{1}{1-0.363}}$.

R&D data are non-governmental funded R&D expenditures, based on Ministry of Internal Affairs and Communications, "The Survey of Research and Development". Since the surveyed category has changed in 1996, 2001 and 2002, the series is extended by annual changes from 1995 data to onwards. The private industry data is constructed mainly from Groningen Growth and Development centre, Faculty of Economics, University of Groningen, "60-Industry Database," and OECD, "Structural Analysis (STAN) database" and "National Accounts" described above are used for the extension of the sample periods. Since "60-Industry Database" is only available from 1979 to 2002, the data is extended to 1960 to 2002, using the other two statistics.

U.S. data

R&D data are Non-Federal funded R&D expenditures, based on National Science Foundation, "The National Patterns of R&D Resources". The private industry data is constructed mainly from Groningen Growth and Development centre, Faculty of Economics, University of Groningen, "60-Industry Database," and OECD, "The International Sectoral Data Base (ISDB)" and "35 KLEM data set" provided by Dale Jorgenson, Harvard University are used for the extension of the sample periods. Since "60-Industry Database" is only available from 1979 to 2002, the data is extended to 1960 to 2002, using the other two statistics.

Table 1

Model Calibration

β	δ	θ	τ^k	α	T
0.977	0.085	0.363	0.45	2.79	112

Notes:

1. The utility function is: $\sum_{t=0}^{\infty} \beta^t \left(\ln(c_t) + \alpha \ln(T - h_t) \right)$

2. δ is the rate of depreciation on capital, θ is the capital share parameter and τ^k is the tax rate on capital income.

Table 2

Standard Deviations of Japanese Filtered Data Expressed as Percentages

	Medium Term Cycle	Medium Frequency	High Frequency
GNP	5.5	5.4	1.2
Consumption	2.9	2.8	1.0
Investment	13.0	12.6	3.4
Total Hours Worked	2.3	2.1	1.0
Capital	7.1	7.1	1.6
R&D	9.4	9.0	2.7
TFP	6.9	6.6	1.9

Notes:

1. Sample period is 1960-2002.
2. Medium term cycle filter retains cycles of duration 40 years or less.
3. Medium frequency filter retains cycles of duration 8 to 40 years.
4. High frequency filter retains cycles of duration less than 8 years.

Table 3

Contemporaneous Correlations of Filtered Japanese GNP and TFP

Medium Term Cycle	Medium Frequency	High Frequency
0.95	0.96	0.86

Notes:

1. Sample period is 1960-2002.
2. Medium term cycle filter retains cycles of duration 40 years or less.
3. Medium frequency filter retains cycles of duration 8 to 40 years.
4. High frequency filter retains cycles of duration less than 8 years.

Table 4

Granger Causality (G.C.) Tests: Japanese Data

(Two variable autoregressions)

Null Hypothesis	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
Number of lags	p value	p value	p value	p value	p value	p value
1	0.282	0.881	0.619	0.383	0.011	0.339
2	0.857	0.974	0.411	0.21	0.041	0.59
3	0.93	0.899	0.005	0.052	0.048	0.061
4	0.867	0.27	0.082	0.012	0.511	0.011

Notes:

1. The Granger Causality tests are based on two variable autoregressions with the number of lags listed in the first column and the two variables listed at the top of each column.

2. Columns 2 -7 report p-values of the test statistic under the null hypothesis. A low value of the p-value is evidence against the null hypothesis.

3. All results are based on Japanese medium term cycle filtered data.

Table 5

Variance Decomposition of Japanese GNP: Bivariate Vector-Autoregression

(Percentage of variance of Japanese GNP at a 10 year forecast horizon explained by Japanese GNP and Japanese R&D)

Ordering:	GNP^{JPN} ordered first, $R\&D^{JPN}$ ordered second		$R\&D^{JPN}$ ordered first, GNP^{JPN} ordered second	
Number of lags	GNP^{JPN}	$R\&D^{JPN}$	$R\&D^{JPN}$	GNP^{JPN}
1	90.69	9.31	72.42	27.58
2	98.44	1.56	51.43	48.57
3	97.58	2.43	56.51	43.49
4	97.64	2.36	45.29	55.71

Notes:

1. All data are medium term cycle filtered.
2. The variance decompositions are based on a Cholesky decomposition with the indicated ordering.

Table 6

Variance Decomposition of Japanese TFP: Bivariate Vector-Autoregression

(Percentage of variance of Japanese TFP at a 10 year forecast horizon explained by Japanese TFP and Japanese R&D)

Ordering:	TFP^{JPN} ordered first, $R\&D^{JPN}$ ordered second		$R\&D^{JPN}$ ordered first, TFP^{JPN} ordered second	
Number of Lags	TFP^{JPN}	$R\&D^{JPN}$	$R\&D^{JPN}$	TFP^{JPN}
1	99.8	0.3	44.4	55.6
2	99.6	0.4	49.9	50.1
3	98.5	1.5	46.9	53.1
4	92.9	7.1	35.2	64.8

Notes:

1. All data are medium term cycle filtered.
2. The variance decompositions are based on a Cholesky decomposition with the indicated ordering.

Table 7

Granger Causality (G.C.) Tests for Japanese TFP

(Three variable autoregressions: Japanese TFP, Japanese R&D and U.S. R&D)

Null Hypothesis	Japanese R&D does not G.C. Japanese TFP	U.S. R&D does not G.C. Japanese TFP
Number of 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

Notes:

1. The Granger Causality tests are based on regression where Japanese TFP is regressed on its own lags and lags of Japanese and U.S. R&D expenditures with lag lengths ranging from 1 to 4.

2. The second column reports p-values of the test statistic under the null hypothesis that Japanese R&D does not Granger Cause Japanese TFP. A low value of the p-value is evidence against the null hypothesis.

3. The third column reports p-values of the test under the null hypothesis that U.S. R&D does not Granger Cause Japanese TFP.

4. All data are medium term cycle filtered.

Table 8
Variance Decomposition of Japanese TFP: Trivariate Vector-Autoregressions

Percentage of variance of Japanese TFP at a 10 year forecast horizon explained by Japanese TFP, Japanese R&D and U.S. R&D.

Number of Lags	TFP^{JPN}	$R\&D^{JPN}$	$R\&D^{US}$
1	58.7	10.2	31.1
2	63.1	6.3	30.6
3	29.9	8.8	61.3
4	26.0	10.6	63.4

Notes:

1. The variance decompositions are based on a Cholesky orthogonalization with Japanese TFP ordered first, Japanese R&D ordered second and U.S. R&D ordered third.
2. The first column reports the number of lags in the VAR.
3. All data are medium term cycle filtered.

Table 9

Granger Causality (G.C.) Tests for Japanese Patents

(Three variable auto-regressions: Japanese TFP, Japanese Patents and U.S. R&D)

Null Hypothesis:	Japanese patents do not G.C. Japanese TFP	U.S. R&D does not G.C. Japanese patents	Japanese patents do not G.C. U.S. R&D
Number of 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

Notes:

1. All of the Granger Causality Tests are based on auto-regressions with three variables: Japanese patents, Japanese TFP and U.S. R&D.
2. The 1st column lists the number of lags of the right hand side variables in the auto-regression.
3. The 2nd - 4th columns report p-values under the null hypothesis. A low value of the p value is evidence against the null hypothesis.
4. All data are medium term cycle filtered.

Table 10

Relative Volatilities Japanese Data and Models

Specification	σ_Y	σ_Z / σ_Y	σ_C / σ_Y	σ_X / σ_Y	$\sigma_{K/Y} / \sigma_Y$	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	0.00	0.51	0.78	0.35	0.13

Notes:

1. σ_a denotes standard deviation of variable a.

2. Y, Z, C, X, K/Y, and H denote gross national product, total factor productivity, consumption, investment, the capital output ratio, and total hours worked respectively.

Table 11

Correlation between Model Predicted Values and Actual Values in Japanese Data

Specification	$Corr(Z^m,Z^d)$	$Corr(Y^m,Y^d)$	$Corr(C^m,C^d)$	$Corr(X^m,X^d)$	$Corr((K/Y)^m,(K/Y)^d)$	$Corr(H^m,H^d)$
Baseline	1.00	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 R&D lags 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 lag 4	-0.26	0.40	0.81	0.11	-0.23	0.02
US R&D lag 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

Notes:

1. $Corr(a,b)$ is the contemporaneous correlation between variables a and b.
2. $Z^m, Y^m, C^m, X^m, (K/Y)^m$, and H^m denote model predicted values of total factor productivity, gross national product, consumption, investment, the capital output ratio and total hours worked respectively.
3. $Z^d, Y^d, C^d, X^d, (K/Y)^d$, and H^d denote Japanese data values of total factor productivity, gross national product, consumption, investment, the capital output ratio and total hours worked respectively.
4. All data are medium term cycle filtered.

Table 12

The Lost Decade: Japanese Data and Model Simulations

	The percent change in:			
	GNP	Consumption	Investment	K/Y
Data	-12.1	-9.0	-22.9	16.9
Model	-12.7	-10.2	-20.9	5.4

Notes:

1. The reported are the percentage changes in medium term cycle filtered actual and simulated data between 1990 to 2002.
2. Model results use the fourth lag of U.S. R&D expenditures to predict current period Japanese TFP.

Table 13

Research and Development Expenditures by Sector Japan and U.S.

R&D expenditures by sector expressed as a percentage share of total industry R&D expenditures		
Industry	JPN	U.S.
Food, beverage and tobacco	2.8	1.2
Textiles, apparel and leather	1.6	0.3
Pulp, paper and printing	1.1	1.0
Chemicals	19.7	11.0
Nonmetalic mineral	2.4	0.8
Basic metals	6.3	1.2
Fablicated metal	1.5	1.1
Machinery and equipment	41.2	36.2
(Electrical equip.)	30.5	18.8
Transport equipment	15.2	32.7

Note:

The reported values are averages over the 1960-2001 sample period.

Table 14

Granger Causality (G.C.) Tests of Japanese Research and Development Expenditure on Japanese Same Industry Output

Null Hypothesis: Japanese R&D does not Granger Cause Japanese industry output				
Industry	p value (# of lags:1)	p value (# of lags:2)	p value (# of lags:3)	p value (# of lags:4)
Food, beverage and tobacco	0.424	0.046	0.106	0.254
Textiles, apparel and leather	0.426	0.348	0.344	0.348
Pulp, paper and printing	0.001	0.010	0.008	0.004
Chemicals	0.763	0.697	0.481	0.441
Nonmetalic mineral	0.597	0.457	0.792	0.764
Basic metals	0.923	0.761	0.955	0.878
Fablicated metal	0.646	0.571	0.934	0.706
Machinery and equipment	0.844	0.100	0.172	0.484
(Electrical equip.)	0.127	0.018	0.222	0.292
Transport equipment	0.395	0.372	0.222	0.373

Notes:

1. The right hand side variables in each regression are industry output and same industry Japanese R&D expenditures.

2. Columns 2 through 5 report p-values under the null hypothesis that Japanese sectoral R&D does not Granger Cause Japanese sectoral output as the number of lags in the regression is varied from 1 to 4. A small p-value is evidence against the null hypothesis.

Table 15

Granger Causality (G.C.) Tests of U.S. Research and Development Expenditure on Japanese Same Industry Output

	Null Hypothesis: US R&D does not Granger Cause Japanese Industry Output			
Industry	p value (# of lags:1)	p value (# of lags:2)	p value (# of lags:3)	p value (# of lags:4)
Food, beverage and tobacco	0.032	0.410	0.684	0.810
Textiles, apparel and leather	0.733	0.164	0.073	0.114
Pulp, paper and printing	0.004	0.045	0.246	0.012
Chemicals	0.478	0.028	0.014	0.037
Nonmetalic mineral	0.251	0.654	0.727	0.818
Basic metals	0.410	0.812	0.699	0.674
Fablicated metal	0.386	0.768	0.524	0.471
Machinery and equipment	0.001	0.002	0.008	0.008
(Electrical equip.)	0.079	0.847	0.153	0.260
Transport equipment	0.084	0.380	0.100	0.226

Notes:

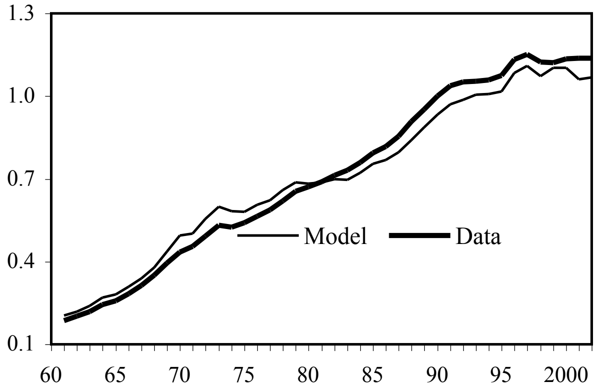
1. The right hand side variables in each regression are industry output and same industry U.S. R&D expenditures.

2. Columns 2 through 5 report p-values under the null hypothesis that U.S. sectoral R&D does not Granger Cause Japanese sectoral output as the number of lags in the regression is varied from 1 to 4. A small p-value is evidence against the null hypothesis.

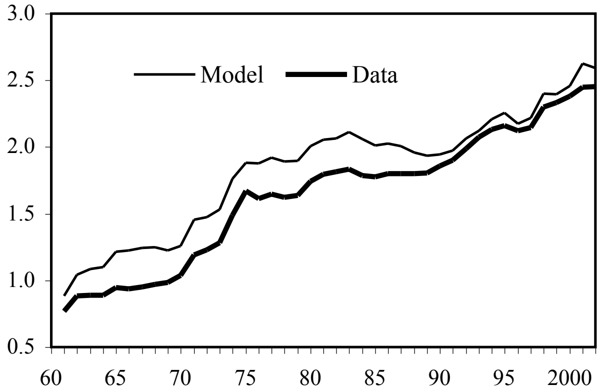
Figure 1

Simulation Results and Actual Japanese Data

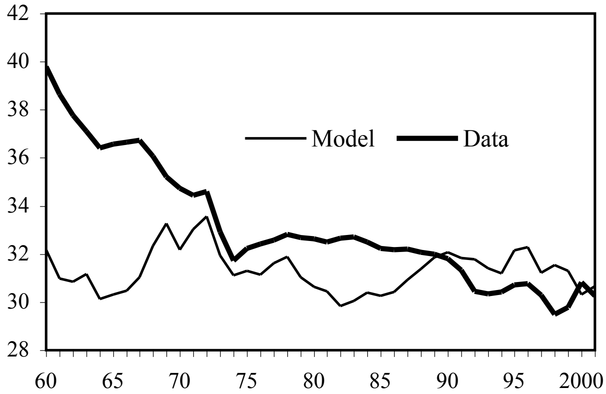
(1)GNP



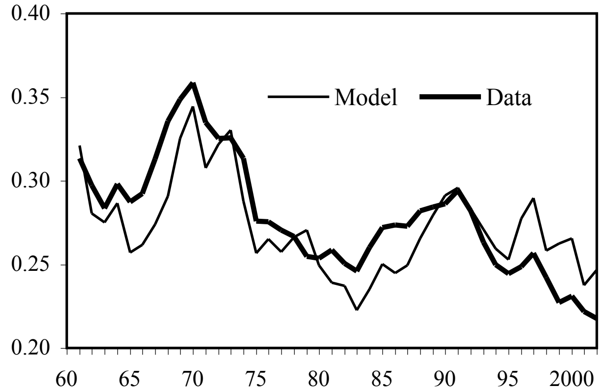
(2)Capital output ratio



(3)Labor input



(4)Investment share of GNP



(5)Consumption share of GNP

(6)Net saving relative to GNP

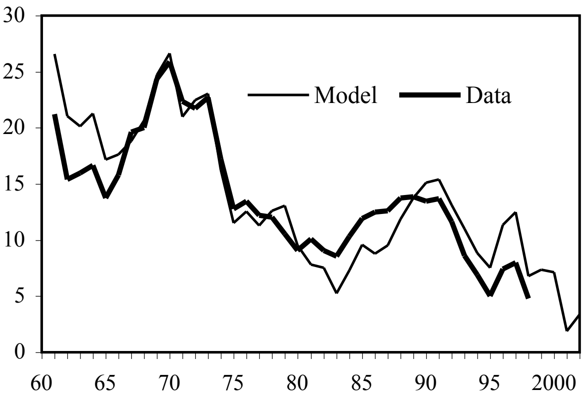


Figure 2

Japanese Medium Term Cycle GNP and TFP

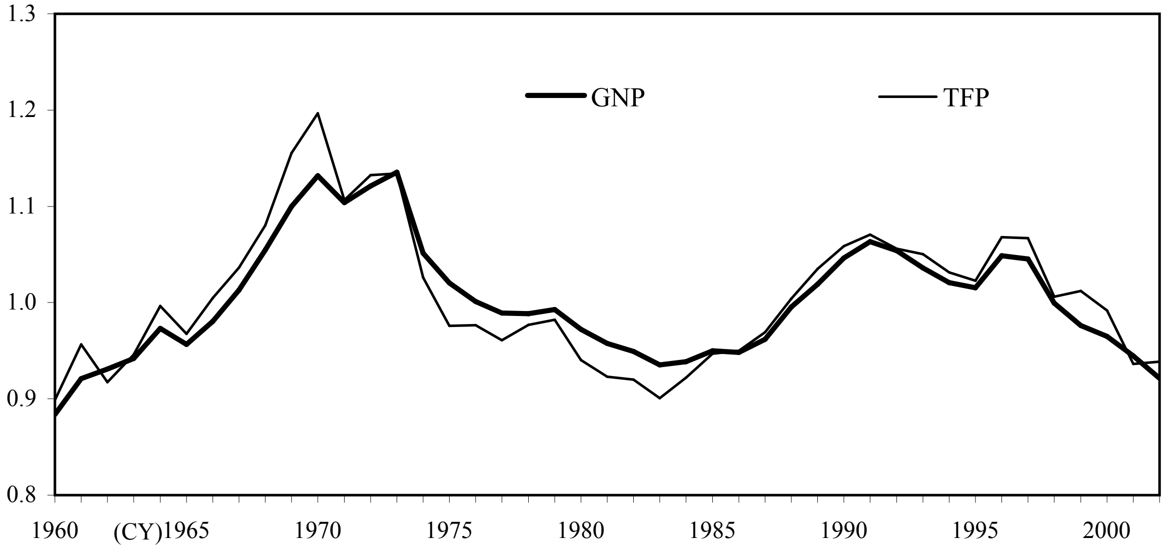
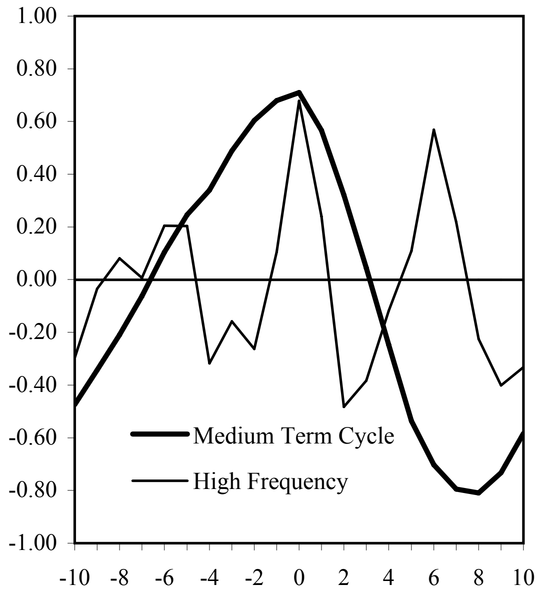


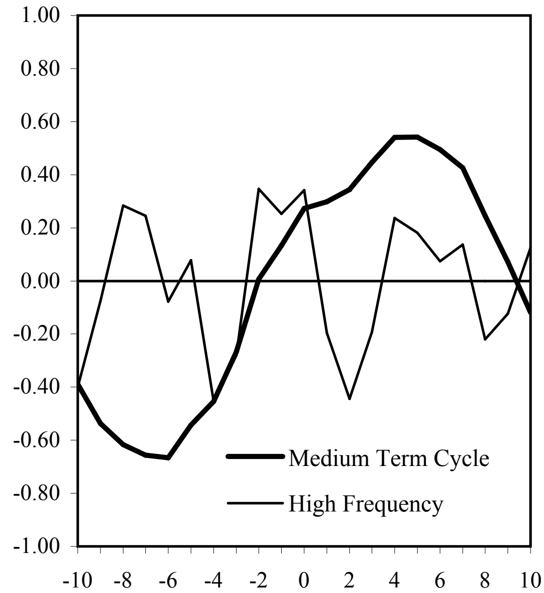
Figure 3

Cross-correlations of Japanese R&D, GNP and TFP

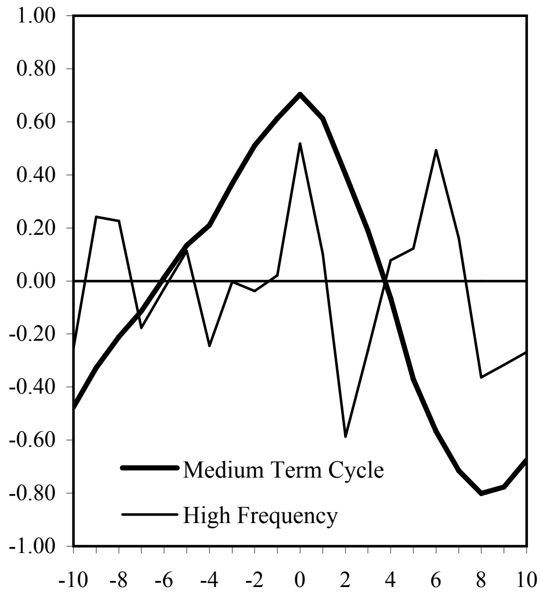
(1)JPN GNP with JPN R&D



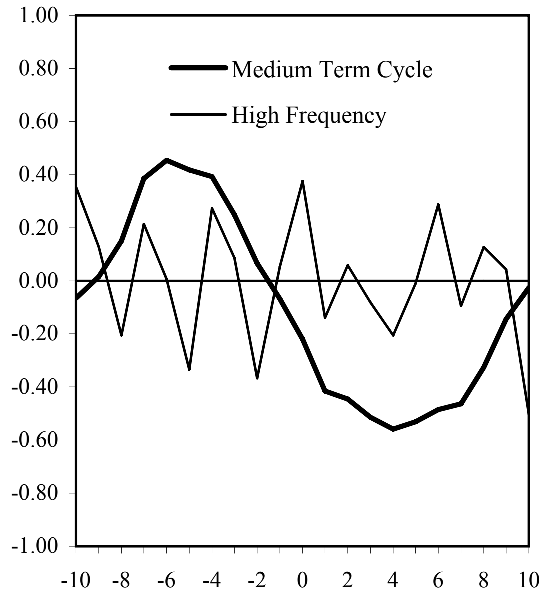
(3)JPN Patents with JPN R&D



(2)JPN TFP with JPN R&D



(4)JPN TFP with JPN Patents



(note) Horizontal axis indicates the number of lags (years).
JPN denotes Japanese data.

Figure 4

Japanese Medium Term Cycle Patents, TFP and R&D

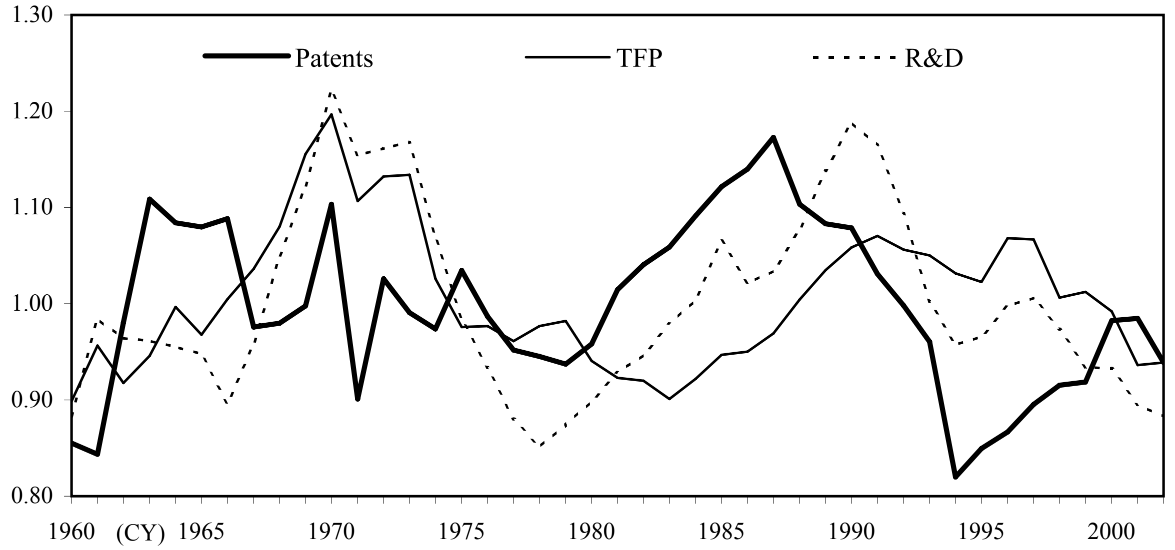


Figure 5

Medium Term Cycle TFP (Japan and U.S.)

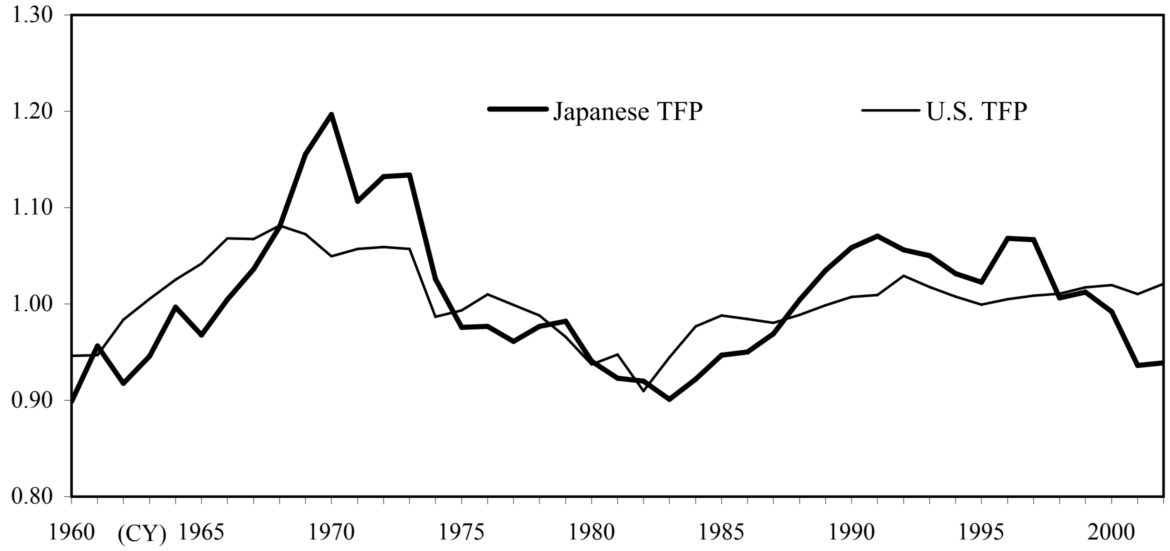
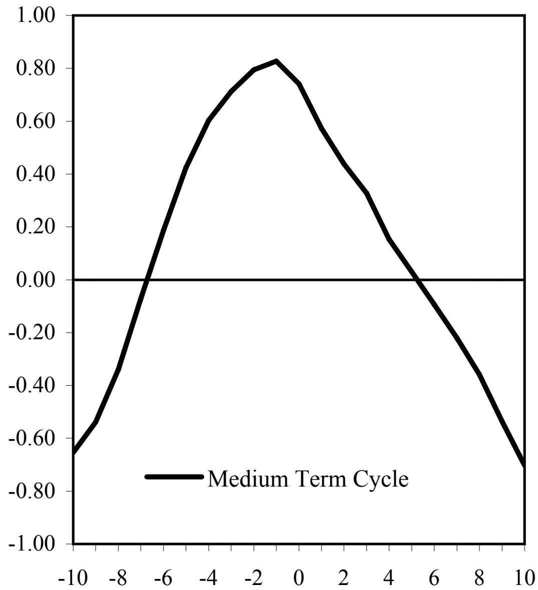


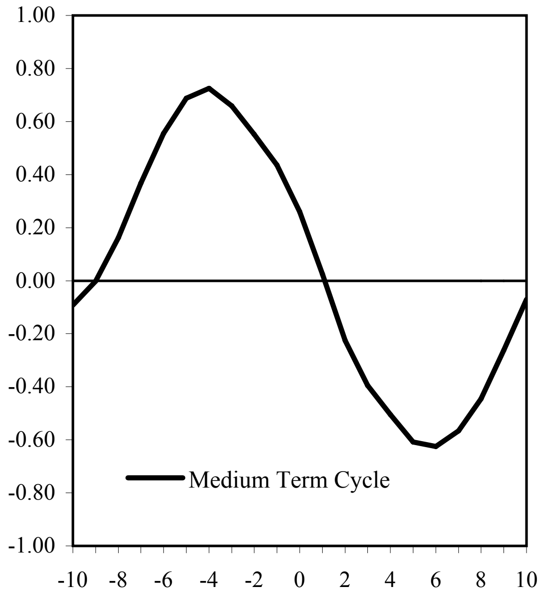
Figure 6

Cross-correlations of TFP and R&D (Japan, U.S.)

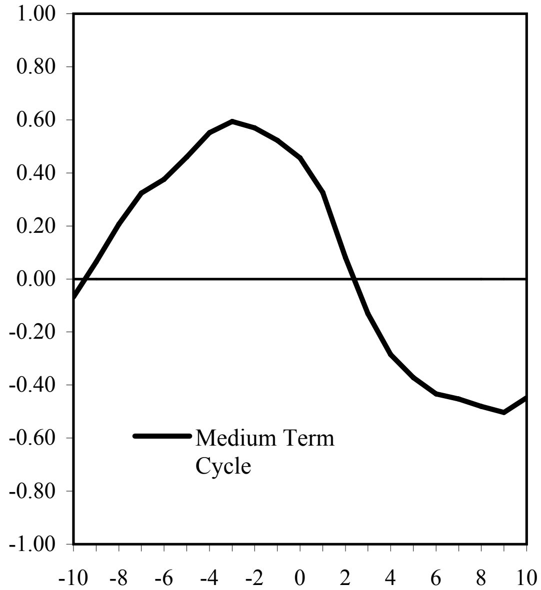
(1)JPN TFP with US TFP



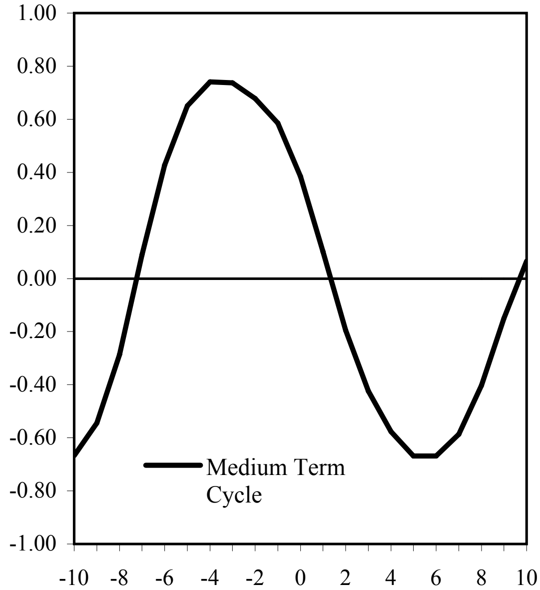
(3)JPN TFP with US R&D



(2)US TFP with US R&D



(4)JPN R&D with US R&D

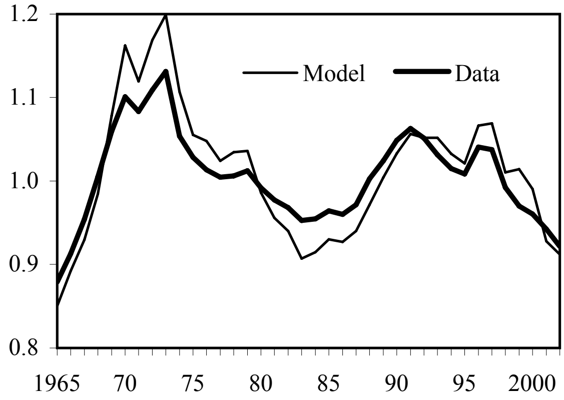


(note) Horizontal axis indicates the number of lags (years).
JPN denotes Japanese data.

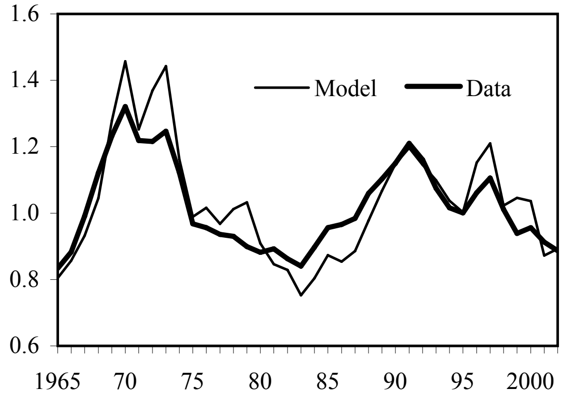
Figure 7

Model Predicted Medium Term Cycles and Japanese Data

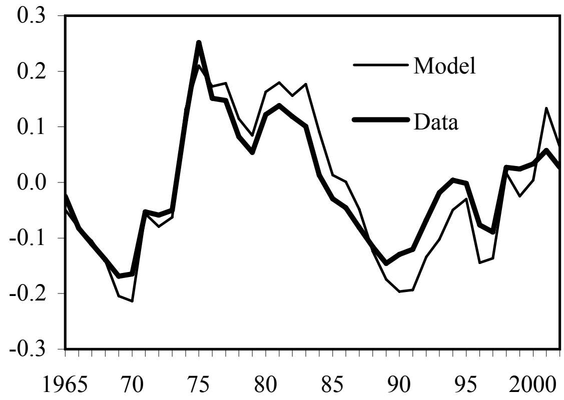
(1)GNP



(4)Investment

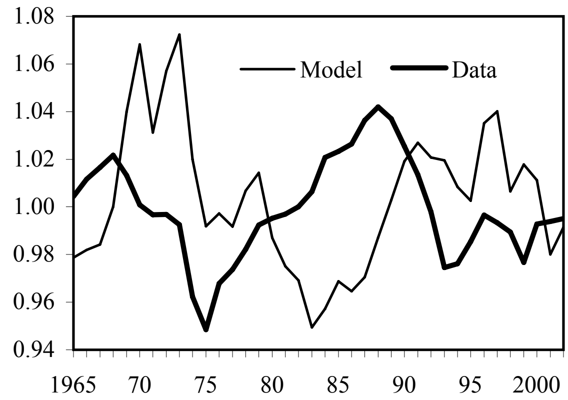


(2)Capital output ratio

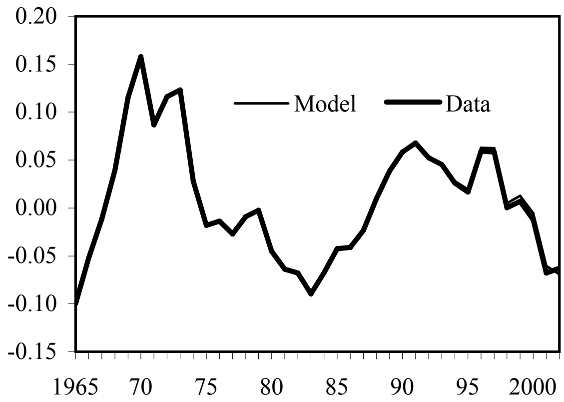


(5)Consumption

(3)Labor input



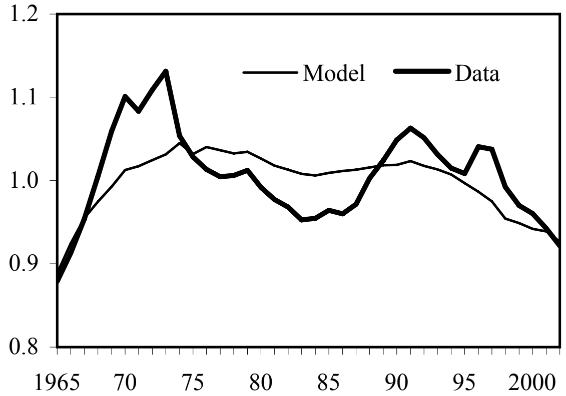
(6)Medium term cycle TFP and predicted TFP



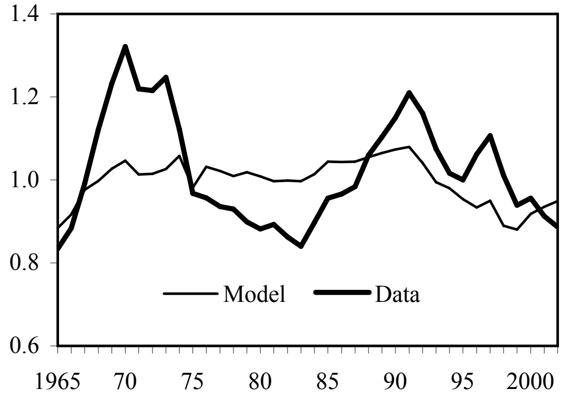
(note) Simulations are conducted from 1965 to 2002.

Figure 8
Simulation with 4th Lag of Japanese Patents Used to Predict Japanese TFP

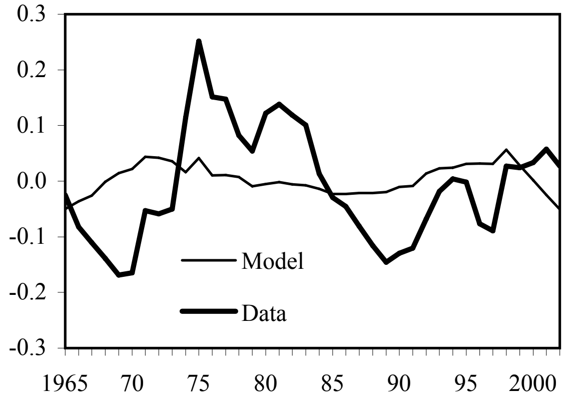
(1)GNP



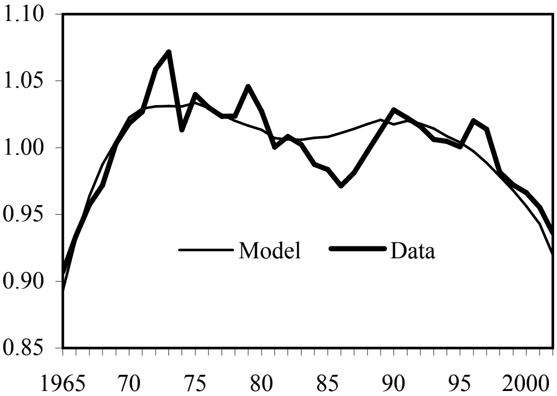
(4)Investment



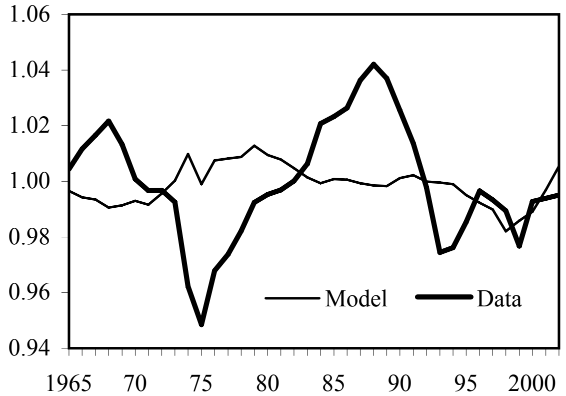
(2)Capital output ratio



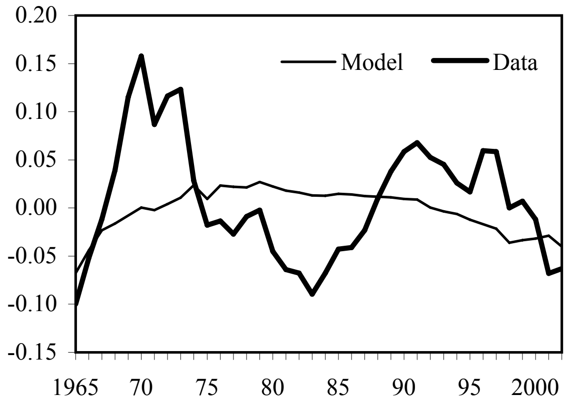
(5)Consumption



(3)Labor input



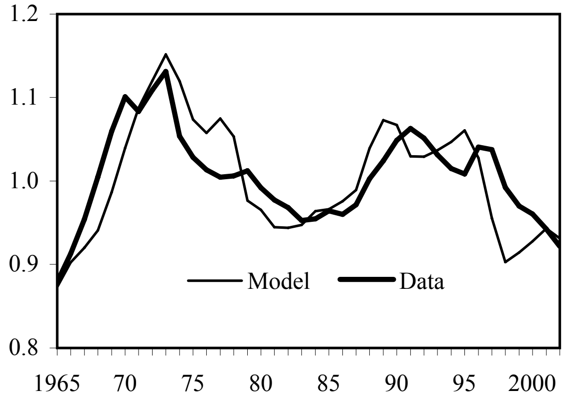
(6)Medium term cycle TFP and predicted TFP



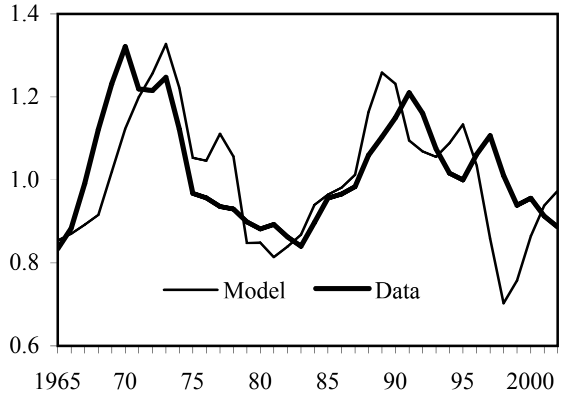
(note) Simulations are conducted from 1965 to 2002, allowing lags.

Figure 9
Simulation with 4th Lag of U.S. R&D Used to Predict Japanese TFP

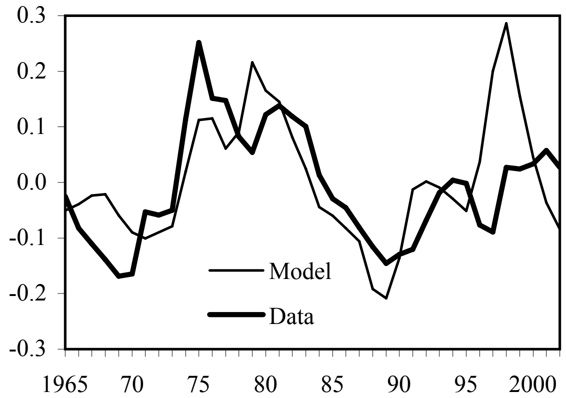
(1)GNP



(4)Investment

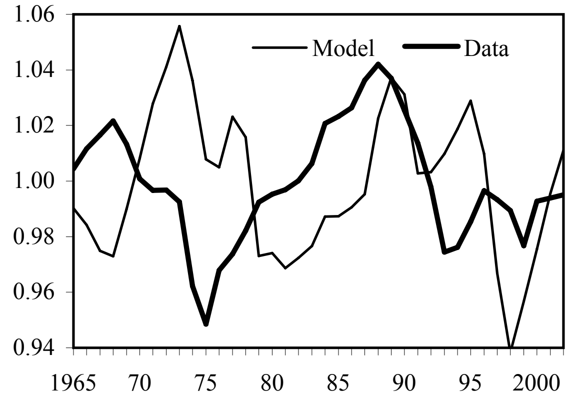


(2)Capital output ratio

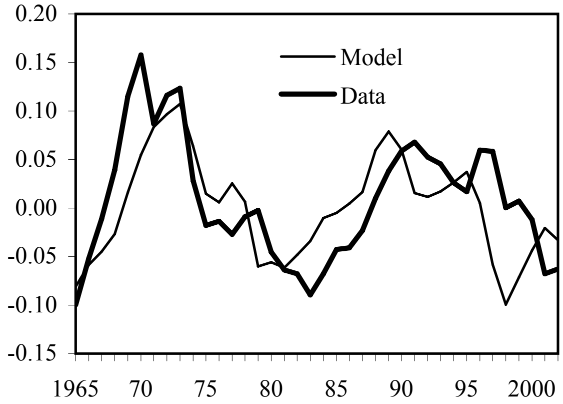


(5)Consumption

(3)Labor input



(6)Medium term cycle TFP and predicted TFP



(note) Simulations are conducted from 1965 to 2002, allowing lags.

Figure 10

Medium Term Cycle R&D (Private industry)