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R. Anton Braun
University of Tokyo

Toshihiro Okada
Kwansei Gakuin University

Nao Sudo
Bank of Japan

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SCHOOL OF ECONOMICS

KWANSEI GAKUIN UNIVERSITY

1-155 Uegahara Ichiban-cho

Nishinomiya 662-8501, Japan

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

R. Anton Braun[a] University of Tokyo

Toshihiro Okada[b] Kwansei Gakuin University

Nao Sudo[c] Bank of Japan

**Abstract**

Between 1960 and 1990 Japanese labor productivity rose from 27 percent of the U.S. to 87 percent. These productivity gains are associated with large variations in Japanese TFP. We find that movements in Japanese TFP are associated with prior movements in U.S. R&D expenditures. Model simulations that isolate the contribution of U.S. R&D to Japanese TFP reproduce the most important swings in Japanese economic activity between 1960 and 2002.

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*a*. toni@e.u-tokyo.ac.jp

*b*. toshihiro.okada@kwansei.ac.jp

*c*. nao.sudou@boj.or.jp

# 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 in 1990. Productivity gains of this magnitude over such a short period are exceptional and Japan has been referred to as a development miracle.[1] Recent research aimed at uncovering the source of these rapid productivity gains has focused on two factors: capital deepening and technology diffusion.

Japan's productivity gains have been associated with a large increase in the capital-output ratio. Between 1960 and 1990 the capital-output ratio tripled rising from 0.8 to 2.4. Christiano (1989) and Chen, İmrohoruğlu and İmrohoruğlu (2006) consider variants of the neoclassical growth model that attribute this increase to reconstruction after World War II (WWII). Chen et al. (2006) consider a version of the neoclassical growth model that combines a low initial capital stock with measured variation in total factor productivity (TFP). Their model reproduces the trend and variations about trend of Japanese per capita output in post WWII data. Their model is silent, however, on the sources of variation in TFP.

One potential factor is technology diffusion. Over time a firm's knowledge about the best technique for combining capital and labor to produce output gradually diffuses to competitors within the same country and firms in other countries. Eaton and Kortum (1999), Howitt (2000), Klenow and Rodriguez (2004) and Parente and Prescott (2004) propose models which reflect this view. In these models the diffusion of business ideas implies that 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.

Parente and Prescott (1994) and Eaton and Kortum (1997) develop models of technological diffusion to analyze Japan's development miracle. 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 World War II. Eaton and Kortum (1997) instead argue that the U.S. had a large stock of business ideas at the end of WWII as compared to Japan and European countries. They develop a model of innovation and diffusion and use cross-country patent and productivity data to parameterize their model in a way that reproduces both the rates of convergence of relative income levels and the magnitude of levels differences in incomes at the end of their data sample period.

Both of these models have the property that convergence is smooth and monotonic. In practice though convergence has not been smooth. Japanese TFP grew at an annualized rate of 7.2 percent between 1960-1973, then fell to 2.2 percent between 1973-1983, increased to 3.6 percent between 1983-1991 and finally fell again to 0.5 percent between

1991-2000. It is our contention that these decade level variations in Japanese TFP growth contain valuable information and that this information indicates that the diffusion of business ideas from the U.S. has been an important ingredient in Japan's growth miracle.

We develop our argument in the following way. We first consider a neoclassical growth model with endogenous labor supply and show that a low initial capital stock in conjunction with measured variation in TFP accounts for the principal movements in GNP, investment, consumption, hours and the capital-output ratio in Japan between 1960 and 2002.

We then turn to analyze the source of variations in Japanese TFP over the 1960 - 2002 sample period. Our empirical analysis is motivated by previous work by Blanchard (1997), Klenow and Rodriguez (2004) and Comin and Gertler (2006). Blanchard (1997) documents medium term comovements in capital-output ratios and unemployment rates among continental European countries. Anglo-Saxon countries display a distinct set of comovements. 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. Comin and Gertler (2006) document large and statistically significant medium term cycles in U.S. data. They find that these cycles are readily associated with events like the productivity slowdown in the 1970s. They go on to show that these cycles contain useful information for modeling the dynamics of creation and adoption of business ideas in U.S. data.

We filter Japanese data to retain medium term cycles with duration of 40 years or less. Japanese data filtered in this way also exhibit a distinctive pattern of comovements. We then look for statistical evidence of lead-lag relationships linking R&D to TFP. Our maintained hypothesis is that enhancing productivity is a time consuming activity. Higher investment in R&D today produces new business ideas over time. Eventually some of these ideas get reflected in higher TFP. We show that an important source of variation in medium term cycle Japanese TFP is the pace of new ideas produced by the U.S. as measured by U.S. private sector R&D expenditures. U.S. R&D leads U.S. TFP by three years and leads Japanese TFP by four years. Variations in domestic ideas as measured by Japanese R&D, on the other hand are 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. Evidence that Japanese R&D Granger Causes Japanese TFP is much weaker. 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.

An analysis of industry level data on R&D provides similar evidence of the important role of diffusion of business ideas from the U.S. Output in R&D intensive Japanese industries is Granger Caused by U.S. same industry R&D expenditures and in most cases Japanese R&D does not Granger Cause same industry output.

We also look at aggregate data on U.S. and Japanese patents. 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.

We then return to the neoclassical model and use it as a device to assess the quantitative roles of domestic and U.S. R&D for other aggregate 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 important role of diffusion of knowledge from the U.S. to Japan. 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 gestation lags are increased the explanatory power of Japanese R&D sharply deteriorates.

Finally, we investigate the role of U.S. R&D in accounting for Japan's experience between 1990 and 2002. 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 cycle 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 about the important role of U.S. R&D for the Japanese economy 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 percent of Japanese productivity growth is due to domestic R&D and 62 percent 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 percent 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 percent 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 important in high income countries too.

The remainder of the paper is organized as follows. Section 2 describes our model. Section 3 documents the important role of variations in TFP in accounting for movements in Japanese GNP, consumption, investment, and the capital-output ratio. Section 4 conducts an empirical analysis that establishes an important role of U.S. R&D account in accounting for medium term cycle fluctuations in Japanese TFP and output. Section 5 uses the model to assess the contribution of U.S. R&D in accounting medium term cycle variations in other macroeconomic variables. Section 6 contains our concluding remarks.

# 2 The Model

We consider a perfect foresight version of the neoclassical growth model with an elastic labor supply. A 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 household's period budget constraint is given by:

$$C_t + X_t = w_t H_t + r_t K_t - \tau(r_t - \delta) K_t \tag{2}$$

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, $\tau$ is the tax rate on capital income, and the depreciation rate on capital is denoted by $\delta$. We include a (constant) tax rate on capital because average corporate tax rates are high in Japan (about 48 percent). When we calibrate the model taking this fact into consideration, the resulting parameterization is quite similar to what one finds using U.S. data.

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 and $\theta$ is a constant with $0 < \theta < 1$.

A competitive equilibrium for this economy is defined in the standard way (see e.g. Ljungqvist and Sargent (2004).

# 3 Calibration and Baseline Simulation Results

Most of the parameters are calibrated using the same methodology as Hayashi and Prescott (2002) with data from 1984-2001. The preference discount parameter $\beta = 0.977$, the capital share parameter, $\theta = 0.363$, the depreciation rate on capital, $\delta = 0.085$, and the capital tax rate, $\tau = 0.45$. Our preference specification, is different from Hayashi and Prescott (2002). So the leisure weight in preferences,$\alpha$, is instead calibrated using the household intertemporal first order condition.

$$\frac{\alpha}{T - h_t} c_t = (1 - \theta) A_t k_t^{\theta} h_t^{-\theta} \tag{7}$$

When calibrating the model 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. (2006) conduct perfect foresight simulations using a similar model. 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 and per capita output between 1960 and 2000. Consider Figure 1, which reports results for our model and Japanese data for the 1961 -2002 sample period. The initial capital stock is set to 21 percent 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, 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 overall conclusion that we draw from Figure 1 though is that one can account for the principal economic events in Japan between 1961-2002 using standard economic theory if one posits a low initial capital stock and conditions on measured variations in TFP.

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. 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 barriers to adoption after 1973 slows the rate at which firms choose to update their technology and this accounts for the productivity slow-down 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 reproduces the timing of convergence of labor productivity in Japan, France, Germany and the U.K. and also the relative levels of labor productivity in these countries at the end of their sample.

Interestingly neoclassical theory in conjunction with a low initial capital stock plus the measured variation in *exogenous* TFP also accounts for the speed of convergence and the output levels facts in Japan. This theory also reproduces movements in other macro variables not considered in these other papers. A second distinction relates to the convergence trajectory. 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. Actual Japanese data, however, exhibits significant swings in TFP growth.

During our sample period TFP has shown two periods of rapid growth and two periods of slow growth and the overall magnitude of the variations in TFP growth have fallen. Japanese TFP grew at an annualized rate of 7.2 percent between 1960-1973, then fell to 2.2 percent between 1973-1983, increased to 3.6 percent between 1983-1991 and finally fell again to 0.5 percent between 1991-2000. These variations in TFP have also been associated with movements in consumption, investment and the capital output ratio that are consistent with the workings of the neoclassical growth model. Taken together the above facts suggest to us that one fruitful way to learn about the sources of Japan's post WWII economic performance is to focus attention on TFP and seek to identify the sources of the medium term variations in Japanese TFP.

We now turn to undertake an empirical investigation of the roles of domestic innovation and diffusion of business ideas from abroad in accounting for medium term variation in Japanese TFP.

# 4 Empirical Results

The primary data source for our Japanese annual data-set is Hayashi and Prescott (2002). The data set used by Hayashi and Prescott (2002) are 1968 system of national accounts (SNA) base series. More recent Japanese data is based on the revised 1993 SNA. We update the Hayashi and Prescott (2002) data-set using data reported in the Annual Report on National Accounts 2004, obtainable from the web-site of Economic and Social Research Institute. The 1968 SNA data are extended using annual changes from the 1993 SNA data.

In an analysis of U.S. data Comin and Gertler (2006) have found that medium term cycles are large and exhibit a distinctive pattern of comovements of the economic variables. We next demonstrate that Japanese data also exhibits a distinctive pattern of medium term cycle comovements and that these comovements provide valuable information about the sources of variation in Japanese TFP.

We take natural logarithms of the data and decompose it into a trend and cycle component using the Christiano and Fitzgerald (2003) band pass filter.[3] The medium term *cycle* component is defined to include all cycles with duration of 40 years or less. In the analysis below we will occasionally decompose the medium term cycle component 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.

Since the focus of this paper is on medium term cycle we don't report information on the trend components. 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.

## 4.1 Facts about the Japanese medium term cycle

Japanese data exhibit large and distinctive medium term cycle fluctuations. Table 1 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 Panel A in Figure 2 which shows a plot of Japanese medium term cycle GNP and TFP. Both variables 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 comovements between GNP and TFP are even stronger in medium term cycle data than in high frequency data. The correlation between the medium term cycle component of GNP and TFP is 0.95 and the correlation between the high frequency component is 0.86.

## 4.2 Domestic Innovation

Our strategy for identifying the domestic innovation channel is to based on the maintained hypothesis that the process of improving technology is time consuming. Investments in R&D today will only produce new business ideas gradually over time and more time will elapse before these ideas get reflected in improvements in the state of technology.[4] Consider panels A and B in Figure 3 which show the cross-correlation functions of R&D with GNP and TFP using medium term cycle filtered and high frequency filtered Japanese data. Figure 3-(A) shows that the cross-correlation function of medium term cycle GNP with R&D reaches its peak of 0.71 at lag zero and then falls sharply as one moves in either direction away from zero. Figure 3-(B) shows that the cross-correlation function of medium term cycle TFP with R&D 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. Under the high frequency filter the peak cross-correlation of TFP with R&D is much lower but again there is no clear evidence that Japanese R&D leads either GNP or TFP.

Another way to ascertain 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 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. These results are reported in column 2 of Table 2. The statistics show no evidence that Japanese medium term R&D Granger Causes Japanese medium term GNP. A Similar, test of Granger Causality based on a bivariate VAR 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 (see column 3 of Table 2).

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 bivariate VAR's described above. In the case of the VAR using R&D and GNP (see Panel A of Table 3), if GNP is ordered first R&D accounts for only 2-9 percent of the variance in GNP at a 10 year horizon. If R&D is ordered first it accounts for 45-72 percent of the variance in GNP at the same horizon. For the bivariate VAR with TFP and R&D (see Panel B of Table 3) when TFP is ordered first R&D accounts for between 0.3 and 7 percent of the variance in TFP. With the other ordering R&D accounts for between 35 and 50 percent of the variance in TFP.

R&D expenditures in Japan are concentrated in a relatively small number of industries: chemicals, transportation, and machinery and equipment. In Japan these three industries account for 76 percent of all industry private R&D. Due to problems in constructing a consistent measure of the capital stock back to 1960 we do not have a consistent measure of TFP for industry level data. But we do have measures of R&D expenditures and industry output.

Table 4 summarizes the results of Granger Causality tests of medium term cycle Japanese R&D on same industry output. Generally speaking the industry level results are consistent with the results for aggregate data. Observe that there is virtually no evidence that same industry domestic R&D Granger Causes output for the three industries with the highest concentrations of R&D expenditures. Machinery and Equipment is statistically significant at the 10 percent significance level for the VAR with two lags but in the other scenarios the evidence of Granger Causality is weaker. For Machinery and Equipment most of the evidence of Granger Causality is concentrated in Electrical Equipment. When we break out this category separately the specification with 2 lags rejects the null hypothesis of no Granger Causality at conventional significance levels. We also report results for other less R&D intensive industry categories in Table 4. The only industry in which domestic R&D shows a consistent pattern of Granger Causality is Pulp, Paper and Printing.

Next we turn to see whether evidence of domestic innovation shows up when we use domestic patent data instead. Patents are an alternative indicator of the flow of ideas. In Kortum and Eaton (1999) investment in R&D over time produces usable business ideas that get patented. The over time some of these business ideas get applied to the production process and raise productivity. 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 person/company who applies 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 internationally.

Panel B of Figure 2 reports plots of medium term cycle Japanese patents 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 Panel B of Figure 2 is that although, 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 large fluctuations that are independent of movements in either TFP or R&D.

Not surprisingly, a formal statistical analysis fails to identify a clear dynamic relationship linking Japanese patents with R&D and TFP. Cross-correlations of Japanese patents with Japanese R&D reported in Panel C of Figure 3 show a peak correlation of -0.67 with the 6th lag of R&D suggesting that higher R&D lowers future patents. Granger Causality tests based on bivariate VARs with Japanese R&D and patents are reported in columns 4 and 5 of Table 2. Japanese R&D Granger Causes Japanese patents at the 10 percent significance level when the number of lags is three or four. However, Japanese Patents Granger Cause Japanese R&D when the number of lags is three or four. The results for TFP and Japanese patents are also mixed. The peak cross-correlation of Japanese patents with TFP is also negative (-0.58) and occurs at lag 4 (see Panel D of Figure 3). Granger Causality tests reported in columns 6 and 7 of Table 2 indicate that TFP

Granger Causes Japanese patents when the number of lags is one, two, or three. However, Japanese patents also Granger Cause Japanese TFP at the 10 percent significance level when the number of lags is three or four.

Overall, it is difficult to find empirical evidence of a strong domestic innovation channel using either R&D or patent data. We next turn to consider evidence about the role of the international diffusion of business ideas to Japan.

### 4.3 Evidence of Diffusion from the U.S. to Japan

Panel C of Figure 2 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. This plot has two noteworthy features. 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 Panel A of Figure 4. 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. Panel B of Figure 4 reports the cross-correlation function of U.S. TFP with U.S. R&D. 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 Japanese TFP with U.S. R&D. Panel C of Figure 4 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 Japanese R&D with U.S. R&D reported in Panel D of Figure 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 use Granger Causality tests to explore the temporal relationship between U.S. R&D, Japanese R&D and Japanese TFP. Table 5 reports Granger Causality tests in which Japanese TFP is regressed on its own lags and lagged values of Japanese and U.S. R&D. The Ganger causality test results 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 that Japanese R&D does *not* Granger Cause Japanese TFP for all choices of lag-length.

Table 6 reports the results of variance decompositions of Japanese TFP. The results correspond to the case where Japanese TFP is ordered first, Japanese R&D is ordered second and U.S. R&D is ordered third. Interestingly, 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 the specification with one lag U.S. R&D explains 31 percent of the variance of Japanese TFP whereas Japanese R&D only explains 10 percent at the 10 year horizon. As the number of lags in the VAR is increased to four the fraction of Japanese TFP explained by U.S. R&D rises to 63 percent and the fraction explained by Japanese R&D drops to 11 percent. Taken together this evidence shows a strong statistical relationship linking U.S. R&D and Japanese TFP. U.S. R&D expenditures lead Japanese TFP by four years, Granger Causes Japanese TFP and accounts for a large fraction of the variance of Japanese TFP even when ordered last.

U.S. industry level data on R&D expenditures are also concentrated in the same relatively small number of industries as in Japan: chemicals, transportation, and machinery and equipment. These three industries account for 80 percent of all industry private R&D in the U.S. as compared to a figure of 76 percent for Japan. If variations in R&D expenditures are an indicator of the flow of ideas from the U.S. to Japan, then we should expect to find evidence of diffusion in R&D intensive industries.

Table 7 reports Granger Causality tests of U.S. same industry R&D on output for each Japanese industry. We wish to emphasize two points. First, the pattern of results shows stronger evidence of Granger Causality in R&D intensive industries. Notice that there is evidence of U.S. R&D Granger Causing same industry output in all three R&D intensive industries. Second, looking across all industries we see lots of instances where U.S. R&D Granger Causes same industry output and few instances where Japanese R&D Granger Causes output (compare with Table 4). U.S. R&D Granger Causes Japanese output for at least one choice of lag length in 6 major industry categories and also electrical equipment. Japanese R&D Granger Causes same industry output in two major categories and electrical equipment.

Next we briefly summarize some of the properties of comovements of U.S. patent applications with U.S. and Japanese R&D and TFP. Due to space considerations we do not report figures or tables for these results. 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 U.S. TFP. It suggests that the strategic incentive to delay the disclosure of innovations emphasized in e.g. Hopenhayn and Squintani (2007) may be important in the U.S. Our results are consistent with the view that companies are waiting to apply for patents until after the idea gets reflected in TFP.[5]

We also investigated the dynamic relationship between U.S. 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 8 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.

Before continuing we briefly highlight the main results from the empirical analysis. 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. The flow of U.S. business ideas appears to be important for Japan as well. 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 and adapting U.S. business ideas may be quite small. If they were large then presumably this would imply that Japanese R&D would lead Japanese TFP. This final finding resembles a previous finding by Klenow and Rodriguez-Clare (2004). They need to assume that a significant fraction of knowledge diffusion is costless if they are to account for cross-sectional differences in country incomes.

If variations in the flow of U.S. business ideas is important for 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 model 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 4 suggest that variations in U.S. R&D expenditures account for a substantial fraction of Japanese TFP movements. We now use our model to assess the role of R&D exenditures for medium term cycle fluctuations in Japanese economic activity more generally. If Japanese 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 the U.S. is important then *previous* levels of U.S. R&D should also help account for current movements in Japanese macroeconomic variables. 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 targeted 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 two variables on Japanese TFP. We do this in the following way. First, we filter Japanese TFP and Japanese and U.S. R&D to retain cycles of less than 40 years. 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 9 reports relative variabilities for medium term cycle filtered Japanese data and simulated 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 5 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 10 reports contemporaneous correlations between model predicted values and actual data values of each time-series. 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 countercyclical. 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 worse than the baseline model for all variables except output. 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 unusual feature of the results is that the correlation of actual TFP with predicted TFP is negative for the Japanese R&D specifications with 3 or 4 lags. Yet these simulations also have the property that the correlation between model output and output in the data is positive. The reason for this is that the correlations reported in Table 10 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 9 and 10 results for a simulation in which only the trend component of TFP is used. A comparison of this specification 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 actual data as reported in Table 10. 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 6 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 7. 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.

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. Panel D of Figure 2 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.[6]

To provide a more concrete picture of the model's performance in the 1990's in Table 11 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 main 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 (forthcoming) find 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.

Consider next industry level evidence from the 1990s. An industry level analysis is particularly interesting because some of the industries we considered above have higher productivity than their American counterparts in 1990s. 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 technological frontier than their U.S. counterparts. It is interesting to see how these industries perform in the 1990s. 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 associated with declines in medium term cycle industry level Japanese output. We measure the change in medium term cycle output from 1990 to 1997 using VARs with 3 lags.[7] 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.[8]

Overall, the disaggregated evidence from the 1990s is consistent with our results from the aggregate analysis. U.S. R&D continues to be an important leading indicator of medium term cycles in Japanese industry data as well as Japanese aggregate data during Japan's Lost Decade.

# 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 (2006) 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 U.S. R&D reproduce some of the most important episodes in post WWII Japanese data including: the Japanese savings puzzle, the slow growth that followed the first oil price shock in the 1970s, the rapid growth Japan experienced in the second half of the 1980s and the anemic growth of the 1990s. Each of these episodes are associated with large prior movements in U.S. R&D expenditures. Our results suggest that the role of domestic demand disturbances or other domestic shocks was small, however, they do 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 (2006).

The lag-relationships we have uncovered linking U.S. R&D to future Japanese TFP suggest that the diffusion of business ideas has been important. However, our results are silent on the mechanics of diffusion. In particular, one would like to know more about how business ideas spread. What fraction is costless or nearly so? What is the role of academic research as compared to direct technology transfer via e.g. licensing agreements. How important is the flow of ideas as compared to machines and equipment? These are the topics of our current research.

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# 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: $TFP = (Y/(K^{0.363}H^{1-0.363}))^{\frac{1}{1-0.363}}$.

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.

# Notes

[1]See e.g. Parente and Prescott (1994)

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

[3]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.

[4]Eaton and Kortum (1999) is an example of a formal model that exhibits these properties.

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

[6]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.

[7]Tests of alternative lag lengths indicated that 3 lags was a choice that worked well for the industries we consider.

[8]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.

**Table 1**: Standard Deviations of Japanese Filtered Data

| | 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 |
| 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. The data is expressed as percentage.

2. Sample period is 1960-2002.

3. Medium term cycle filter retains cycles of duration 40 years or less.

4. Medium frequency filter retains cycles of duration 8 to 40 years.

5. High frequency filter retains cycles of duration less than 8 years.

**Table 2**: Granger Causality (G.C.) tests, bivariate auto-regressions: Japanese data

| 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 | 0.210 | 0.041 | 0.590 |
| 3 | 0.930 | 0.899 | 0.005 | 0.052 | 0.048 | 0.061 |
| 4 | 0.867 | 0.270 | 0.082 | 0.012 | 0.511 | 0.011 |

Notes:

1. The Granger Causality tests are based on bivariate autoregressions using the two variables listed at the top of each column and the number of lags listed in column one.

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 3**: Variance Decomposition

A. Variance decomposition of Japanese GNP: bivariate vector-autoregression

| | $GNP^{JPN}$ 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 | 90.7 | 9.3 | 72.4 | 27.6 |
| 2 | 98.4 | 1.6 | 51.4 | 48.6 |
| 3 | 97.6 | 2.4 | 56.5 | 43.5 |
| 4 | 97.6 | 2.4 | 45.3 | 55.7 |

B. Variance decomposition of Japanese TFP: bivariate vector-autoregression

| | $TFP^{JPN}$ 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. The table shows a percentage of variance of Japanese GNP (TFP) at a 10 year forecast horizon explained by Japanese GNP (TFP) and Japanese R&D.

2. All data are medium term cycle filtered.

3. The variance decompositions are based on a Cholesky decomposition with the indicated ordering.

**Table 4**: 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 5**: Granger Causality (G.C.) Tests for Japanese TFP

| 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. 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 6**: Variance Decomposition of Japanese TFP: Trivariate Vector-Autoregressions

| 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 table shows a percentage of variance of Japanese TFP at a 10 year forecast horizon explained by Japanese TFP, Japanese R&D and U.S. R&D.
2. 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.
3. The first column reports the number of lags in the VAR.
4. All data are medium term cycle filtered.

**Table 7**: Granger Causality (G.C.) Tests of U.S. Research and Development Expenditure on Japanese Same Industry Output

| Null Hypothesis: U.S. 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).

**Table 8**: Granger Causality (G.C.) Tests for Japanese Patents

| 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 9**: Relative Volatilities Japanese Data and Models

| Specification | $\sigma_Y$ | $\sigma_Z / \sigma_Y$ | $\sigma_C / \sigma_Y$ | $\sigma_X / \sigma_Y$ | $\sigma_{K/Y} / \sigma_Y$ | $\sigma_H / \sigma_Y$ |
|---|---|---|---|---|---|---|
| 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 |
| 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. $\sigma_a$ 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.

3. All data are medium term cycle filtered.

**Table 10**: 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 |
| 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 11**: 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
3. All data are medium term cycle filtered.

**Figure 1**: Simulation Results and Actual Japanese Data

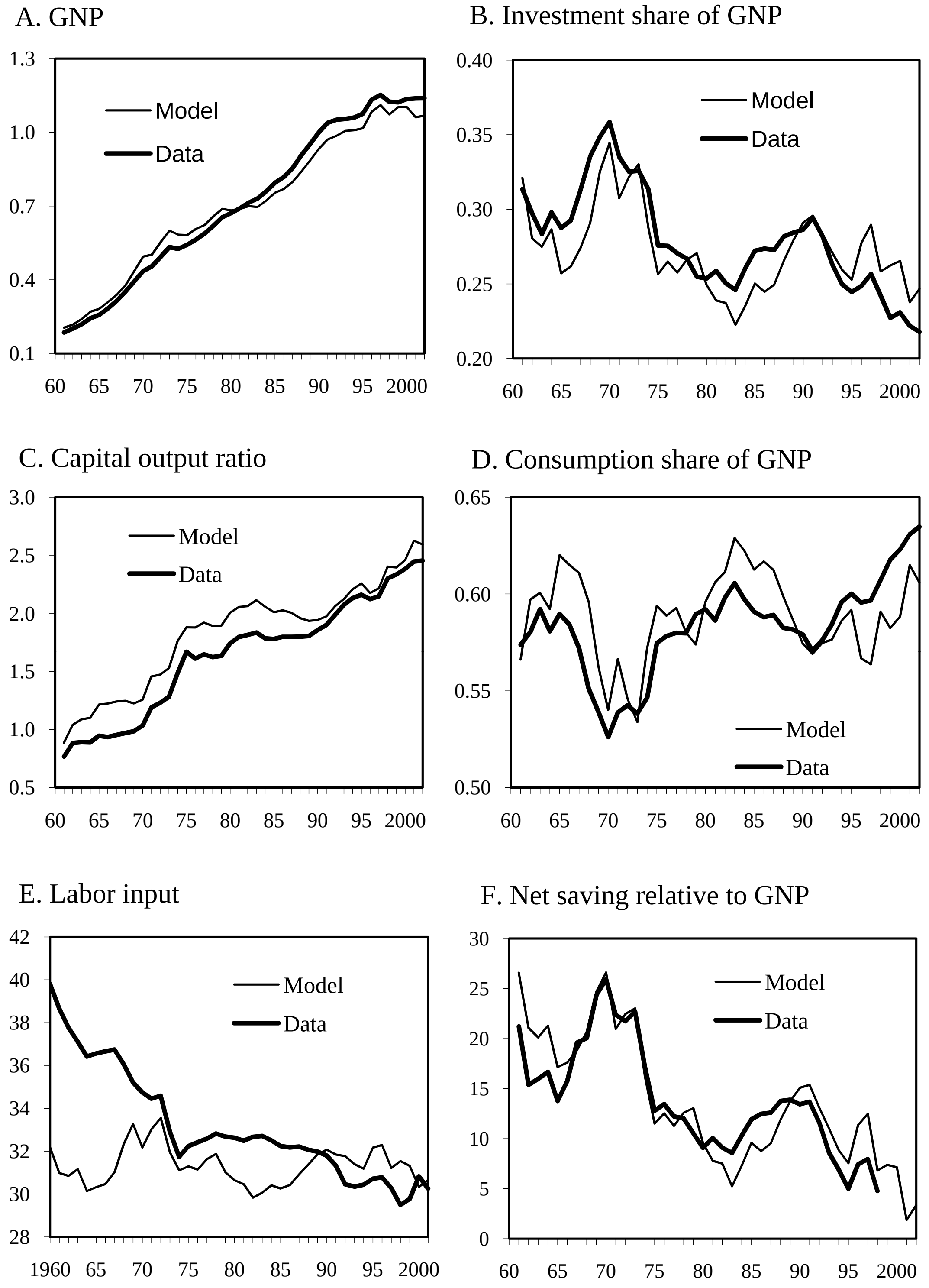
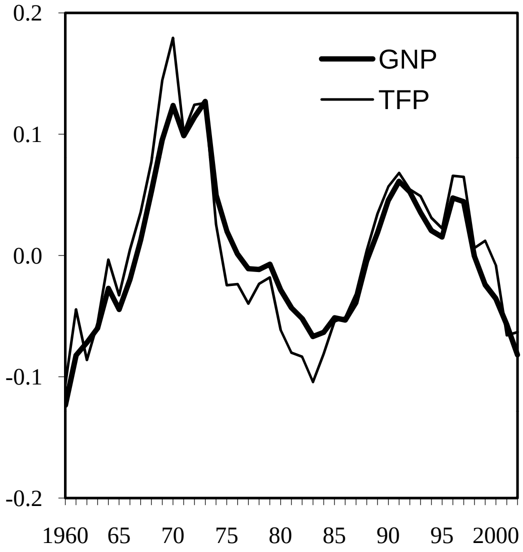
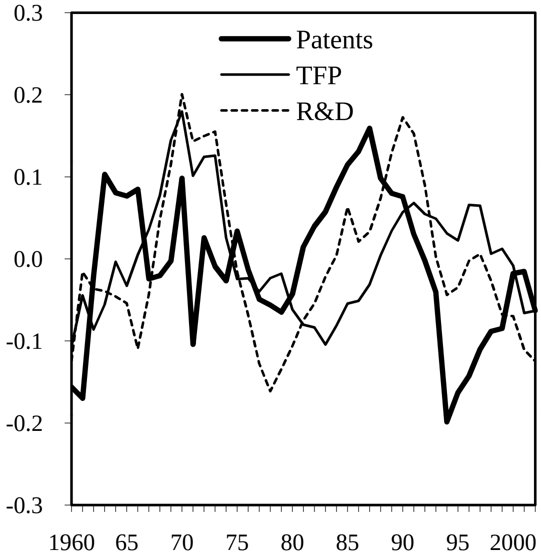


**Figure 2**: Medium Term Cycle Data

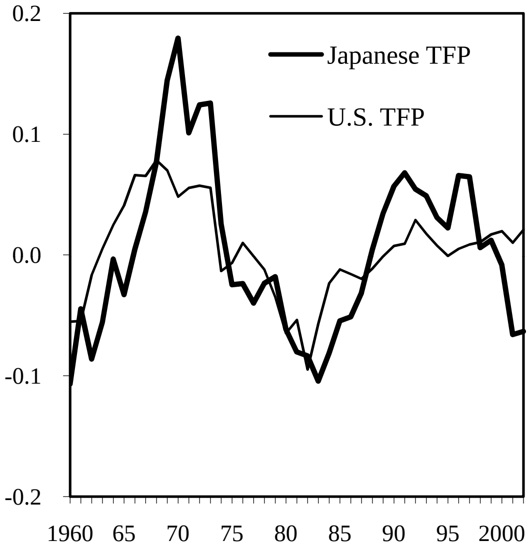
A. Japanese Medium Term Cycle GNP and TFP




B. Japanese Medium Term Cycle Patents, TFP and R&D




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




D. Medium Term Cycle R&D (Private industry)

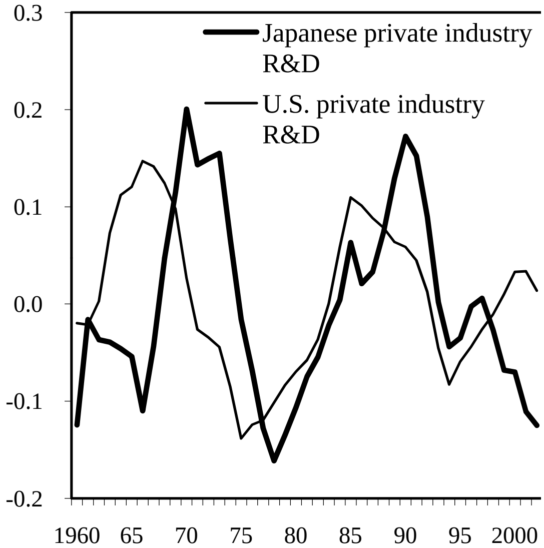
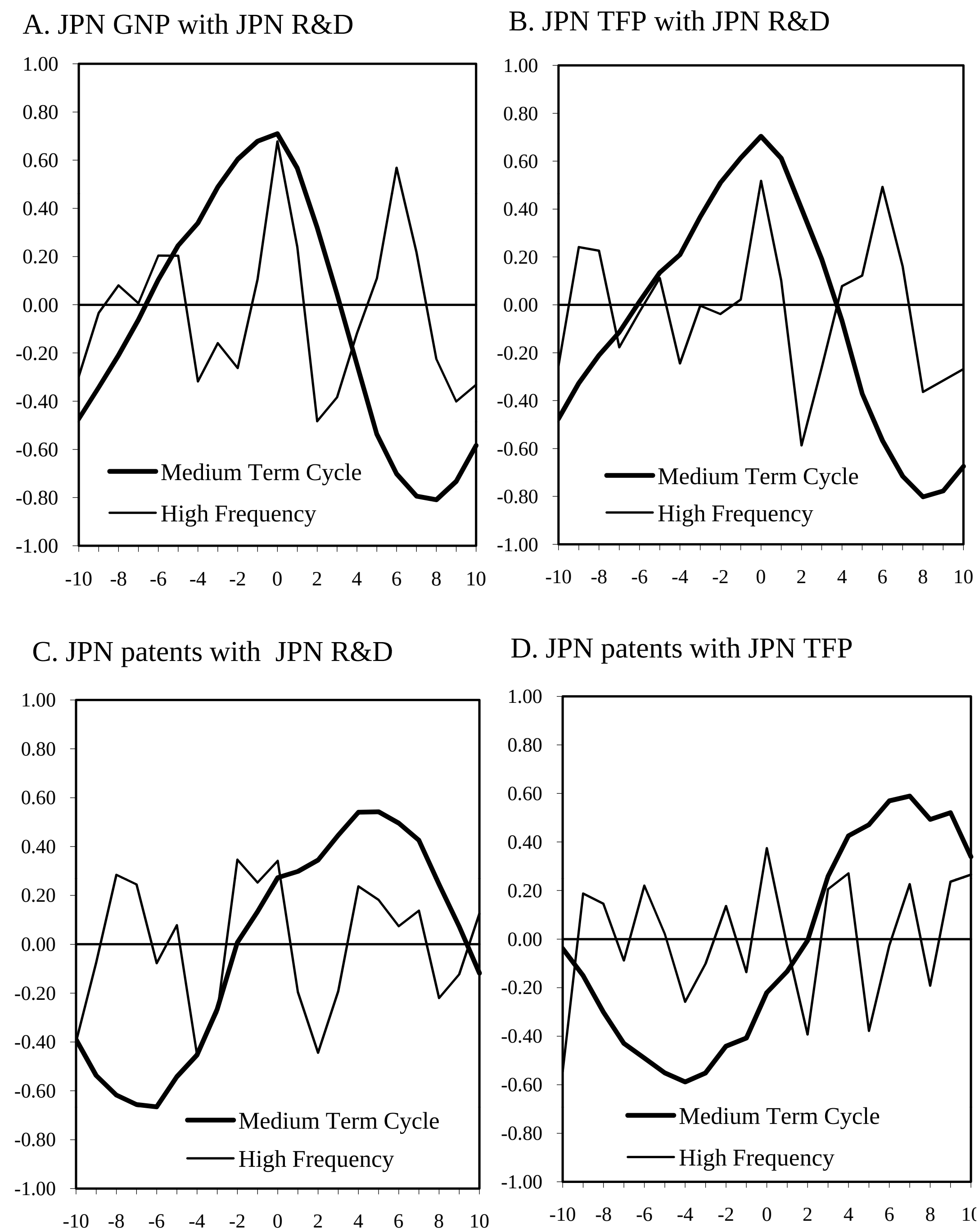
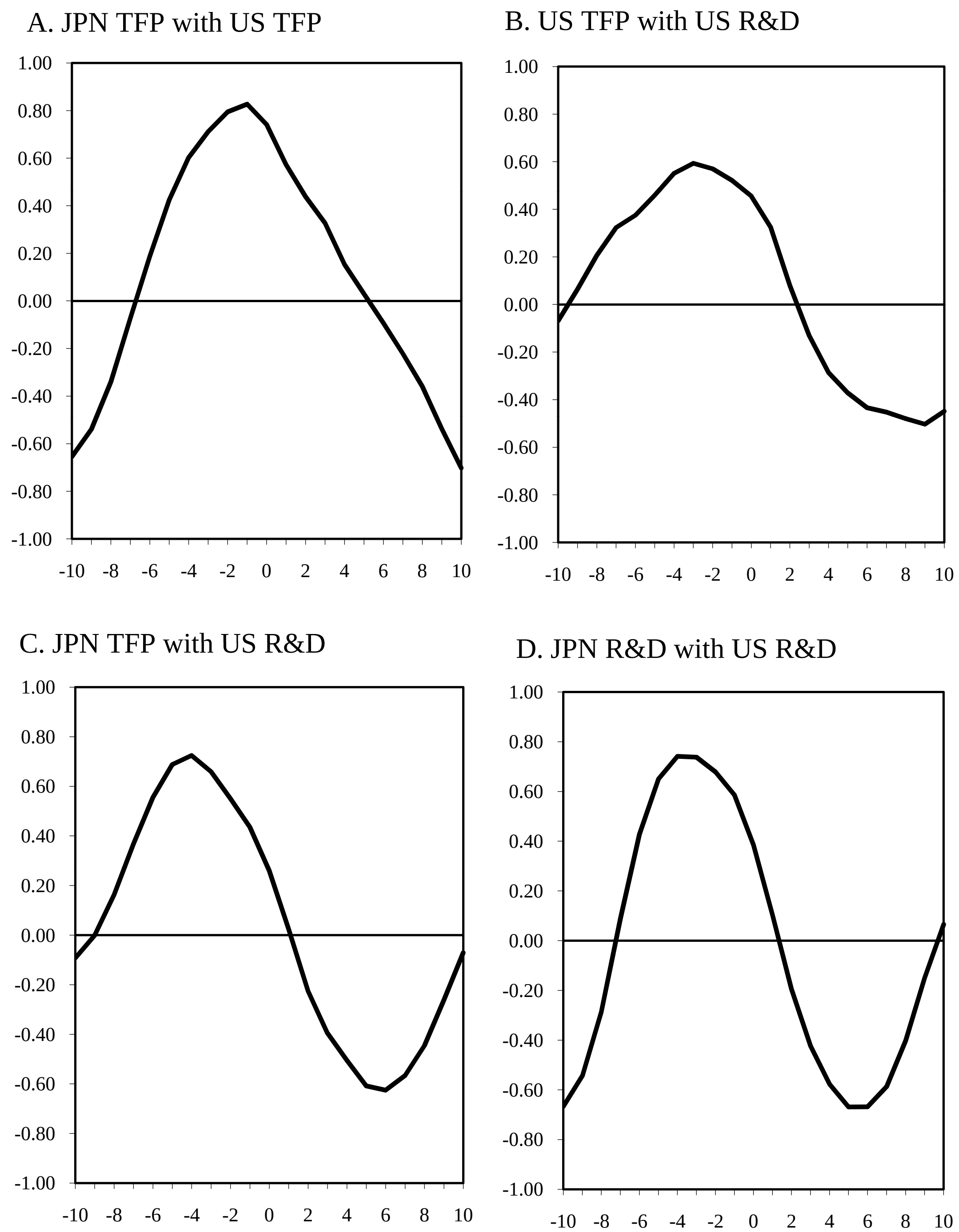


**Figure 3**: Cross-correlations of Japanese R&D, GNP and TFP



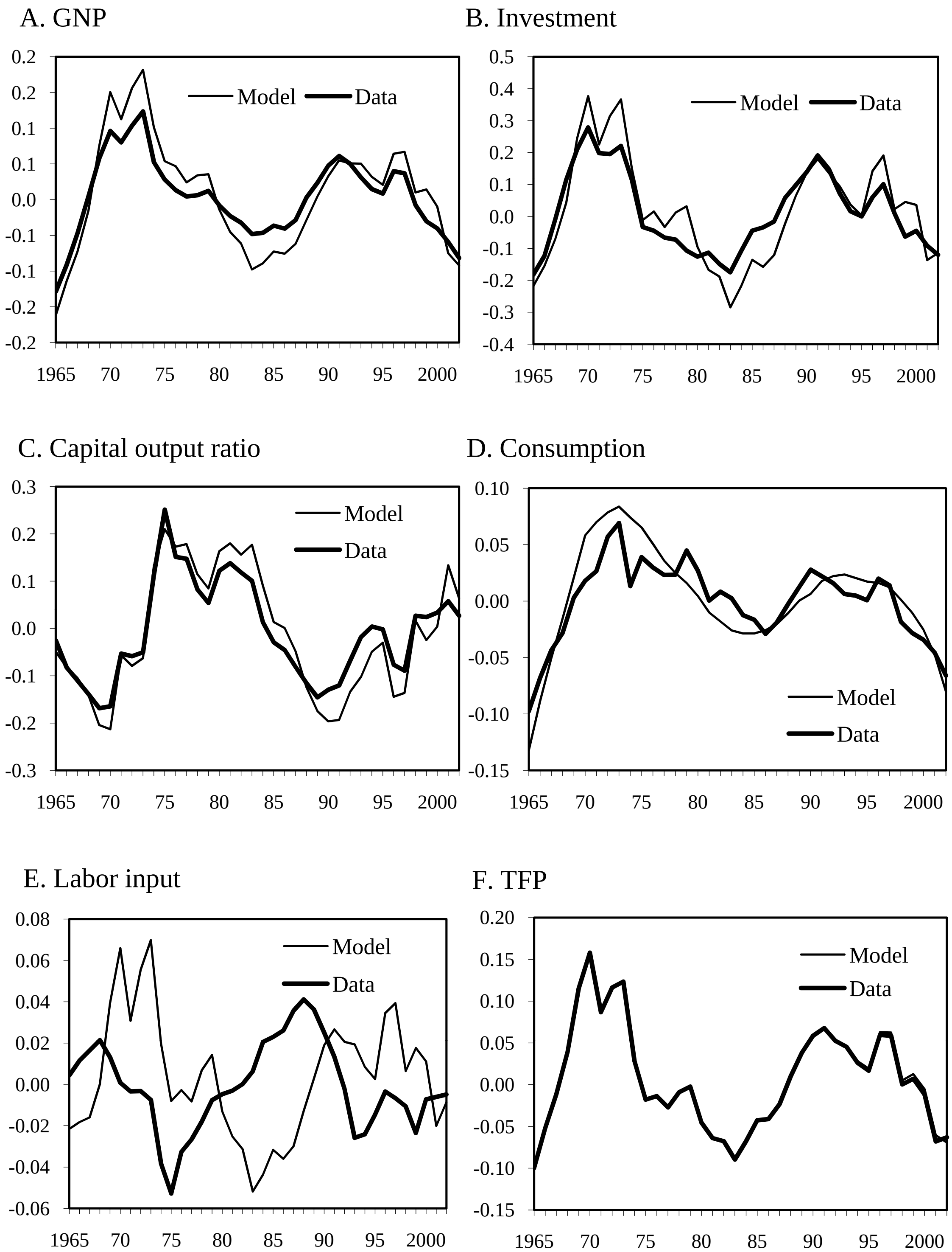

(note) The horizontal axis lists lags (-), leads(+) of the second variable.
JPN denotes Japanese data.

**Figure 4**: Cross-correlations of TFP and R&D (Japan, U.S.)



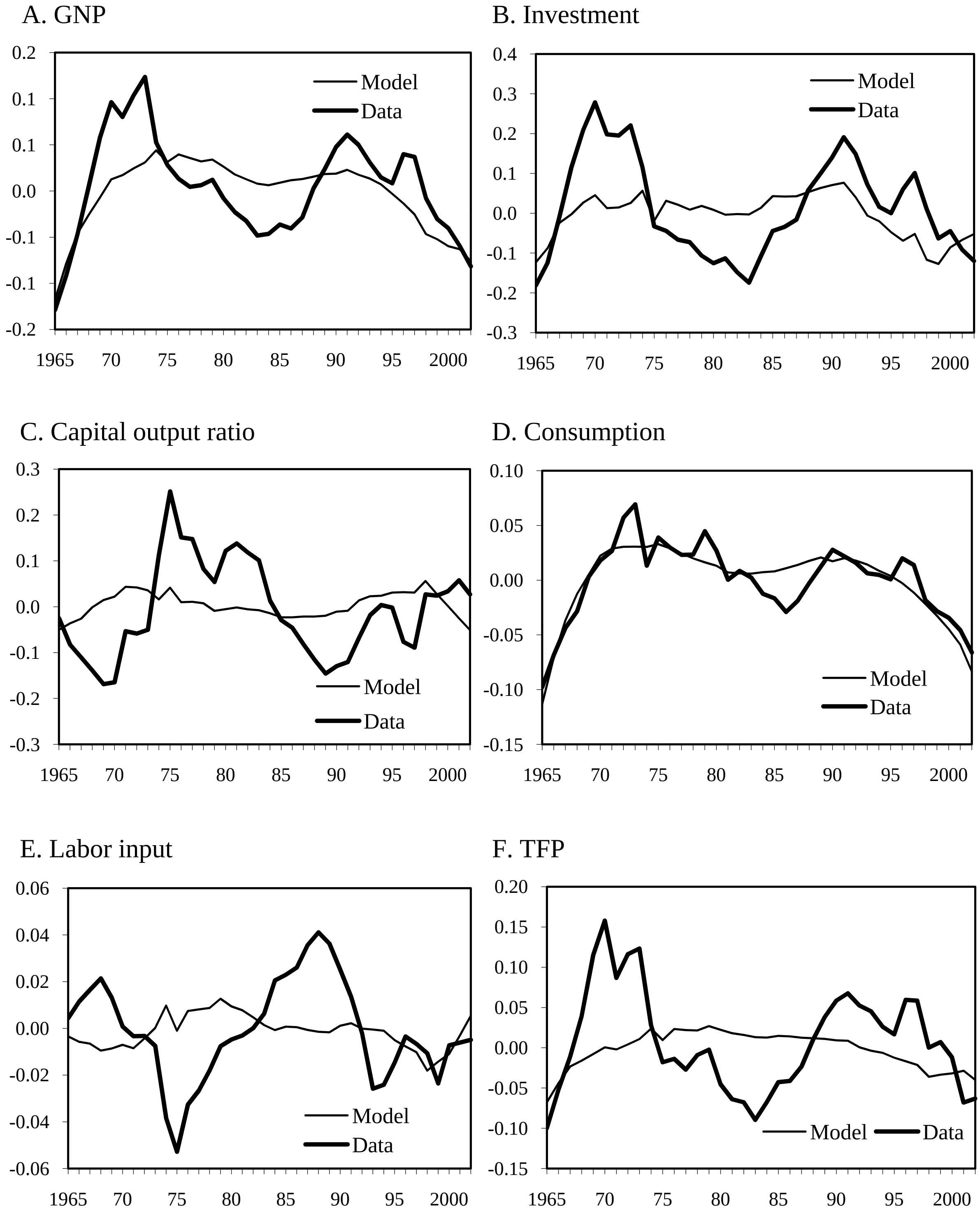

(note) The horizontal axis lists lags (-), leads(+) of the second variable.
JPN denotes Japanese data.

**Figure 5**: Model Predicted Medium Term Cycles and Japanese Data



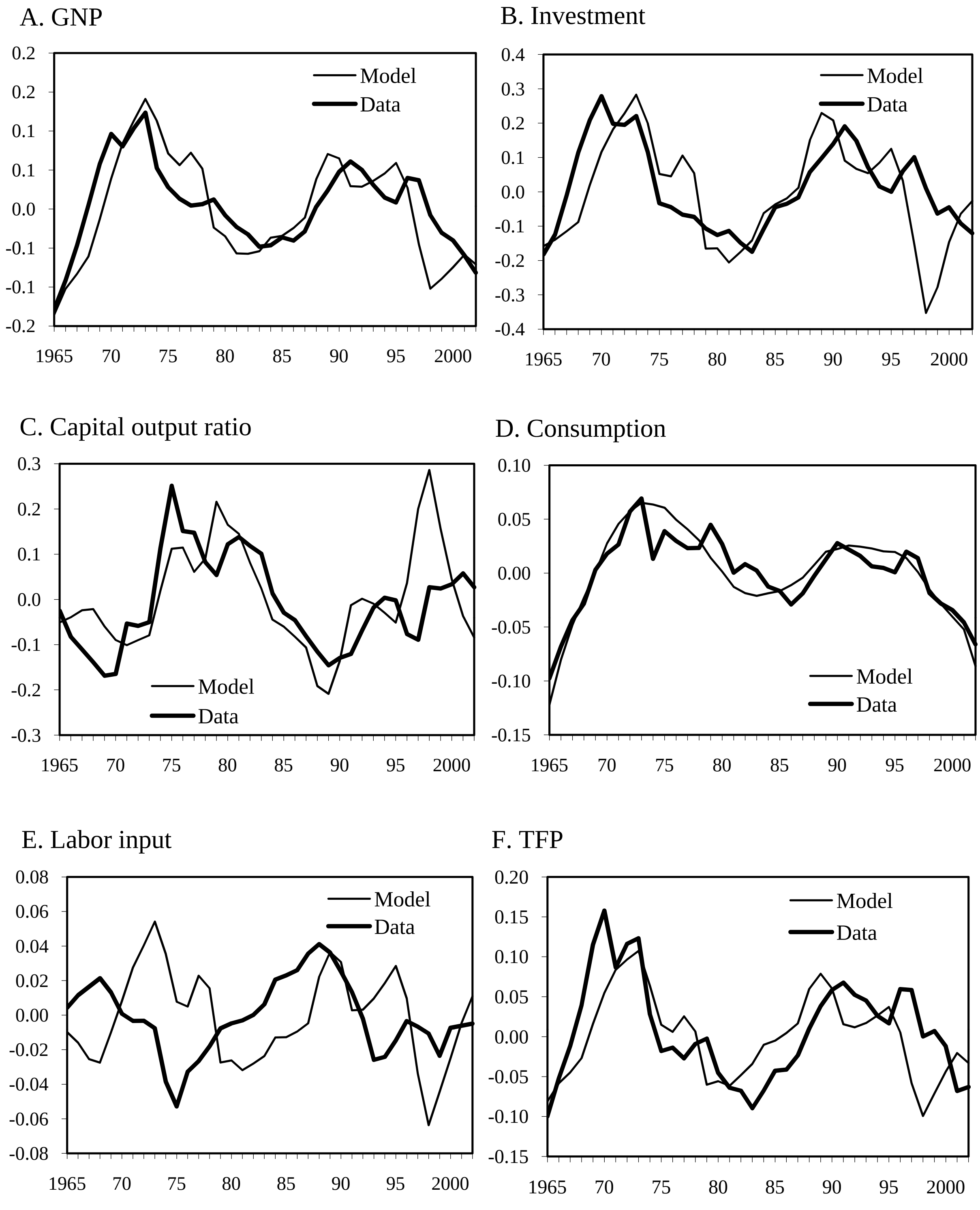

(note) Simulations are conducted from 1965 to 2002.

**Figure 6**: Simulation with 4th Lag of Japanese Patents Used to Predict Japanese TFP




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

**Figure 7**: Simulation with 4th Lag of U.S. R&D Used to Predict Japanese TFP




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