Essays on Energy and Macroeconomic Dynamics

by
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Contents

List of Tables

List of Figures

Chapter 1

Introduction

This thesis is based on three papers that investigate the role of energy price and technology in macroeconomic dynamics. Because of the small share of energy in production, it may seem that energy plays only a minor role in accounting for macroeconomic phenomena. However, there are several reasons why energy should not be ignored in macroeconomic analyses. First, although the share of energy in production is small, it is well known that capital stock and energy are complementary in the short run. This implies that energy price shocks could have a large negative impact on aggregate variables. Second, a number of empirical studies show that the sharp rise in the relative price of oil (or, more generally, energy) led to economic recessions in major developed countries, at least prior to the mid-1980s. The seminal work in this field (Hamilton, 1983) shows that increase in oil prices preceded all but one U.S. recession between 1948 and 1972. Third, the declining effect of oil price shocks on output after the mid-1980s in the United States and other developed economies is reported by several studies, notably Blanchard and Gali (2008) and Katayama (2013). Because the diminished effect of oil price shocks can be a good candidate in accounting for the reduced volatility of aggregate variables, it is essential to document the role of energy in what economists are calling the "Great Moderation." These topics are further investigated in each chapter as follows.

Chapter 2 begins by describing the benchmark model based on that developed by Kim and Lougani (1992), who incorporate energy as a third input into an otherwise standard real business cycle (RBC) model. Since it is such a simple model, the justification for some assumptions such as no residental energy consumption, no possibility of stockpiling energy, and zero net exports are discussed with some data observations. Extension of the benchmark model is also discussed in details to address some energy-related issues presented in Chapter 3. The first extension is the inclusion of energy-saving technological change. In Chapter 3, it is examined to what extent the improvements in energy-saving technology are attributed to the declining energy intensity observed following the first oil crisis in Japan. The second extension is the introduction of endogenous capacity utilization. It is also investigated whether the modified model can do a better job than a standard RBC model with energy in accounting for the severe recession observed after the first oil crisis.

Substitutability between energy and other inputs (especially capital stock) is also reviewed in Chapter 2. This substitutability is important since it is expected that low substitutability between energy and other inputs would cause a serious decline in output in response to increases in relative price of energy. A number of previous studies, using translog cost function, show that energy and capital stock are complementary whereas energy and labor, and capital and labor have good substitutability.

Based on the discussion in Chapter 2, Chapter 3 consists of three applications of the benchmark model and its extension to the energy-related economic phenomena in Japan and the United States.

Japan's economy showed a considerable decline in energy dependence following the first oil crisis in 1973. In particular, the energy–Gross National Product (GNP) ratio (real energy use divided by real GNP) stood at 2.7% in 1973 but subsequently declined sharply. By 1988, it had fallen to approximately 1.4%, i.e., almost half the 1973 value, and has shown only a slight upward trend since then.

Against this background, the first application examines quantitatively the reasons behind the drop in the energy–GNP ratio observed in the 1970s and 1980s using a simple neoclassical growth model with energy as a production input. The substitution effect is the first candidate investigated to possibly account for the sharp drop in the energy–GNP ratio in 1973. When the relative price of energy rises, energy is substituted with other inputs such as labor and capital. In turn, as value added increases, we would expect the input of energy per unit of value added, or the energy–GNP ratio, to decrease. The simulation result using the actual time series of the relative price of energy shows that the substitution effect alone is weak and cannot account for the decline in the energy–GNP ratio.

The second candidate investigated as a possible explanation for the decline in the energy–GNP ratio, focusing more on a long-term perspective, is improvements in energy-saving technology. The measured level of energy-saving technology as a residual in the production function shows that energy-saving technology substantially improved after the first oil crisis. In addition, including the estimated series of energy-saving technology as an additional exogenous variable into the benchmark model successfully generates a simulated energy–GNP ratio path consistent with the actual data.

The second application focuses more on a specific macroeconomic episode, the severe recession after the first oil crisis in Japan. The standard RBC model with energy is well known to be unable to generate large drops in the value added observed following the energy-price increases in the 1970s, although previous empirical studies have confirmed the importance of energy prices. Against this background, the chapter's discussion first confirms that the standard RBC model taking the actual relative price of energy as an exogenous variable fails to account for the Japanese economy's sluggishness after the first oil crisis. This failure implies that a strong mechanism to amplify the effect of the sharp rise in the relative price of energy is essential to generate the severe recession observed after the first oil crisis.

In this application, following Greenwood et al. (1988), the endogenous capacity utilization rate is incorporated in the benchmark RBC model and examined to determine to what extent capacity utilization amplifies the effect of sharp rises in the relative price of energy upon value added and other aggregate variables. It is shown that the capacity utilization model successfully generates a large negative effect from a sharp rise in the relative price of energy. In addition, the analysis shows that stagnation in total factor productivity (TFP) growth in the benchmark RBC model was spurious due to the declining capacity utilization rate. It further demonstrates that the purified TFP series, in which the effect of time-varying capacity utilization is removed from TFP in the benchmark model, shows steady growth even after the first oil crisis.

The third application emphasizes the role of improvements in energy-saving technology upon the "Great Moderation," referring to the mitigated volatility of output and other aggregate variables that began in the mid-1980s in the United States. Several reasons for the "Great Moderation" have been discussed in previous studies, which can be broadly divided into two groups. The first group focuses on the importance of the reduced volatility of exogenous shocks, and is known as the "good luck" hypothesis. For instance, Arias, Hansen, and Ohanian (2007) show that output volatility declines simply because the volatility of TFP became approximately half its original value. The second group focuses on structural changes. Jaimovich and Siu (2009) claim that demographical change can account for approximately one-fifth to one-third of the “Great Moderation” observed in the United States. McConnell and Perez-Quiros (2000) emphasize the role of better inventory management, whereas Clarida, Gali, and Gertler (2000) underscore an improvement in monetary policy.

To examine the role of improvements in energy-saving technology on the “Great Moderation,” the time path of energy-saving technology is estimated via the methodology employed in Chapter 2, then fed into a standard RBC model. The simulation results show that the impulse response of value added to a 10% energy-price shock is mitigated from − 2.47% to − 1.66% due to improvements in energy-saving technology. Out stochastic simulation also shows that the volatility of GNP decreases by about 25 percentage points in response to energy price shocks due to improvements in energy-saving technology. These simulation results indicate that improvements in energy-saving technology have a non-negligible effect on the “Great Moderation.”

Chapter 2

Energy and Macroeconomics

2.1 Introduction

This chapter describes the benchmark model, its extension and data construction method employed throughout the thesis. In Chapter 3, three research questions: (i) what caused the declining Japan's energy intensity after the first oil crisis, (ii) to what extent the standard RBC model with energy is able to replicate the severe recession following the first oil crisis in Japan, and (iii) what is the role of improvements in energy-saving technology on the Great Moderation observed after the mid 1980s in the United States, are addressed using the models introduced in this chapter. In our analysis, one of the most important and controversial paramters is the elasticity of substitution between capital stock and energy (ε). In this chapter, the estiamtes in previous studies are also surveyed to justify our assumption that capital stock and energy is complementary in the short run.

2.2 The model

The benchmark model employed in this thesis is based on that developed by Kim and Loungani (1992), who incorporate energy as a third input into an otherwise standard real business cycle model.[1] The model assumes that there is a representative household with N_t members at time t. In addition, for simplicity, it is assumed that the size of household does not grow over time.[2] The household chooses the path of consumption, leisure, and investment so as to maximize the life-time utility function

$$\max_{\{c_t,h_t,k_{t+1}\}_{t=0}^{\infty}} \sum_{t=0}^{\infty} \beta^t N_t \Big[(1-\alpha)\ln c_t + \alpha \ln(1-h_t)\Big], \tag{2.1}$$

subject to

$$C_t + X_t = w_t H_t + r_t K_t \tag{2.2}$$

$$X_t = K_{t+1} - (1-\delta)K_t, \tag{2.3}$$

where C_t is aggregate consumption, X_t is aggregate investment, w_t is the wage rate, H_t is aggregate hours worked, r_t is the rental rate of capital, δ is the depreciation rate, and β is the discount factor. The time endowment is normalized to unity and is divided into labor and leisure.

The representative firm faces the following profit maximization problem:

$$\max_{\{K_t,H_t,E_t\}} Y_t - r_t K_t - w_t H_t - p_t E_t \tag{2.4}$$

[1] Kim and Loungani (1992) assume that fluctuations in the relative price of energy are stochastic, while the model employed here incorporates the actual path of the relative energy price into the model. In other words, there is no uncertainty in the model here, as in Hayashi and Prescott (2002, 2008) and Chen et al. (2006).

[2] The simulation results remain largely unaffected when this assumption is relaxed and the population is allowed to grow.

subject to

$$Y_t = (\Gamma_t H_t)^{1-\theta}\left[(1-\mu)K_t^{\frac{\varepsilon-1}{\varepsilon}} + \mu E_t^{\frac{\varepsilon-1}{\varepsilon}}\right]^{\frac{\varepsilon}{\varepsilon-1}\theta}. \tag{2.5}$$

where Y_t is gross output, Γ_t is total factor productivity (TFP), p_t is the relative price of energy, and E_t is aggregate energy use. As discussed in the next section, several studies, such as Hassler, et al. (2012), suggest that the elasticity of substitution between energy and other inputs is considerably less than unity. Therefore, a nested constant elasticity of substitution production function with constant returns to scale is used.[3] The firm imports energy from abroad at an exogenously given price p_t per unit.[4] TFP is also exogenous to the firm.

The resource constraint is as follows:

$$C_t + X_t = Y_t - p_t E_t \equiv V_t, \tag{2.6}$$

where V_t denotes value-added at time t. That is, output produced domestically is either consumed, invested, or exported as payment for imported energy. Note that exports equal imports in each period, so that the trade balance is always set at zero for simplicity. This assumption does not admittedly fit with the data since the nominal net exports share in nominal GDP in Japan ranges from about -2.0% to 4.0% over the period 1955–1998. It is left for future research to evaluate our model in a more realistic environment in which net exports vary over time. Finally, as in the

[3]Hassler et al. (2012) employ an alternative specification of the production function, namely:

$$Y_t = \left[(1-\gamma)[A_t K_t^{\alpha} L_t^{1-\alpha}]^{\frac{\varepsilon-1}{\varepsilon}} + \gamma[A_t^E E_t]^{\frac{\varepsilon-1}{\varepsilon}}\right]^{\frac{\varepsilon}{\varepsilon-1}},$$

where A_t is capital/labor-augmenting technology and A_t^E is fossil energy-augmenting technology. The simulation results shown below are robust to this alternative production function as well.

[4]In the case where fossil fuels are extracted domestically, an alternative interpretation of the energy price would be that p_t represents the unit cost of fossil fuel energy extraction. However, since Japan imports almost all its fossil fuel energy from abroad, this interpretation is not employed here.

studies by Hayashi and Prescott (2002, 2008) and Chen et al. (2006), it is assumed that agents have perfect foresight about the sequence of exogenous variables.[5] The model is then solved numerically by applying a shooting algorithm given the initial capital stock level and the path of exogenous variables. The initial capital stock is taken from the actual data.

Note that it is assumed that the representative firm is the only enegy-user so that the household does not consume energy at all. Although this is doubtlessly unrealistic, most of the previous studies also ignore the household energy consumption due to the small energy consumption share by residential. One exception is the study conducted by Dhawan and Jeske (2006) which focus on the role of consumer durables in response to energy price shocks and conclude that the inclusion of consumer durables mitigates the effect of rises in energy price on aggregate variables. They assume, in an otherwise standard real business cycle model with energy for production input, that aggregate consumption (C_t^A) consists of three types of consumption in the following manner:

$$C_t^A = N_t^{\gamma}\left(\theta D_{t-1}^{\rho} + (1-\theta)E_{h,t}^{\rho}\right)^{\frac{1-\gamma}{\rho}}, \tag{2.7}$$

where N is consumption of services excluding energy, D is flow of services from the stock of durable goods, and E is energy use.[6] Since there are two investment opportunities for the representative household (durable goods investment and capital stock investment), their returns (R^D and R) have to be equal at equilibrium. In their specification and calibrated parameter values, they show that both R^D and R decline in response to a positive energy price shock, but R^D declines more severely than R. This difference induces the household to rebalance the asset portfolio in the way

[5] Stochastic version of the benchmark model is also examined in Appendix. The main simulation results are robust to the different expectation scheme.

[6] According to their calibration, the elasticity of substitution between energy and durable goods, $1/(1-\rho)$, is about 0.26. This relatively low elasticity of substitution is consistent with our intuition that gasoline is necessary to drive a car and that electricity is essential to watch TV at home.

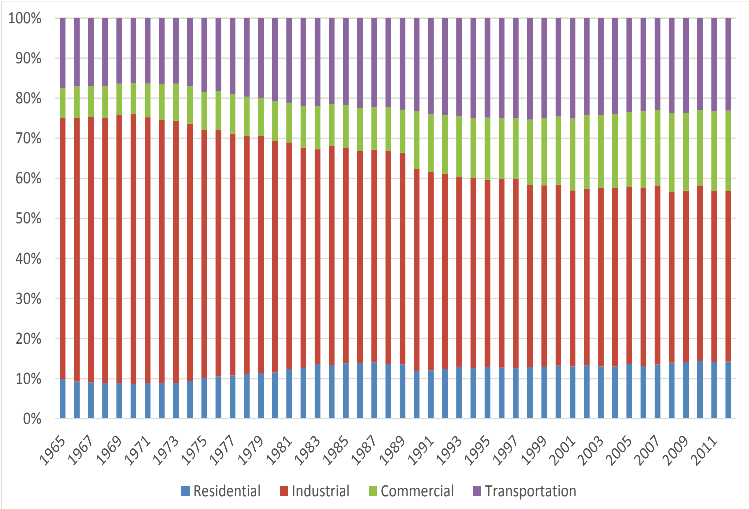

Figure 2.1: Final consumption share of energy by sector in Japan (1965–2012).

that it decreases the durable goods investment and increases the capital stock investment. The latter effect mitigates the effects of energy price shocks, leading them to conclude that energy price shocks cannot be a driving force for business cycles.

Although the extension of standard RBC model as shown in Dhawan and Jeske (2006) is worth investigating further, it is simply assumed that energy use is only necessary for production throughout the thesis, again due to the small residential energy consumption share. Figure 2.1 displays the final consumption share of energy by sector in Japan over the period 1965–2012 and the data are taken from the "Comprehensive Energy Statistics" provided by the Agency for Natural Resources and Energy. Although the residential share has an upward trend, it ranges from 10% to 15% over the sample period, leading us to conclude that ignoring the household energy consumption would not cause a serious bias for the analysis conducted below.

Possibility of energy as a stock variable

Throughout the thesis, energy is defined as a flow, not a stock variable. However, some fraction of imported energy (especially oil) is indeed stockpiled strategically to prepare for unanticipated suspensions of oil imports in the future. Figure 2.2 shows trend in days' supply of oil reserves in Japan. With the help of Oil Stockpiling Act legislated in 1975, the oil reserves demonstrate an upward trend throughout the sample period.[7]

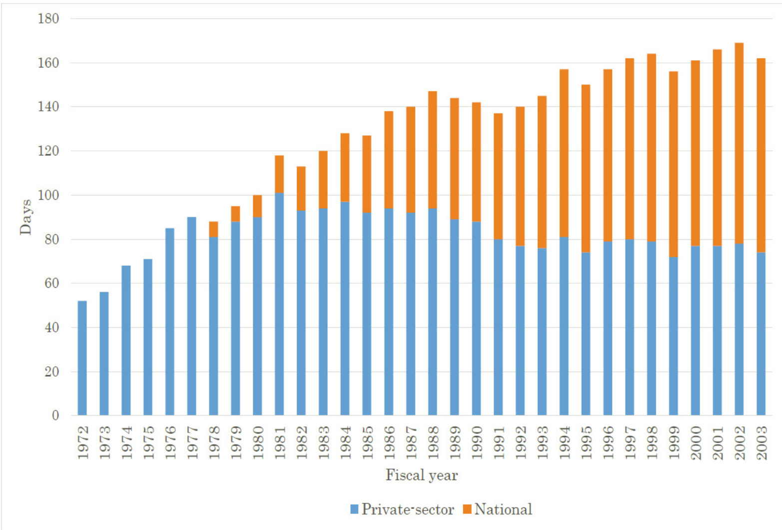

Figure 2.2: Days' supply of oil reserves in Japan
Source: Agency for Natural Resources and Energy.

Figure 2.3 illustrates the percentage share of inventry changes in total domestic supply of primary energy. -1%, for example, means that 1% of total domestic supply of primary energy is stored in that year. As can be seen, although primary energy is indeed stockpiled and unpiled over time, its magnitude is limited. The percentage share of inventry changes varies approximately from -2.5% to 2.0% over 1953–2000.

[7]Oil Stockpiling Act was amended in 1981 and it was also obligated to stockpile liquefied petroleum gas.

In sum, it would be more rigorous to define energy as a stock variable and incorporate an intertemporal decision making in our model. However, we decided to assume that all imported energy is consumed within a year for simplicity and modifying our model in that way is left for future research.

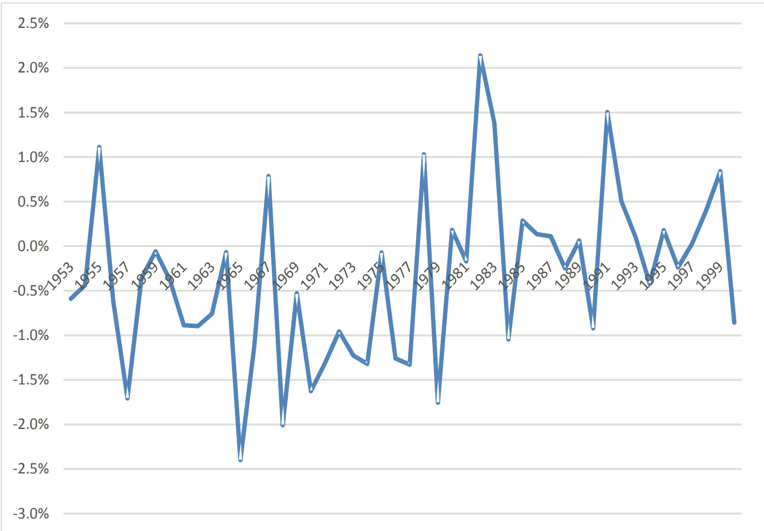

Figure 2.3: Percentage share of inventry changes in total domestic supply of primary energy. *Source*: General Energy Supply and Demand Balance, Agency for Natural Resources and Energy.

2.3 Extension of the benchmark model

The benchmark model described so far is a simple neoclassical growth model with energy as a production input. However, two more features need to be added in the benchmark model to account for several important energy-related macroeconomic phenomena such as the continuous decline in energy–GNP ratio after 1973 and the large negative impact of the sharp rise in the relative price of energy on macroeconomic variables in the first oil crisis.

The first feature needs to be added is energy-saving technological change. After the first oil crisis in 1973, energy dependence in Japan's economy declined considerably and one possible candidate to account for this trend is improvements in energy-saving technology. A number of empirical studies have sought to examine the role of energy-saving technological change. For instance, Popp (2002), using U.S. patent data from 1970 to 1994, examines the impact of increases in energy prices on energy-efficiency innovations. He finds that a rise in energy prices has a statistically significant positive impact on energy-efficiency innovations. Newell et al. (1999) investigate whether energy prices affect the energy efficiency of new models of energy-using consumer durables, such as room air conditioners and gas water heaters, and conclude that for some products the direction of innovation is influenced by changes in energy prices. For Japan, Fukunaga and Osada (2009) measure energy-saving technological change by estimating time-varying biases of technical change. They report that the bias of technical change for energy input in the 1980s was energy-saving.

Another strand of studies deals with energy-saving technological change from a theoretical perspective. Alpanda and Peralta-Alva (2010) introduce technology-specific capital and irreversible investment in a two-sector model and succeed in generating the drop in the energy-output ratio observed in the United States after the first oil crisis. Meanwhile, Hassler et al. (2012) develop a neoclassical growth model with non-renewable resources and measure the level of energy-saving technology in the United States, assuming perfect competition in input markets, and find that energy-saving technological progress commenced in 1973.

These two theoritical papers described above assume that the improvments in energy-sainvg technology are exogenous. While this assumption makes models more tractable, it is doubtlessly more realistic to assume that energy-saving technological progress is endogenously induced by rises in relative price of energy. Smulders and de Nooji (2003), for instance, endogenize the energy-saving tecnological change by incorporating energy use in the model in which the quality of intermediate goods improves through R&D investment. They assume that the production of final goods depends on labor services (Y_L) and energy (resource) services (Y_R) and that each service of type ($i = L, R$) is produced through the following production function:

$$Y_i = S_i^{\beta} \int_0^1 q_{ik} x_{ik}^{1-\beta} dk, \tag{2.8}$$

where S_i is the use of raw input i, q_{it} is the quality of intermediates of variant k in the production of type i services, and x_{ik} is the associated use. In addition, they assume that the quality of intermediate goods is improved by the R&D investment conducted by the intermediate goods producers. Combining these assumptions, they show that the energy-saving technology is an increasing function of (i) size of market measured by the value share, (ii) productivity in R&D activity, and (iii) appropriability of R&D investments. The value share of energy ($p_{Y_R} Y_R / Y$) usually increases following the sharp rise in relative price of energy since energy use does not respond significantly in the short run but output does. Thus, the model predicts that improvements in energy-saving technology occur after the rise in relative price of energy.[8]

There are also some other theoritical papers dealing with endogenous energy-saving technological change, not based on the trasitional (Romer-type) endogenous growth models. Atkeson and Kehoe (1999) and Diaz et al. (2004) construct a model to account for the well-knwon empirical finding that energy use does not change much in the short run after the rise in relative price of energy, but does significantly in the long run. Atkeson and Kehoe (1999) assume that existing capital goods require energy in fixed proportions to operate and provide capital services. Thus, in

[8] See Gillingham et al. (2008) and Loschel (2002) for comprehensive surveys for modeling endogenous technological changes in environmental economic models.

the short run, it is not optimal for firms to reduce the energy use much following the increase in relative price of energy. However, in the long run, firms replace the old energy-using machines with new ones embodying a high energy efficiency. Diaz et al. (2004) construct a model slightly different from that in Atkeson and Kehoe (1999). They assume that capital can be used either to produce output or to reduce the energy use to run the plant, and interpret the latter as energy-saving innovation. They also assume that capital reallocation from one use to another is costly. Under these assumptions, they successfully reproduce the low elasticity of energy use in the short run and high elasticity in the long run. Although the purpose of these two papers are not modeling an endogenous energy-saving technological change, we can interpret purchasing new energy-efficient machines and spending some resources to reduce the energy use to run the plant as energ-saving activities.

Now, the question that should be answered is whether treating energy-saving technological change as exogenous causes any harmful effects on our analyses. This is hard to answer since we haven't tried to endogenize the technological changes. However, some data observed in Japan show consistency with the predictions obtained by the endogenized version of models described above. For example, Smulders and de Nooji (2003) predict that the improvements in energy-saving technology is driven by the increase in the value share of energy. In Japan, the value share of energy increased from 1.77% in 1973 to 4.60% in 1974 and from 3.80% in 1979 to 5.67% in 1980. Therefore, while it is not still sure that if two approaches provide similar extent of energy-saving technological progress, they seem to be not too far. Although it is worth investigating further the possibility of endogenizing energy-saving technological change, it is assumed to be exogenous for the sake of brevity and modeling endogenous technological change and its application to Japan's economy are left for future research.

In this thesis, the level of energy-saving technology is measured as follows. First, z_t is added into the production function:

$$Y_t = (\Gamma_t H_t)^{1-\theta}\left[(1-\mu)K_t^{\frac{\varepsilon-1}{\varepsilon}} + \mu(z_t E_t)^{\frac{\varepsilon-1}{\varepsilon}}\right]^{\frac{\varepsilon}{\varepsilon-1}\theta}. \tag{2.9}$$

where z_t is the level of energy-saving technology. In macroeconomic analyses, the level of technology, such as z_t here, is generally measured as a residual. However, that strategy does not work in this case, since there are two unknowns $\{\Gamma_t, z_t\}$ but only one equation (Equation 2.9), given the parameter values and the actual time series for Y_t, H_t, K_t and E_t. To estimate z_t, the first-order condition for energy use shown below is additionally used. That is, Equations (2.9) and (2.10) are solved simultaneously for Γ_t and z_t:

$$p_t = \theta\mu\left(\frac{Y_t}{B_t}\right)\left(\frac{B_t}{z_t E_t}\right)^{\frac{1}{\varepsilon}} z_t, \tag{2.10}$$

where $B_t \equiv \left[(1-\mu)K_t^{\frac{\varepsilon-1}{\varepsilon}} + \mu(z_t E_t)^{\frac{\varepsilon-1}{\varepsilon}}\right]^{\frac{\varepsilon}{\varepsilon-1}}$. Since the effect of energy-saving technological progress is removed from TFP growth, Γ_t is now renamed "modified TFP." The calculated level of energy-saving technology and its role in accounting for the decline in energy–GNP ratio are discussed in Chapter 3.

The second feature needs to be added into the benchmark model is an endogenous capacity utilization rate. It is well known that the standard RBC model with energy cannot generate the large drops in value added following the energy price increases in the 1970s, although previous empirical studies have confirmed the important role of energy prices. To generate the large drop in value added after the rise in the relative price of energy, a strong mechanism to amplify the effect of the sharp rise in the relative price of energy on value added is required. In this thesis, the endogenous capacity utilization, a simple amplification mechanism of exogenous shocks, is incorporated into the benchmark model.

In the model with endogenous capacity utilization, the representative household faces the same problem as in the benchmark model, except that the depreciation cost of capital is now borne by the representative firm instead of the household. Thus, the budget constraint of the household at time t is

$$C_t + K_{t+1} - K_t = w_t H_t + r_t K_t. \tag{2.11}$$

The firm now is able to change its capacity utilization rate endogenously, so that the time t gross output is produced according to

$$Y_t = (\Gamma_t H_t)^{1-\theta} \left[(1-\mu)(u_t K_t)^{\frac{\varepsilon-1}{\varepsilon}} + \mu(z_t E_t)^{\frac{\varepsilon-1}{\varepsilon}} \right]^{\frac{\varepsilon}{\varepsilon-1}\theta}, \tag{2.12}$$

where u_t is the capacity utilization rate. As in Greenwood at el. (1988), it is assumed that a more intensive use of the capital stock depreciates it more quickly:

$$\delta_t = \frac{1}{\phi} u_t^{\phi}, \tag{2.13}$$

where $\phi > 1$. Capital stock is accumulated according to the following equation:

$$K_{t+1} = (1-\delta_t)K_t + X_t. \tag{2.14}$$

There is another way to incorporate the capacity utilization rate into the model with energy, first proposed by Finn (2000). She employs the standard Cobb-Douglass production with capacity utlization:

$$Y_t = H_t^{1-\theta}(u_t K_t)^\theta, \tag{2.15}$$

where energy use does not appear in the production function. Instead, the capacity utilization rate is directly dependent on the energy use in accordance with:

$$\frac{E_t}{K_t} = \frac{\nu_0 u_t^{\nu_1}}{\nu_1}, \quad \nu_0 > 0, \nu_1 > 1. \tag{2.16}$$

That is, energy per unit of capital stock is required more to increase the capacity utilization rate. In this formulation, a positive energy price shock at time t decreases E_t/K_t, resulting in the decline in the capacity utilization through Equation (2.16). Similarly, with our specification following Greenwood et al. (1988), a rise in relative price of energy dampens the marginal product of capacity utilization, also leading to the decrease in capacity utilization. Although the model structures are slightly different from one another, the mechanisms working behind are quite similar, at least qualitatively. Therefore, throughout this thesis, the specification a la Greenwood et al. (1988) is employed, which is believed to be the most common way to incorporate the capacity utilization in macroeconomic models.

In sum, the representative firm maximizes the following profit function:

$$\pi_t \equiv Y_t - w_t H_t - (r_t + \delta_t) K_t - p_t E_t \tag{2.17}$$

subject to Equations (2.12), (2.13), and (2.14) given the initial capital stock and the actual time series of all exogenous variables. An additional optimality condition in this model is the first order condition for the capacity utilization rate. That is,

$$u_t^{\phi-1} K_t = \theta(1-\mu)\left(\frac{Y_t}{\tilde{B}_t}\right)\left(\frac{\tilde{B}_t}{u_t K_t}\right)^{\frac{1}{\varepsilon}} K_t, \tag{2.18}$$

where $\tilde{B}_t \equiv \left[(1-\mu)(u_t K_t)^{\frac{\varepsilon-1}{\varepsilon}} + \mu(z_t E_t)^{\frac{\varepsilon-1}{\varepsilon}}\right]^{\frac{\varepsilon}{\varepsilon-1}}$. The left hand side of Equation (2.18) shows the additional depreciation of capital stock if the firm increases the capacity utilization rate by one unit. The right hand side represents the additional output the firm gains by raising the capacity utilization rate by one unit. Equation (2.18) requires that the marginal cost and benefit must be equal at optimum.

In order to obtain the TFP series taking the effect of capacity utilization into account, the actual time series for the capacity utilization rate is required. According to previous studies, there are at least three ways to obtain these series. The first is to use official statistics. The Ministry of Economy, Trade, and Industry (METI) provides the "Operating Ratio," which is calculated by dividing the actual production level by production capacity. Since the "Operating Ratio" published by METI is based on a survey of firms, the data are likely to be quite reliable. The shortcoming of these data, however, is that they only cover certain industries of the manufacturing sector, so that they do not provide an appropriate indicator of capacity utilization in the economy as a whole. The second way would be to use a proxy variable for the capacity utilization rate. Burnside et al. (1995), for example, use electricity consumption as a proxy. This seems like a reasonable assumption, since firms use more electricity when operating more machines. On the other hand, this indicator is likely to be downwardly biased when there are improvements in energy-saving technology. That is, electricity consumption can decline due not only to a drop in the capacity utilization rate, but also to improvements in energy-saving technology.

The third way to obtain the actual series for capacity utilization is to use the first order condition for the capacity utilization rate. In this chapter, following Burnside and Eichenbaum (1996), this third methodology is employed. Specifically, the empirical counterpart of the capacity utilization rate is obtained by exploiting Equation (2.18). This means that it will also be necessary to recalculate the capital stock series, since the depreciation rate is no longer constant over time when applying the perpetual inventory method. In the analysis here, the time series of the capacity utilization rate and capital stock are obtained simultaneously as follows. First, the first order condition

$$u_{1973}^{\phi-1} = \theta(1-\mu)\left(\frac{Y_{1973}}{\tilde{B}_{1973}}\right)\left(\frac{\tilde{B}_{1973}}{u_{1973}K_{1973}}\right)^{\frac{1}{\varepsilon}} \tag{2.19}$$

is solved for the capacity utilization rate in 1973. Next, the depreciation rate for 1973 is calculated as follows:

$$\delta_{1973} = \frac{1}{\phi}u_{1973}^{\phi}. \tag{2.20}$$

Finally, plugging δ_{1973} into the law of motion for capital stock,

$$K_{1974} = (1-\delta_{1973})K_{1973} + X_{1973}, \tag{2.21}$$

yields the capital stock in 1974. This procedure is repeated for each year up to 1978. ϕ is calibrated so that the series of δ_t generated by the procedure above is equal to 0.100, which is the depreciation rate for capital stock in the benchmark model. This procedure leads to $\phi = 2.001$.

Figure 2.4 displays the imputed capacity utilization rate and METI's "Operating Ratio" for comparison. As can be seen, although both series show a decreasing trend after the first oil shock, the trend in the imputed capacity utilization rate is much smoother than that in the "Operating

Figure 2.4: Imputed capacity utilization rate and METI's "Operating Ratio," both normalized to 100 in 1973.

Ratio." The substantial drop in the capacity utilization rate implied by the "Operating Ratio" may look more realistic, but it needs to be remembered that the "Operating Ratio" is constructed using data only for certain industries in the manufacturing sector. The Appendix provides further justification for using the imputed capacity utilization rate instead of the "Operating Ratio" by constructing a crude measure of the capacity utilization rate in the non-manufacturing sector and showing that this series is much less volatile than the "Operating Ratio."[9]

The obtained TFP series are displayed in Figure 2.5. A notable feature is that TFP in the benchmark model continues to be sluggish, whereas in the capacity utilization model TFP follows a steady growth path. The average growth rates of TFP over the period 1973–1978 are 0.72% in the benchmark model and 2.16% in the capacity utilization model. This discrepancy arises simply

[9]This result is also in line with findings by Miyazawa (2012) for Japan in the 1990s, which show that the capacity utilization rate imputed by using the first order condition for the capacity utilization rate is much less volatile than the "Operating Ratio."

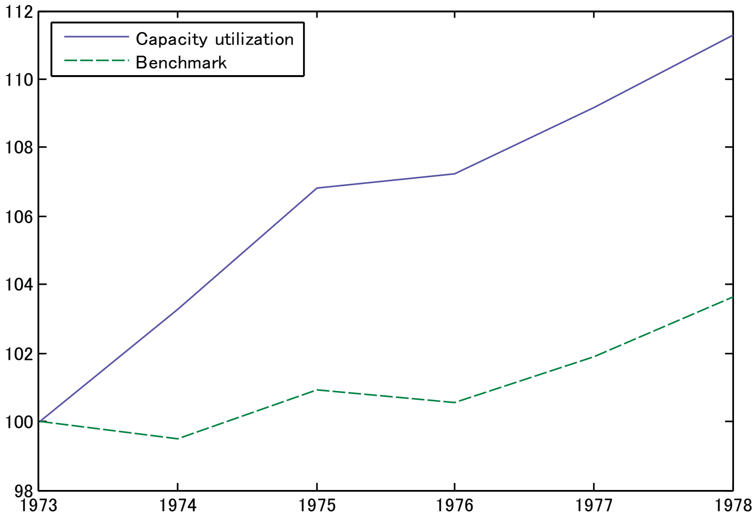

Figure 2.5: Comparison of the two TFP series, both normalized to 100 in 1973.

because the imputed capacity utilization rate follows a decreasing trend, as shown in Figure 2.4. In other words, the stagnation of the TFP growth rate in the benchmark model was spurious. The role that endogenous capacity utilization and the purified TFP played on the severe recession following the first oil crisis is investigated in Chapter 3.

So far, the benchmark model and its extension are described in the growth context. That is, these models are applied to analyze the transition to the balanced growth path. However, they are also applicable to studies in business cycles which are the fluctuation around the balanced growth path.

The model employed here to examine the role of energy-saving technological change on the "'Great Moderation" observed in the United States is based on the standard RBC model developed by Hansen (1985). There is a representative household who has preferences defined over consumption and leisure as follows:

$$E_0 \sum_{t=0}^{\infty} \beta^t \left[(1-\alpha) \ln C_t + \alpha \frac{\ln(1-\bar{H})}{\bar{H}} H_t \right] \tag{2.22}$$

where E_0 is the expectation operator conditioned on information known at time 0. In this economy, labor is indivisible so that workers either work $\bar{H}$ hours or not at all. The indivisibility of labor is incorporated in the model because it is consistent with the fact that most fluctuations in aggregate hours worked come from variations in employment, not in hours worked in the U.S., as shown in Table 3.4.[10] As in the extended model described earlier, the representative firm can adjust capacity utilization rate to absorb exogenous shocks so that the production function is specified as follows:

$$Y_t = A_t (\Gamma_t H_t)^{1-\theta} \left[(1-\mu) K_t^{\frac{\varepsilon-1}{\varepsilon}} + \mu (z_t E_t)^{\frac{\varepsilon-1}{\varepsilon}} \right]^{\frac{\varepsilon}{\varepsilon-1}\theta} \tag{2.23}$$

where A_t is transient component of technology. It is assumed that A_t and p_t are exogenous to the firm and follow an AR(1) as follows:

$$\ln A_{t+1} = \rho_A \ln A_t + \zeta_{t+1} \tag{2.24}$$

$$\ln p_{t+1} = \rho_p \ln p_t + \nu_{t+1} \tag{2.25}$$

where ζ_{t+1} and ν_{t+1} are independent and identically distributed normal random variables.

Using these three models (the benchmark model, the capacity utilization model, and the busines cycle model) described above, some energy-related questions such as wheather the severe recession following the first oil crisis in Japan can be reproduced by the benchmark model are investigated in Chapter 3. Before proceeding to tackle these questions, let us discuss the key parameter in our

[10] This indivisibility enlarges the impact of a technology shock on the labor supply. See Hansen (1985) for details.

analysis, the elasticity of substitution between capital stock and energy in the next subsection.

2.4 The elasticity of substitution between inputs

Since the first oil crisis in 1973, a number of studies have examined the effect of increases in energy price on macroeconomic variables. To evaluate the quantitative impact of rises in energy price, it would be no doubt that one of the most important parameters is the elasticity of substitution between energy and other inputs, especially capital stock. In this subsection, the previous studies estimated the elasticity of substitution are briefly reviewed.

The seminal work of estimating the elasticity of substitution between energy and other inputs would be Berndt and Woold (1975). They derive the input demand equations from translog cost function and obtain the Allen elasticity of substitution by estimating the input demand equations under the certain restrictions. Translog cost function is developed by Christensen et al. (1973) and its main idea is to put less restrictions to estimate the elasticities of substitution as much as possible. That is, instead of employing a specific cost function form such as Cobb-Douglas or a constant returns to scale (CES), a second-order Taylor-series approximation in logarithms to an arbitrary cost function is used. Suppose[11] there exist a twice-differentiable cost function $C = C(Y, P_K, P_L, P_E, P_M)$, where C is total cost, Y is output, and P_K, P_L, P_E, P_M are the prices of capital stock (K), labor (L), energy (E), and material (M), respectively. Then, a second-order Taylor-series approximation in logarithms around $\ln Y = \ln P_K = \ln P_L = \ln P_E = \ln P_M = 0$

[11]The following discussion is based on Berndt and Wood (1975) and Murota (1984).

provides the following translog cost function

$$
\begin{aligned}
\ln C = {} & \alpha_0 + \alpha_Y \ln Y + \alpha_K \ln K + \alpha_L \ln L + \alpha_E \ln E + \alpha_M \ln M \\
& + \frac{1}{2} \ln Y (\beta_{YY} \ln Y + \beta_{YK} \ln K + \beta_{YL} \ln L + \beta_{YE} \ln E + \beta_{YM} \ln M) \\
& + \frac{1}{2} \ln P_K (\beta_{YK} \ln Y + \beta_{KK} \ln K + \beta_{KL} \ln L + \beta_{KE} \ln E + \beta_{KM} \ln M) \\
& + \frac{1}{2} \ln P_L (\beta_{YL} \ln Y + \beta_{KL} \ln K + \beta_{LL} \ln L + \beta_{LE} \ln E + \beta_{LM} \ln M) \\
& + \frac{1}{2} \ln P_E (\beta_{YE} \ln Y + \beta_{KE} \ln K + \beta_{LE} \ln L + \beta_{EE} \ln E + \beta_{EM} \ln M) \\
& + \frac{1}{2} \ln P_M (\beta_{YM} \ln Y + \beta_{KM} \ln K + \beta_{LM} \ln L + \beta_{ME} \ln E + \beta_{MM} \ln M).
\end{aligned}
\tag{2.26}
$$

Since cost function is homogenous of degree one in input prices, linear homogeneity imposes the following restrictions on the parameters in the cost function above

$$
\begin{aligned}
\alpha_K + \alpha_L + \alpha_E + \alpha_M &= 1 \\
\beta_{KK} + \beta_{KL} + \beta_{KE} + \beta_{KM} &= 0 \\
\beta_{KL} + \beta_{LL} + \beta_{LE} + \beta_{LM} &= 0 \\
\beta_{KE} + \beta_{LE} + \beta_{EE} + \beta_{ME} &= 0 \\
\beta_{KM} + \beta_{LM} + \beta_{EM} + \beta_{MM} &= 0.
\end{aligned}
\tag{2.27}
$$

Taking the derivative of both sides of Equation (2.26) with respect to $\ln P_i (i = K, L, E, M)$ and applying Shephard's Lemma[12], gives

$$\begin{aligned}\frac{\partial \ln C}{\partial \ln P_i} &= \frac{P_i}{C}\frac{\partial C}{\partial P_i} = \frac{P_i I}{C} = S_i \\ &= \alpha_i + \beta_{iY} \ln Y + \beta_{ii} \ln P_i + \sum_{\substack{j=K \\ (j \neq i)}}^{M} \beta_{ij} \ln P_j, \quad (I, i, j = K, L, E, M)\end{aligned} \tag{2.28}$$

where S_i is cost share of input i in the total cost. Since the left hand side of Equation (2.28) is just cost share of input i and the right hand side depends only on output and input prices, it is possible to estimate Equation (2.28). Berndt and Wood (1975), using the United States manufacturing data over the period 1947–1971, esimate Equation (2.28) subject to Equation (2.27) by three-stage least squares.

Our final goal is to obtain the Allen elasticity of substitution between energy and other inputs, especially capital stock. The Allen elasticity measures the percentage change in input i given a 1 % change in input price j, remaining output and the prices of all other inputs constant, and it is frequently used elasticity in the case of many inputs.[13] By definition of Allen elasticity of substitution, two inputs are substitutes if the elasticity is positive and complements if the elasticity is negative.

Following Uzawa (1962), the Allen elasticity of substitution between input i and j can be obtained as

$$\sigma_{ij} = \frac{CC_{ij}}{C_i C_j} \tag{2.29}$$

[12]Shephard's Lemma states that the partial derivative of cost function with respect to input price i leads to the demand function of input i. That is, $\frac{\partial C}{\partial P_i} = I$ where I is the demand function for input i.

[13]See Thompson (2006) and Frondel (2010) for comparison of Allen elasticity with other elasticities such as Morishima elasticity.

where $C_i = \frac{\partial C}{\partial P_i}, \frac{\partial^2 C}{\partial P_i \partial P_j}$. Plugging the estimates obtained by estimating Equation (2.28) subject to Equation (2.27) into Equation (2.29) provides the following experssion of Allen elasticity of substitution in the translog cost function

$$\sigma_{ij} = \frac{\beta_{ij} + S_i S_j}{S_i S_j}, \quad (i, j = K, L, E, M, i \neq j). \tag{2.30}$$

Berndt and Wood (1975) show that the estimated σ_{KE} range between -3.09 and -3.53 and conclude that energy and capital stock are complements.

The translog cost function approach to estimate the elasticity of substitution between inputs has been also employed in many other studies. Hudson and Jorgenson (1974), using the same dataset as Berndt and Wood (1975), employ the similar translog const function specification and report σ_{KE} is about -1.39. Fuss (1977), using the Canadian manufacturing data over the period 1961–1971, show that $\sigma_{KE} = -0.21$. In Japan, using the annual aggregate data over 1965-1981, Ito and Murota (1984) estimate the translog const function in Equation (2.26) including additional technology term but excluding material (M) for simplicity. The estimated result is $\sigma_{KE} = -1.31$. They also show that σ_{KE} has an increasing trend, ranging from -1.86 in 1973 to -0.65 in 1981, indicating that the comprimentarity between energy and capital stock decreased following the first oil crisis. Wago (1983), using the quarterly Japanese data over 1965–1979, also estimates the translog cost function including technology therm and reports that σ_{KE} is about -.282 on average. In sum, there is ample evidence, based on the analysis of time-series data, that σ_{KE} is negative, indicating that energy and capital stock are complements. [14]

[14] There is an argument that the estimation with time-series data only captures the short-run elasticity while the analysis with cross-section data reflects the long-run elasticity. For instance, Griffin and Gregory (1976) use the nine-country pooled cross-section data over 1955–1969 and estimate that σ_{KE} ranges between 1.02 and 1.07. Pindyck (1979), using the ten-country pooled cross-section data over 1959-1973, also reports that σ_{KE} takes the value from 0.36 to 1.48 (0.59 in Japan). Thus, the emprical studies based on (pooled) cross-section data show that energy and capital stock are indeed substitutes in the long run, which is quite reasonable since energy-consuming machines

Most of the previous studies shown above also estimate the elasticity of substitution between other combination of inputs. As for the elasticity of substitution between energy and labor (σ_{EL}), the estimates of Berndt and Wood (1975), Hudson and Jorgenson (1974), Ito and Murota (1984), and Wago (1983) are 0.64, 2.16, 0.98, and 1.15, respectively. In an analogous way, the elasticities of substitution between capital and labor (σ_{KL}) are estimated as 1.01, 1.09, 0.53, and 1.23. In all cases, both σ_{EL} and σ_{KL} are positive, indicating that energy-labor and capital-labor are substitutes. Furthermore, the averaged σ_{KL} over four previous studies is about 0.97 while the averaged σ_{EL} is about 1.23 (both not far from unity). Therefore, taking all empirical evidence described above into consideration, it would be a suitable first approximation to assume the following nested CES production function for analysis,

$$Y_t = (\Gamma_t H_t)^{1-\theta}\left[(1-\mu)K_t^{\frac{\varepsilon-1}{\varepsilon}} + \mu E_t^{\frac{\varepsilon-1}{\varepsilon}}\right]^{\frac{\varepsilon}{\varepsilon-1}\theta}. \tag{2.31}$$

In the following chapter, the production function is specified as Equation (2.31) and ε is set at close to zero to reflect the empirical evidence that capital stock and energy use are complements.

2.5 Data construction

As the last part of Chapter 2, this subsection describes the data construction methodology employed in the current study.

are likely to be replaced with energy-saving ones in the long run. However, since the elasticity of substitution in our model (ε) captures the short-run substitution, complementarity between capital stock and energy is assumed throughout the thesis.

Energy

The energy-related variables are real energy use, E_t, and relative price of energy, p_t. The data source for the energy-related variables is the "Trade Statistics of Japan" published by the Ministry of Finance. Although the "General Energy Supply and Demand Balance" published by the Agency for Natural Resources and Energy has more detailed information (such as what percentage of the total domestic supply of primary energy comes from nuclear power generation), the "Trade Statistics of Japan" is suitable for our analysis since it provides data on energy prices that are essential to examine the impact of the substitution effect and to estimate the series of energy-saving technology. Note also that it is implicitly assumed that all energy needed for production are imported from abroad. However, this can be justified by the fact that almost all energy is imported in Japan.

The energy-related variables are constructed based on the methodology developed by Atkeson and Kehoe (1999). Real energy use E_t at time t is calculated as follows:

$$E_t \equiv \sum_i P_{i,0} Q_{i,t}, \tag{2.32}$$

where i denotes the type of energy. In the analysis here, there are three types of energy: petroleum, coal, and liquid natural gas. $P_{i,0}$ is the price of type i energy in the base year 1990. Note that $P_{i,0}$ is the CIF (cost, insurance, and freight) price converted into Japanese yen, so that exchange rate changes are already taken into account. $Q_{i,t}$ is the quantity of imported type i energy in year t.

To construct the relative price of energy, the energy price deflator at time t, denoted as DEF_t^P, is derived as follows:[15]

[15] It is widely known that Paasche price index tends to have a downward bias. In Appendix, Laspeyres energy price index is also constructed, and it is examined whether the difference between these two price indices are problematic.

$$DEF_t^P \equiv \frac{\sum_i P_{i,t} Q_{i,t}}{\sum_i P_{i,0} Q_{i,t}}. \tag{2.33}$$

Then, the relative price of energy, p_t, is constructed by dividing the energy price deflator by the GNP deflator (whose base year is also 1990):

$$p_t \equiv \frac{DEF_t^P}{DEF_t^V}, \tag{2.34}$$

where DEF_t^V is the GNP deflator at time t.

In the United States case which is analyzed in the context of the "Great Moderation" in Chapter 3, the data on energy price and energy use are taken from the U.S. Energy Information Administration (2009). Nominal energy price is calculated as weighted average of nominal consumer price estimates for each fossil fuel (coal, natural gas, and petroleum). Then it is divided by GNP deflator to obtain real energy price. Energy use is defined as unweighted sum of energy consumption of fossil fuels in three sectors (commercial, industrial, and transportation[16]), all measured in billion British thermal units (Btu). Nuclear electric power is excluded from the definition of energy due to the data limitation of price in each sector.[17]

Other variables

The working age population is defined as the number of people between ages 15–64 and is obtained from the "Census Population" published by the Ministry of Internal Affairs and Communications. The average weekly hours worked per employed person (ℓ_t) is sourced from the "Monthly Labor Survey" published by the Ministry of Health, Labor and Welfare; the number of employed persons

[16]Residential sector is excluded as our model assumes that the representative household does not consume energy.

[17]This simplification would not significantly affect our simulation results since the nuclear electric power consumption accounts for 0% of total primary energy consumption in 1949 and 8.8% in 2009.

(M_t) is derived from the 1968 SNA (System of National Accounts) produced by the Economic and Social Research Institute, Cabinet Office. Then, the empirical counterpart of h_t is calculated as follows,

$$h_t = \frac{\ell_t * M_t}{N_t * 16 * 7}. \tag{2.35}$$

Following Otsu (2009), it is assumed that the maximum number of hours worked per day is 16.

The rest of the variables are obtained from the 1968 SNA. The 1968 SNA is used for analysis since the 1993 SNA is not available before 1980. Since the models employed in this thesis contain no government sector, it is necessary to adjust the data from the 1968 SNA to match up the series in the models.[18] In the 1968 SNA, real value added (real GNP in this chapter) is decomposed into the following parts:

$$V_t = C_t + X_t + G_t + NX_t + NFP_t \tag{2.36}$$

where V_t is real value added, C_t is real "Private final consumption expenditure," X_t is the sum of real "Gross fixed capital formation" and real "Change in inventories," G_t is real "Final consumption expenditure of government," NX_t is real "Net exports (excluding real energy imports)," and NFP_t is real "Net factor payment." The nominal values are converted into real values by dividing them by the constant 1990 yen deflator.

Following Hayashi and Prescott (2002), real "Final consumption expenditure of government " is included in C_t and real "Net exports (excluding real energy imports)" and real "Net factor payment" are incorporated in X_t. That is,

[18]See Cooley (1995), Hayashi and Prescott (2002), and Conesa et al. (2007) for data construction strategies to ensure consistency with neoclassical growth models.

$$V_t = C_t^{'} + X_t^{'} \tag{2.37}$$

where $C_t^{'}$ is the sum of C_t and G_t and $X_t^{'}$ is the sum of X_t, NX_t, and NFP_t. V_t, $C_t^{'}$, and $X_t^{'}$ are the empirical counterparts of value added, aggregate consumption, and aggregate investment, respectively.

Finally, the capital stock series are constructed using the perpetual inventory method. The initial capital stock, K_{1970} is set so that $K_{1970}/V_{1970} = 1.29$,[19] which is taken from the dataset constructed by Hayashi and Prescott (2002). The series of subsequent values of capital stock is obtained by the law of motion for capital stock, Equation (2.3).[20]

[19]In fact, the value of K_{1970}/V_{1970} in 1970 is 1.04 in Hayashi and Prescott (2002). Their calculation of capital stock does not include the government capital, whereas ours does. Therefore, the government capital–value added ratio (0.25) is added up to 1.04, leading to 1.29 in total.

[20]For the United States part in Chapter 3, the data on hours worked and employment are taken from Cociuba, Prescott and Ueberfeldt (2009). The data on the other variables are taken from the Bureau of Economic Analysis (BEA) and the same data adjustment to match up the series in the models is conducted.

Chapter 3

Applications of macroeconomic models with energy

In the previous chapter, the benchmark model is first constructed and the methodology employed for obtaining the level of energy-saving technology is described. Since the series of energy-saving technology are one of the most important exogenous variables in the current study, the possible drawbacks in our methodology are carefully discussed. In addition, following Cooley (1995), Hayashi and Prescott (2002), and Conesa, et al. (2007), the method employed to adjust the data from the 1968 SNA to match up the series in the models is described in the data construction section.

In this capter, three research questions introduced in Chapter 1; (i) what caused the declining Japan's energy intensity after the first oil crisis, (ii) to what extent the standard RBC model with energy is able to replicate the severe recession following the first oil crisis in Japan, and (iii) what is the role of improvements in energy-saving technology on the Great Moderation observed after the mid 1980s in the United States, are addressed using the models introduced in Chapter 2.

3.1 Case1: Energy-saving technological change in Japan

After the first oil crisis in 1973, energy dependence in Japan's economy declined considerably. Figure 1 depicts the relationship between the natural logarithm of energy use[1] and real gross national product (GNP)[2] over 1955–1998. As illustrated in Figure 1, over 1955–1972, the energy use proportionally increased as the economy grew. This relationship changed dramatically, following the first oil crisis. During 1973–1988, real GNP grew by 73.6% whereas energy use actually declined by 7.4%. That is, energy use relative to real GNP (energy–GNP ratio, hereafter) dropped substantially over 1973–1988.

In addition, the first oil crisis forced households and firms to change their behavior drastically. A notable example is that the first oil crisis brought on a panic in which people rushed to hoard toilet paper. This, caused by the unfounded romor, first took place in Osaka in November, 1973, and spreaded across cities, followed by the price rise in other necessities such as detergent, sugar, and soy sauce. In addition, neon signs were turned off late at night and elevators at department stores stopped to conserve energy. In the long run, people replaced their automobiles and other durable goods with more energy-efficient models.

Against this background, this section aims to examine quantitatively the reasons for the drop in the energy–GNP ratio observed in the 1970s and 1980s, using a simple neoclassical growth

[1] The data for energy use is taken from the "General Energy Supply and Demand Balance" published by the Agency for Natural Resources and Energy, and it is calculated as the domestic supply of fossil fuels (petroleum, coal, and liquid natural gas) measured in petajoules. The domestic supply of fossil fuels is treated as the energy use here, since most of the total annual domestic energy supply is consumed within the country. For instance, only 5.7% and 1.5% of total domestic energy supply were exported and accumulated as an inventory respectively in 1970.

[2] Real GNP is obtained using the GNP deflator with 1990 as the base year.

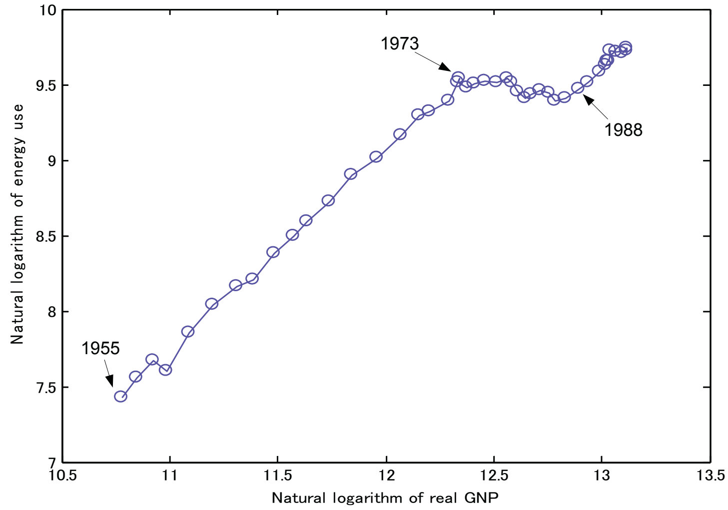

Figure 3.1: The relationship between energy use and real GNP

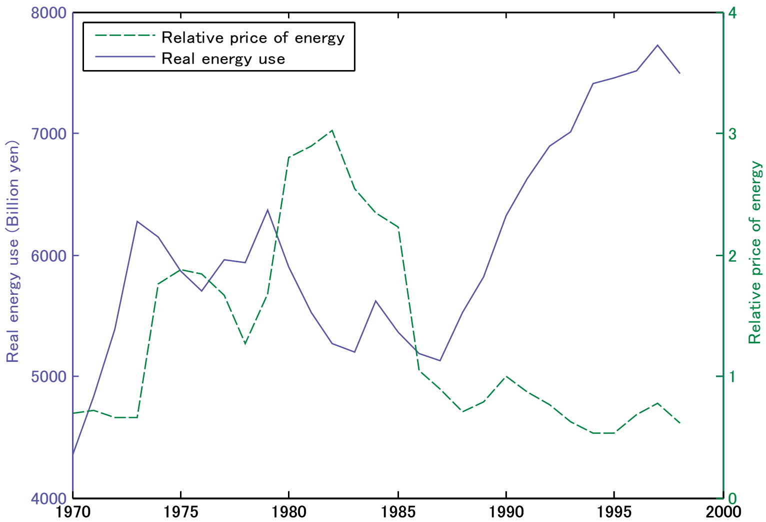

Figure 3.2: Real energy use and relative energy price

model with energy as an input. Attempts at explaining the drop in this ratio generally focused on two possibilities: (i) the substitution effect, and (ii) energy-saving technological progress. The substitution effect works as follows. When the relative price of energy rises, it is substituted with other inputs such as labor and capital. Thus, as value added increases, we would expect the input of energy per unit of value added, or the energy–GNP ratio, to decrease. The trends in actual relative price of energy and real energy use are depicted in Figure 3.2; the relative price of energy is calculated by dividing the energy price deflator by the GNP deflator. Since the price data for energy use is not available in the "General Energy Supply and Demand Balance," this chapter alternatively uses the "Trade Statistics of Japan" published by the Ministry of Finance, under the assumption that Japan imports all its energy required for production.[3] Real energy use is calculated as the total quantity of imported fossil fuels (petroleum, coal, and liquid natural gas) evaluated at base year price. As can be seen, the relative price of energy spiked in 1973, the year of the first oil shock, and again in 1979, the year of the second oil shock, and that by the mid-1980s, prices had more than tripled when compared with that at the beginning of the 1970s. However, real energy use (measured in billion yen) dipped following the first oil shock and declined substantially following the second. Therefore, the substitution effect emerges as one possible factor for the drop in the energy–GNP ratio.

The second possible factor to account for the drop in this ratio is the improvement in energy-saving technology. It is entirely possible that the sharp rises in the relative price of energy in the 1970s increased the demand for more energy-efficient products, leading to aggressive research and development (R&D) expenditure. Since the energy–GNP ratio only shows a modest increase

[3] According to the Agency for Natural Resources and Energy (2012), the share of domestically supplied energy (excluding nuclear power generation) in total energy supply was 14.9%, 6.7%, and 5.8% in the 1970s, 1980s, and 1990s, respectively. Therefore, it would not be unrealistic to assume that Japan imports all its energy needed for production.

after 1985, when the relative price of energy dropped sharply, it is plausible to consider that the Japanese economy became less energy-dependent owing to energy-saving technological change.

To examine the role of these two possible factors in accounting for the drop in the energy–GNP ratio, two simulations are conducted using a simple neoclassical growth model with energy. In the first simulation, the actual path of the relative price of energy is fed into the model as an exogenous variable to examine the quantitative impact of the substitution effect on the energy–GNP ratio. In the second simulation, the actual series of energy-saving technology are estimated as residuals. Then, an estimated path of energy-saving technology is additionally fed into the model to examine the role of energy-saving technological change.

Our findings are as follows. The substitution effect owing to changes in the relative price of energy is weak and, taken alone, cannot account for the drop in the energy–GNP ratio. However, once the estimated path of energy-saving technology is incorporated into the model, the energy–GNP ratio generated by the model fits well with the actual data.

3.1.1 Calibration

The model is calibrated to the Japanese economy for 1970–1998.[4] The values for β and θ are set at 0.976 and 0.362, taken from Hayashi and Prescott (2002). δ takes the value 0.100, a conventional value for annual data. The leisure weight in preferences, α, is obtained by solving the intra-temporal optimal condition for α,

$$\left(\frac{\alpha}{1-\alpha}\right)\left(\frac{h_t}{1-h_t}\right) = (1-\theta)\frac{y_t}{c_t}, \quad \text{for} \quad t = 1970, ..., 1998. \tag{3.1}$$

[4]The analysis ends in 1998 since the 1968 SNA (System of National Accounts) data, the data source for many aggregate variables in this chapterr, is not available after 1998. As our focus is on the economic reasons behind the changing dynamics of energy–GNP ratio observed in the 1970s and 1980s, this coverage of years is sufficient.

and averaging them over 1970-1998. To calibrate μ, the production function and the first-order condition for energy use are combined as follows:

$$\frac{1-\mu}{\mu} = \left(\frac{\theta Y_t - p_t E_t}{p_t E_t}\right)\left(\frac{E_t}{K_t}\right)^{\frac{\varepsilon-1}{\varepsilon}}, \quad \text{for} \quad t = 1970, ..., 1998. \tag{3.2}$$

Equation (3.2) is then solved for μ, and μ is then averaged over 1970–1998.

As discussed in Chapter 2, previous studies provide numerous estimates of ε, the elasticity of substitution between capital stock and energy. In addition to the estimates obtained using micro dataset discussed in Chapter 2, several authers also estimate it using aggregate dataset. For instance, Backus and Crucini (2000) report a value of $\varepsilon = 0.09$, while Miyazawa (2010), on conducting a generalized method of moments estimation, reports values of $\varepsilon = 0.100$ and $\varepsilon = 0.086$. Finally, Hassler et al. (2012)[5] use maximum likelihood estimation and arrive at an elasticity of substitution between energy and the capital/labor composite of 0.0044 (which was not statistically significant). Given these results, ε is set to 0.1 throughout this thesis and sensitivity check is provided in Appendix.

The path of exogenous variables beyond the observation period also needs to be specified in order to conduct the simulation below. Here, it is simply assumed that the relative price of energy, p_t, and the TFP growth rate after 1998 are the same as the averages over 1970–1998. The calibration results are shown in Table 3.1.

3.1.2 Results

As can be seen in Figure 3.2, there were two major spikes in the relative price of energy in the 1970s, one in 1973 and another in 1979. Using the simple growth model introduced here, let us

[5]Note that their production function, shown in footnote 3, is slightly different from the one employed here.

Parameters	Description	Value
ε	Elasticity of subst. btw. capital and energy	0.100
θ	Capital/Energy composite share	0.362
δ	Depreciation rate of capital	0.100
β	Discount factor	0.976
α	Leisure weight in preferences	0.712
μ	Share of energy in capital-energy composite	0.162

Table 3.1: Parameter values

now examine whether the substitution effect alone, triggered by the surge in the relative energy price, can explain the observed decline in the energy–GNP ratio. The simulation results are shown in Figure 3.3.

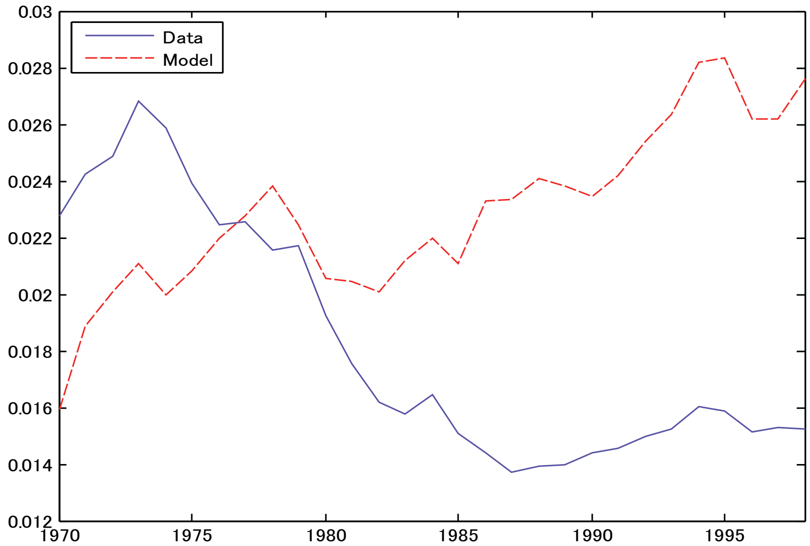

Figure 3.3: Energy–GNP ratio (benchmark model)

The vertical axis represents the energy–GNP ratio. In the data, this ratio stood at 2.7% in 1973 but declined sharply subsequently. By 1988, it had fallen to about 1.4%, that is, almost half of the 1973 value, and since then, has shown only a slight upward trend. The simulation results[6]

[6]In the simulation, the actual series of TFP growth rate is also fed into the model. The TFP growth rate,

Variables	1970–79	1980–89	1990–98	1970–1998
TFP	2.46%	3.52%	1.58%	2.58%
Modified TFP	2.19%	1.96%	1.01%	1.77%
Energy-saving technology	5.47%	6.60%	1.65%	4.37%

Table 3.2: Average annual growth rates of exogenous variables

show that energy price fluctuations influence the energy–GNP ratio, but not substantially. This ratio does decrease after 1973 and 1979 but to a limited extent. In addition, in the model, the energy–GNP ratio continues to rise in the mid-1980s reflecting the downturn in the relative price of energy, while in the actual data the ratio declines. In sum, it is concluded that the substitution effect alone fails to account for the drop in the energy–GNP ratio.

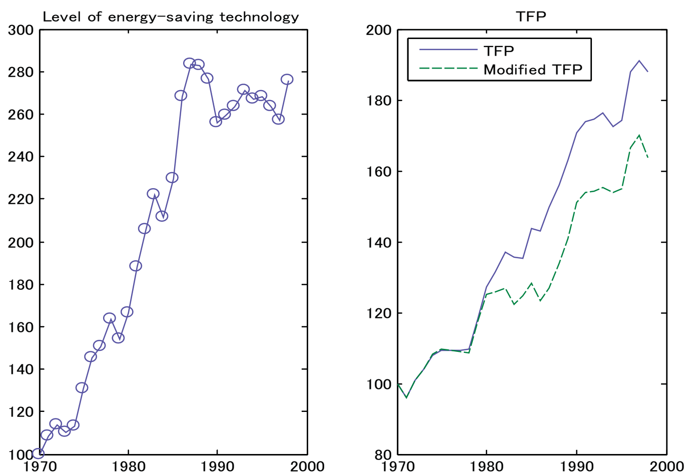

Figure 3.4: Measured level of energy-saving technology, TFP and modified TFP. The initial levels are normalized to 100.

The fact that the energy–GNP ratio generated by the model overpredicted the actual data suggests that the possible presence of of energy-saving technological progress. Following the method-

however, does not play a crucial role in changes in the energy–GNP ratio since improvements in TFP simply result in a simultaneous increase in energy use and GNP. In other words, exogenous changes that diminish energy use for a given level of GNP are needed to reproduce the trend shown in Figure 3.3.

ology described in Chapter 2, the measured level of energy-saving technology, TFP and modified TFP are displayed in Figure 3.4 and the average annual growth rates of these series in each period are summarized in Table 3.2. As can be seen, the growth in the energy-saving technology in the 1970s and 1980s was substantial. Indeed, the average annual growth rates of energy-saving technology were 5.47% and 6.60% in the 1970s and 1980s, respectively. These improvements in energy-saving technology partially account for the growth of TFP, resulting in a lower rate of growth in modified TFP. For example, the growth rate of TFP in the 1980s was 3.52%, whereas that of modified TFP was only 1.96%.

Overall, the average annual growth rate of TFP over 1970–1998 was 2.58%, whereas the modified TFP growth rate was only 1.77%. This suggests that about $31.4\% \simeq 100 * (1 - (1.77/2.58))$ of the TFP improvements in this period is attributable to energy-saving technological progress. This number may be too large, and there are at least two possible reasons to think why this might be the case. First, the definition of energy here excludes nuclear power owing to the lack of price data. This implies that substituting nuclear power for fossil fuels results in improvements in energy-saving technology. In Appendix, the extent to which the growth of energy-saving technology is mitigated by the inclusion of nuclear power is briefly examined. Second, during the period under study, Japan's industrial structure changed from one dominated by heavy industries (such as steel and shipbuilding) to one dominated by knowledge-intensive industries (such as electronics), which decreased energy use. This change, although not directly related to energy-saving technological progress, is included in the measured z_t.

Another problem with the z_t series is that it suggests that the level of energy-saving technology occasionally declines; this implication is in contrast to our perceptions of technology. It is likely that because z_t is measured as a residual, it contains elements not related to energy-saving technological progress. Thus, short-term fluctuations in z_t need to be interpreted with a degree of caution; however, from a longer-term perspective, Figure 3.4 is likely to present a relatively accurate picture of improvements in the level of energy-saving technology.

The discontinuance of improvements in energy-saving technology in the 1990s is also noteworthy and may be triggered by the following two possible reasons. First, the chronic slump in the Japanese economy in the 1990s, well known as the "Lost Decade," may have weakened firms' incentives to increase R&D expenditure related to energy-saving technology. According to the "Survey of Research and Development" provided by the Ministry of Internal Affairs and Communications, the average annual growth rates of R&D expenditure (natural sciences and engineering only) were 14.6% and 9.9% in the 1970s and 1980s and only 2.2% in the 1990s. Second, Japan's energy efficiency may have reached some kind of upper-bound in the late 1980s. In fact, the Agency for Natural Resources and Energy (2012) shows that in 1990s, the primary energy supply relative to real GDP was 2.6 in the United States and 2.3 in the European Union (27 countries) in comparison with 1.0 in Japan. In sum, while the estimated levels of energy-saving technology probably have some factors not related to the true technological progress in energy efficiency, it captures, at least, the trend of the improvements in energy-saving technology.

Finally, the impact of energy-saving technological progress on the dynamics of the energy–GNP ratio is examined. In addition to the relative energy price, the actual time path of the level of energy-saving technology shown in the left panel of Figure 3.4 is fed into the model. Figure 3.5 presents the simulation results generated by the model considering only the substitution effect, labeled "Benchmark" and the model considering the substitution and the energy-saving technology effects, labeled "Energy-saving technology." This time, the model with energy-saving technological progress closely fits the data. The reason is as follows. After 1973, the level of energy-saving

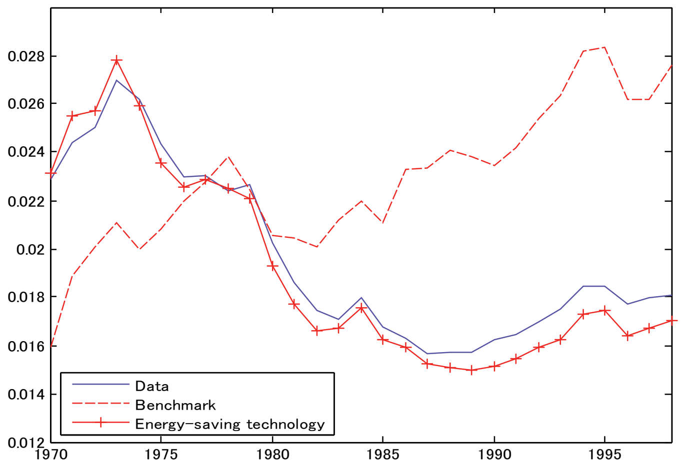

Figure 3.5: Energy–GNP ratio with energy-saving technology

technology started to increase considerably, and by the end of the 1980s, it more than tripled. Owing to this progress in energy-saving technologies, the energy required to produce a given amount of output for a given level of capital stock and hours worked declined. As a result, the energy–GNP ratio decreased over this period.

Figure 3.6 displays the comparison of the simulation results for other aggregate variables. As can be seen, the model with energy-saving technology does a better job in accounting for the dynamics of other aggregate variables. This is because better model prediction of the energy use, driven by the improvements in energy-saving technology, also serves to improve the model explanation power for other aggregate variables.

There is a possible extension to improve the analysis presented here. As discussed earlier, because the energy-saving technology is measured as a residual, it probably contains other factors not related to energy-saving technological change. This means that it is necessary to measure the "pure" energy-saving technological change. In fact, the previous studies using micro-data such as

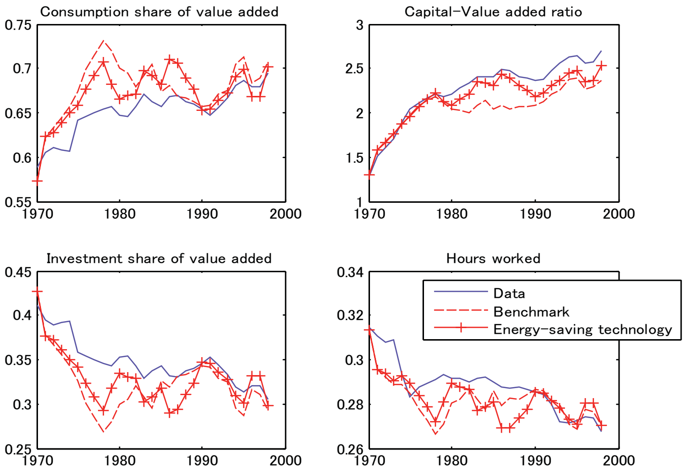

Figure 3.6: Comparison of the simulation results

patent and plant level data show that the contribution of the induced energy-saving technological change to the declining energy intensity seems to be smaller than that calculated in this thesis. For instance, Linn (2008) builds a dynamic model consisting of entrants and incumbents and derive the following equation for estimation:

$$\ln\left(E_{it}/Y_{it}\right) = \beta_1 N_{it} \ln p_{Ejst} + \beta_2 \ln p_{Ejst} + \beta_3 N_{it} + \mathbf{X_{it}}\gamma + \varepsilon_{it}, \tag{3.3}$$

where i, j, s, t represent plant, industry, state, and year, E/Y is energy intensity, N is an entrant dummy equaling 1 in the year the plant enters and 0 otherwise, p_E is energy price, and X is a set of control variables including state fixed effects and so on. The idea is that the difference in the energy intensity between entrants and incumbents represents the additional flexibility of entrants in adopting new efficient technologies, enabling us to obtain accurate improvements in energy-saving technology. Using plant level data from the Census of Manufactures in the United States, he estimates that β_1 is about -0.1 in the various specifications, meaning that the energy intensity in entrants declines around 1% more than the incumbents with 10% rise in energy price. With the actual data on energy price and energy intensity over the period 1972–1982, he concludes that the energy-efficiency improvements in entrants accounts for a quarter of the observed change in energy intensity.

Newell et al. (1999), using the Sears Catalog data on room air conditioner, central air conditioner, and gas water heater over the period 1958–1993, also examine whether the rise in relative price of energy induces the increses in energy efficiency. They estimate the following equation for each consumption durable good mentioned above.[7]

$$\ln k_{it} = \alpha + \left(\beta_{10} + \beta_{11} t + \beta_{12} t^2 + \beta_{13} \ln p_{t-j} + \beta_{14} s\right) \ln f_{it} + \beta_2 \ln c_{it} + \varepsilon_{it}, \tag{3.4}$$

where i indexes product models, t indexes time, k is product cost, f is energy flow, c is cooling or heating capacity, p is relative price of energy, and s is the level of energy efficiency standards imposed by the government. Since it usually costs more to produce more energy-efficient product models, β_{10} is expected to be negative. The key parameter, β_{13}, indicates how much the production cost of more energy-efficient models is affected by the changes in relative price of energy. With energy-saving technological progress, β_{13} is expected to be positive. Lastly, they assume the three-year lag in energy price effect, setting $j = 3$. Their estimation results show that β_{10} is negative and statistically significant in all three durable goods, and β_{13} is postive and statististically significant in two durable goods out of three. They also decompose the casuses of improvements in energy-efficiency into three portion: overall (autonomous) technological progress portion, price-induced portiona, and standards-induced portion and show that price-induced portion accounts for about

[7] To be precise, Eq (3.4) is for central air conditioners and other two equations have slightly different independent variables. See Eq (2)-(4) in Newell et al. (1999).

28–46 % of total change in energy efficiency and most of the rest is attributed to the overall improvements in technology.

Popp (2002), using U.S. patent data from 1970 to 1994, also looks at the impact of increases in energy prices on energy-efficiency innovations. He regresses the fraction of energy-related patents in all patent applications on energy price (and its lags), stock of knowledge, and other independent variables such as R&D expenditure by the U.S. Department of Energy. He also finds that the rise in energy prices has a statistically significant positive impact on energy-efficiency innovations.

In Japan, there are several papers estimating the biases of technical change, using aggregate and industrial data. According to Acemoglu (2002), technical change, expressed as change in A below, is labor-biased if

$$\frac{\partial \frac{\partial F/\partial L}{\partial F/\partial K}}{\partial A} > 0. \tag{3.5}$$

Under the assumption that all input markets are perfectly competitive, marginal rate of substitution equals its relative price. Thus, taking the relative price as given, labor-biased technical change increases the labor share. This is the reason labor-biased technical change is also called labor-using technical change. Following the definition of biases of technical change described above, Sato (2013), using the Japan Industrial Productivity Database (JIP Database) from 1973 to 2008, estimates the biases of technical change in Japan. He employs the translog cost function with five inputs (capital, labor, electricity inputs, energy inputs excluding electricity, and material inputs) and derives the biases of technical change by estimating the log cost function and cost share equations simultaneously. Sato (2013) shows that while no industry exhibits electricity-saving technical change, seven out of twelve manufacturing industries and two out of four service industries exhibit energy-saving technical change over 1973–2008. Similarly, Fukunaga and Osada (2009) estimate the biases of technical change in Japan, using aggregate data over 1970–2008 and JIP Database over 1973-2005. Their analysis differs from Sato (2013) in that the biases of technical change are allowed to be time-varying. Fukunaga and Osada (2009) find that the biases of technical change are energy-saving in the 1980s and gradually switch to energy-using around 2000.

In sum, (purified) energy-saving technological change, induced by the rise in relative price of energy, identified by microdata seems smaller than our predictions using aggregate data. On the one hand, this may be attributed to more desirable environments microdata usually provides to identify the causality from one variable to the other, remaining other explanatory variables unchanged. Thus, the true induced energy-saving technnological progress may be actually smaller than what we obtained using aggregate data.

On the other hand, microdata is often only available in some specific industries, plants, and households so that it needs to be interpreted with caution in an aggregate environment. For instance, Linn (2008) only uses data for manufacturing industries and Newell et al. (1999) focus only on three durable products. Furthermore, if broader definition of energy-saving technological change which includes the change in industrial structure from energy-consuming industries (such as steel and shipbuilding) to less energy-consuming industries (such as services) is employed, empirical studies using only some specific industries would underestimate the technological changes. Thus, more empirical studies are needed from both macro- and micro-level and they are left for future research.

Appendix 1: Comparison of two energy price indices

It is widely known that Passche price index generally has a downward bias whereas Laspeyres price index has an upward bias. Since the energy price deflator shown in Chapter 2 is constructed as Passche index, it is worth examining to what extent it suffers from a downward bias, especially for the period far from the base year, 1990. In this Appendix, the significance of downward bias in Passche energy price index is discussed by comparing it with Laspeyres energy price index. The following equations show the calculation of each price index.

$$\text{Passche index:} \quad DEF_t^P = \frac{\sum_i P_{it}Q_{it}}{\sum_i P_{i1990}Q_{it}}, \quad \text{t=1970,1971,...,1998,} \tag{3.6}$$

$$\text{Laspeyres index:} \quad DEF_t^L = \frac{\sum_i P_{it}Q_{i1990}}{\sum_i P_{i1990}Q_{i1990}}, \quad \text{t=1970,1971,...,1998,} \tag{3.7}$$

where i represents type of energy.

Figure 3.7 displays the comparison of Passche and Laspeyres energy price indices. Passche energy price index is idential to the one shown as energy price deflator in Chapter 2. As expected, Passche index is lower than Laspeyres index in the early 1970s. For instance, Passche index takes 27.0 while Laspeyres index is 32.4 in 1970, leading to about 20% discrepancy between these two price indices. This may have a non-negligible effect on the analyses conducted in this thesis. However, since the energy price deflator is divided by the GNP deflator, also Passche price index suffering from a downward bias, to form a relative price of energy, it is believed that most of the downward biases are cancelled out each other, making the biases in total less severe.[8]

[8]In Figure 3.7, Passche index is occationally exceeds Laspeyres index (slightly though), especially after the end of 1970s, which does not generally occur. This is attributed to the positive correlation between relative price and relative quantity. For instance, the correlation between the relative price of oil and liquid narutal gas and the relative quantity of those over 1980–1998 is 0.76 and the correlation between the relative price of oil and coal and the relative quantity of those in the same period is 0.75. This inverts the direction of substitution bias in both price indices, resulting in the unusal relationship between Passche and Laspeyres indices.

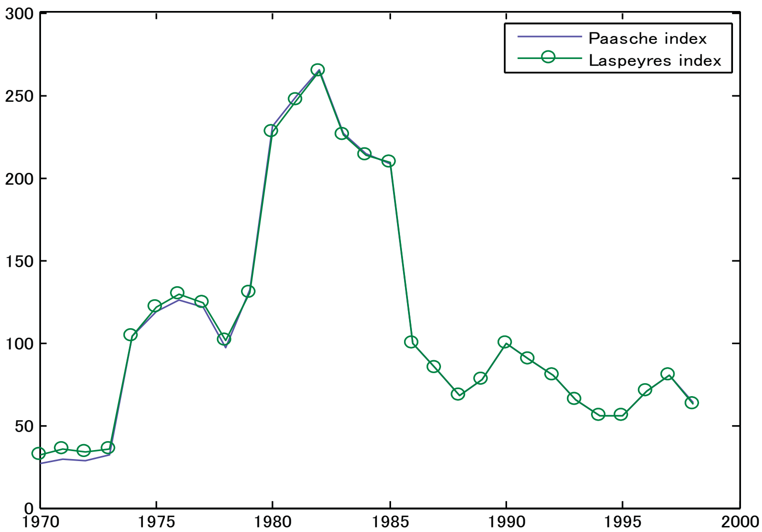

Figure 3.7: Comparison of two energy price indices (1990=100)

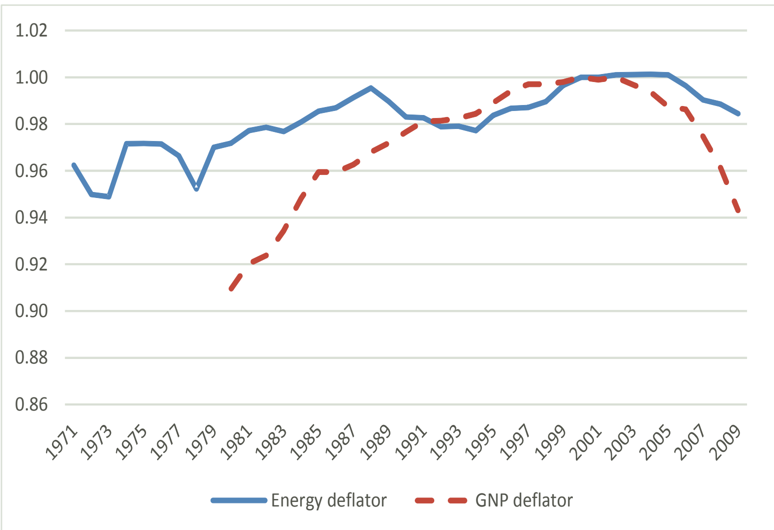

Figure 3.8: Fixed-base index divided by chain-linked index (base year is 2000)

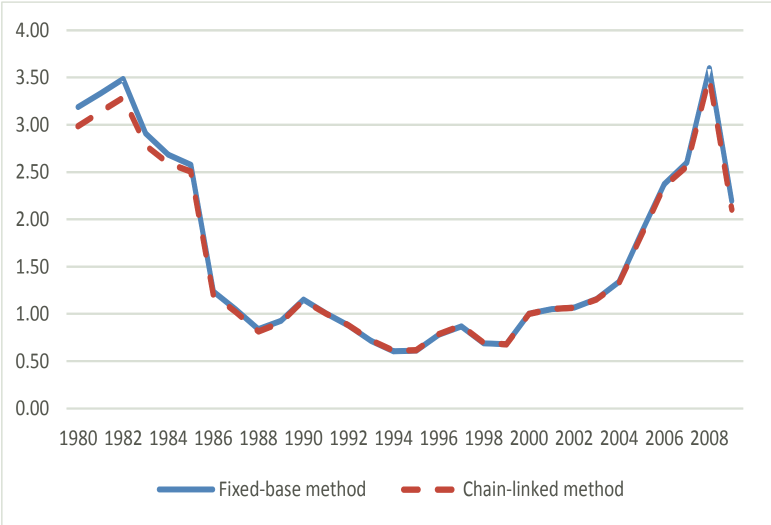

Figure 3.9: Relative price of energy in two different deflating methods

To further investigate the possibility of biases, it would be also useful to look at deflators constructed by chain-linked method. As the chain-linked index always treats last year as a base year, it is expected to mitigate the possible biases observed in base-year index, especially when a particular year is distant from the base year.

Fig 3.8 compares two deflating methods by dividing fixed-base index by chain-linked index. GNP deflator calculated by chain-linked method starts in 1980 since no calculation is conducted before that year. As you can see, there is a large discrepancy between fixed-base and chain-linked GNP deflator. This implies that the substitution between different goods are active in response to the chage in relative price of goods, leading to a serious downward bias in fixed-base GNP deflator, expecially in the beginning of the 1980s. On the other hand, the corresponding bias seems minor in the energy price deflator. As described in footnote 8, this is probably because the relative demand of different types of energy does not respond in a way the standard theory predicts to the changes in relative price of them.

Fig 3.9 compares the relative prices of energy in two different deflating methods. Reflecting the severe downward biase of GNP deflator observed in the beginning of the 1980s, the relative price of energy calculated by chain-linked method is 2.98, which is slightly lower than that obtained by fixed-base method, 3.19. Unfortunately, it is impossible at this stage to examine wheather this discrepancy is larger in the 1970s due to the lack of data. Judging from the patter of two deflators observed in Figure 3.8, that possibility is not deniable. We will wait that exercise until the chain-linked GNP deflator is available in the 1970s.

Appendix 2: Inclusion of nuclear power generation

As discussed earlier, a shortcoming of the estimated level of energy-saving technology is that substituting nuclear power generation for fossil fuel energy is interpreted as an improvement in energy-saving technology. In this Appendix, the crude estimation of the energy supply by nuclear power generation is attempted and the extent to which inclusion of nuclear power generation influences the level of energy-saving technology and other simulation results is examined.

Since data on imports are used to construct real energy use, one way to include the nuclear power generation into the definition of energy is to use the imported quantity of uranium ore, a raw material for nuclear power generation. The drawback of this approach, however, is that spent nuclear fuel is reused repeatedly, owing to which it becomes difficult to obtain the price information.

In this Appendix, it is simply assumed that the inclusion of nuclear power generation into the definition of energy does not affect the relative price of energy. Then, the real energy use E_t is inflated based on the ratio of the energy supply by nuclear power generation to the energy supply by fossil fuels.[9]

Figure 3.10 displays real energy use and estimated levels of energy-saving technology with and without nuclear power generation. As can be seen, the difference between the energy use with and without nuclear power generation broadens over the later periods, reflecting that the share of energy supply by nuclear power generation in total supply has had an upward trend since the beginning of the 1970s. The right side of Figure 3.10 shows that the path of energy-saving technology after considering nuclear power generation as well is located below the original path, indicating that the improvements in energy-saving technology were partially spurious caused by substituting nuclear

[9]The data source is the "General Supply and Demand Balance" provided by the Agency for Natural Resources and Energy.

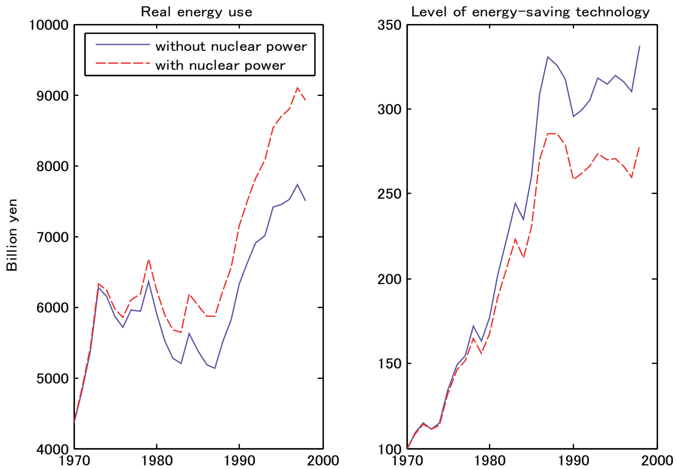

Figure 3.10: Real energy uses and the series of energy-saving technology with and without nuclear power generation

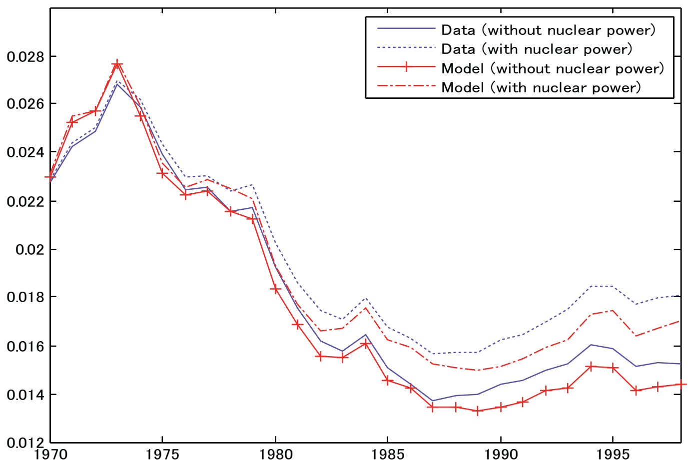

Figure 3.11: Energy–GNP ratio with the inclusion of nuclear power generation into the definition of energy

power for fossil fuel.

Figure 3.11 shows the effect of the inclusion of nuclear power generation in the energy–GNP ratio. Once nuclear power generation is considered, the actual energy–GNP ratio becomes higher than in the original data in the 1980s and 1990s owing to the prevalence of nuclear power generation. The simulation result, however, also tracks the actual energy–GNP ratio well. This simply reflects that the improvements in energy-saving technology dampened during the late 1980s and 1990s, as shown in the right panel of Figure 3.10.[10] In sum, although the inclusion of nuclear power generation into the definition of energy provides more purified energy-saving technology, it does not affect the main result in this chapter that the drop in energy–GNP ratio was triggered mainly by the improvements in energy-saving technology.

[10]The simulation result for other variables on inclusion of nuclear power generation is almost identical to the one without it.

3.2 Case2: Capacity Utilization and the Effects of Energy Price Increases in Japan

The role of the relative price of energy in accounting for recessions has been investigated extensively in a large number of studies. The seminal work in this area is Hamilton (1983), which shows that all but one of the U.S. recessions over the period 1948–1972 were preceded by increases in oil prices.[11] Since then, two separate research topics in this area seem to have attracted the attention of many researchers. The first topic is the declining effect of oil price shocks in recent decades. As is well known, global oil prices rose as much in the 2000s as they did in the 1970s. However, it seems that output and inflation in most developed countries were not much affected by the continuous rise in oil prices observed in the 2000s.[12] The second topic is the failure of standard models to generate the large negative impact of oil price shocks on value added observed in the 1970s. For example, using structural vector autoregression and data for the United States over 1947:2–1980:3, Rotemberg and Woodford (1996) show that a 10% increase in the oil price results in a drop in output by 2.5% after five to seven quarters, whereas the standard one-sector stochastic growth model predicts only a 0.5% decline in output.

In this subsection, the second topic is further investigated by analyzing the severe recession following the first oil crisis in Japan. In doing so, a simple neoclassical growth model with energy as an input for production is constructed, calibrated to the Japanese economy. As expected, the benchmark model with the actual time series of the relative price of energy shows an only modest effect on value added. Specifically, value added drops only by 0.7% in 1974 in the benchmark model

[11] Also see Mork (1989), Hamilton (1996, 2003, 2009), Loungani (1986), Hooker (1996, 2002), Leduc and Sill (2004), and many others.

[12] See, for example, the discussions of Blanchard and Gali (2008), Blanchard and Riggi (2009), and Katayama (2013) on this topic.

compared to 4% in the data. This limited impact of the relative price of energy on value added is in line with the results of previous studies for other countries. For instance, using data for the United States, Kim and Loungani (1992) report that in the standard real business cycle (RBC) model with energy, only 16–35% of output volatility can be attributed to energy price shocks. Similarly, Aguiar–Conraria and Wen (2007), also focusing on the United States, show that in the standard RBC model, the first oil crisis leads only to a 2% drop in value added compared with an actual contraction of 8% in the data.

One interpretation of failure of the benchmark model to replicate the actual drop in value added is that increases in the relative price of energy actually do not play a great role and other exogenous variables such as total factor productivity (TFP) play a more important role in explaining recessions. For example, Hayashi and Prescott (2002) show that the prolonged economic stagnation in Japan following the collapse of bubble economy at the beginning of the 1990s, the so-called "Lost Decade," can be mainly accounted for by the slowdown in the TFP growth rate in the 1990s. However, our benchmark model taking actual TFP into account also fails to reproduce the sluggishness of the economy after the first oil crisis.[13] The limited role of the relative price of energy also contradicts the empirical findings of Hamilton (1983) and Rotemberg and Woodford (1996), which show that the oil price shocks had a large negative impact.[14]

To generate the large drop in value added after the rise in the relative price of energy, a strong mechanism to amplify the effect of the sharp rise in the relative price of energy on value added is required. The most commonly used amplification mechanism in previous studies is the

[13]This may seem a little surprising since feeding actual TFP series into a model often produces a good fit with the data. However, there also exist a number of economic episodes the actual series of TFP alone fail to replicate. See for example, Cole and Ohanian (1999), Beaudry and Portier (2002) and Conesa et al. (2007).

[14]For the case of Japan, Burbidge and Harrison (1984) estimate a seven-variable VAR model with monthly data for the period January, 1961 through June, 1982, and find that oil price increases have had a statistically significant effect on Japanese industrial production. Hutchison (1993) also estimates a four-variable VAR model with quarterly data over 1964:2–1977:4 and shows that oil price shocks decreased Japan's real GNP.

endogenous capacity utilization rate. Finn (2000) ties capacity utilization to energy consumption and successfully reproduces the sharp drop in value added caused by the oil price shock.Similary, Aguiar–Conraria and Wen (2007) introduce endogenous capacity utilization and the spillover effects across firms into an otherwise standard RBC model and show that energy price shocks alone are able to account for the stagnation in value added following the first oil shock in 1973.[15]

As discussed briefly in Chapter 2, in this subsection, the endogenous capacity utilization rate is incorporated in the benchmark model following Greenwood et al. (1988), and it is examined to what extent capacity utilization amplifies the effect of the sharp rise in the relative price of energy on value added and other aggregate variables. The analysis is closely related to the studies by Finn (2000) and Aguiar–Conraria and Wen (2007) but differs in two respects. First, energy-saving technological change is incorporated in order to reproduce the downward trend in real energy use. Neither Finn (2000) nor Aguiar–Conraria and Wen (2007) discuss how closely their simulated energy use follows the actual data. Second and more importantly, the role of purified TFP, in which the effects of variable capacity utilization are extracted from the original TFP, in the recession following the first oil shock is also investigated. Again, neither Finn (2000) nor Aguiar–Conraria and Wen (2007) examine the effects of time-varying (purified) TFP on aggregate variables.

Before going into the details of the model, it is useful to summarize the dynamics of exogenous variables and aggregate variables over the period 1973–1978 in Japan.[16] The first row of Figure 3.12 depicts two key exogenous variables: the relative price of energy and TFP. The relative price

[15]Another amplification mechanism of the relative price of energy investigated in previous studies is imperfect competition. Rotemberg and Woodford (1996) show that a modest degree of imperfect competition leads to a larger effect of an energy price increase on both output and real wages. In this subsection, this amplification mechanism is not used since endogenous capacity utilization is simpler to incorporate and is the mechanism most commonly used in previous studies.

[16]Since the main focus of this chapter is the first oil crisis and its consequences for the Japanese economy, the analysis ends in 1978.

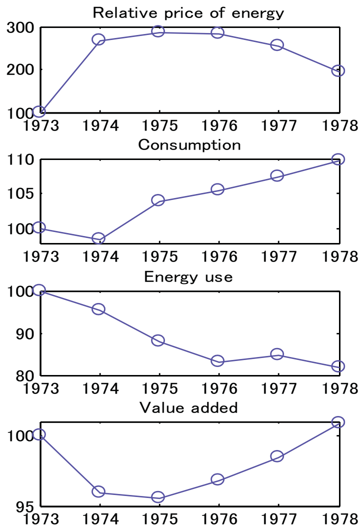

Figure 3.12: Paths of exogenous variables and aggregate variables per working-age population (15–64) over the period 1973–1978.

of energy is calculated by dividing the energy price deflator by the GNP deflator, while TFP is obtained as the Solow residuals in the standard production function with energy as shown in Chapter 2. As can be seen, the upsurge in the relative price of energy in 1974 was substantial and by 1975, the relative price of energy had jumped almost threefold from its level in 1973, before showing a gradual downward trend thereafter. Another exogenous change in the Japanese economy in this period is the slowdown in TFP growth. The average annual growth rate of TFP over the period 1973–1978 was only 0.72% and the growth rate was in fact negative from 1973 to 1974 and from 1975 to 1976.[17] This implies that the estimated TFP contains some noise not related to the true productivity measure, and this issue is attempted to be resolved later by endogenizing

[17]For the period before 1970, the growth rate of TFP cannot be estimated due to the lack of energy-related data. However, using the standard Cobb–Douglas production function, Hayashi and Prescott (2002) show that the average annual growth rate of TFP in Japan for 1960–1973 was 6.5% compared with 0.8% for 1973–1983 and 3.7% for 1983–1991.

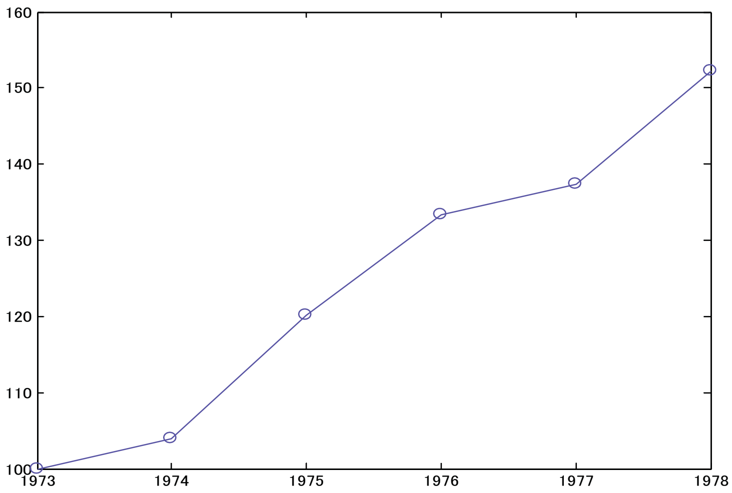

Figure 3.13: The level of energy-saving technology normalized to 100 in 1973.

capacity utilization.

The rest of Figure 3.12 displays aggregate variables per working-age population. All variables except hours worked are detrended by 2%. Two notable features can be gleaned from Figure 3.12. First, value added declined by around 5% in 1975, and it took several years to return to the 2% linear trend. Second, all other aggregate variables also show substantial declines, especially energy use. Unlike the other variables, energy use continued to decline following the first oil shock in 1973 and did not recover, which likely is the result of energy-saving technological change, the role of which in reproducing the decline in energy use is discussed in Section 3.2.1.

3.2.1 Energy-saving technological change in the 1970s

Figure 3.13 displays the estimated level of energy-saving technology, using the methodology described in Chapter 2, normalized to 100 in 1973. As can be seen, rapid growth of energy-saving technology is observed following the first oil shock in 1973. In fact, the estimated average annual growth rate of energy-saving technology over the period 1973–1978 is 8.76%. These improvements in energy-saving technology are included in the original TFP growth rate estimated using a production function without energy-saving technological change. That is, the growth rate of TFP when assuming that z_t is unity is 1.67%. On the other hand, the modified TFP growth rate, which strips out improvements in energy-saving technology, that is, when z_t takes the estimated time-varying values, is 0.72%. Throughout this subsection, the estimated time-varying levels of energy-saving technology are always fed into the model, so that the effect of energy-saving technological change is always excluded from the TFP series.

3.2.2 Calibration

In standard RBC models such as those by Prescott (1986) and King and Rebelo (2000), parameter values are set so that the steady state in the models is consistent with growth observations. This strategy is reasonable, since it is assumed in standard RBC models that per-capita variables are basically on a balanced growth path. They deviate from the balanced growth path only if the economy is hit by shocks. On the other hand, in the case of the Japanese economy in the 1970s, it seems more reasonable to assume that it was in a transition to a balanced growth path rather than on a balanced growth path.[18] Therefore, using growth observations to calibrate parameters would probably not be appropriate here. As an alternative strategy, therefore, some parameter values are calibrated using only data for the period 1973–1978, while the values of other parameters, which

[18]For instance, the growth accounting exercise using Japanese data conducted by Hayashi and Prescott (2002) shows that the capital-output ratio was increasing and labor input per capita declining during the period 1973–1983, which is a typical transitional pattern observed in standard neoclassical growth models when the initial capital stock is less than the steady state level. On the other hand, the average growth rates of the capital-output ratio and labor input per capita during the period 1983–1991 were close to zero and the average growth rates of output per capita and TFP were almost identical, which implies that the Japanese economy was converging to a balanced growth path in this period.

are usually regarded as constant over time, are either set at conventional values or taken from previous studies.

Combining the production function and the first order condition for energy use gives

$$\frac{1-\mu}{\mu} = \left(\frac{\theta Y_t - p_t E_t}{p_t E_t}\right)\left(\frac{E_t}{K_t}\right)^{\frac{\varepsilon-1}{\varepsilon}}, \quad \text{for} \quad t = 1973, 1974, ..., 1978. \tag{3.8}$$

Equation (3.8)[19] is solved for μ each year and μ is then averaged over 1973–1978, yielding $\mu = 0.005$.[20] The first order condition for h_t condition gives

$$\left(\frac{\alpha}{1-\alpha}\right)\left(\frac{h_t}{1-h_t}\right) = (1-\theta)\frac{y_t}{c_t}, \quad \text{for} \quad t = 1973, 1974, ..., 1978. \tag{3.9}$$

Equation (3.9) is solved for α and α is then averaged over 1973–1978, resulting in $\alpha = 0.709$. β and θ are set at 0.976 and 0.362, respectively, which are the values used in Hayashi and Prescott (2002). δ is set at the conventional value for annual data, 0.100. Finally, the elasticity of substitution between capital stock and energy use is set to 0.1, as explained in Section 3.1. Table 3.3 summarizes the calibration results.

Parameter	Description	Value
ε	Elasticity of subst. btw. capital and energy	0.100
θ	Capital/Energy composite share	0.362
δ	Depreciation rate of capital	0.100
β	Discount factor	0.976
α	Leisure weight in preferences	0.709
μ	Share of energy in capital-energy composite	0.005

Table 3.3: Parameter values

[19]The calibrated value of μ is needed in order to obtain the time series for z_t, whereas the series of z_t is needed to calibrate μ. Thus, to calibrate μ, it is assumed that z_t takes unity over 1973–1978.

[20]The calibrated value of μ becomes almost zero when E_t and K_t are measured in billion yen. To avoid this problem, E_t is multiplied by 50 and p_t is divided by 50. Since $p_t E_t$ remains unchanged, the simulation results shown below are not affected by this manipulation.

3.2.3 Simulation results with benchmark model

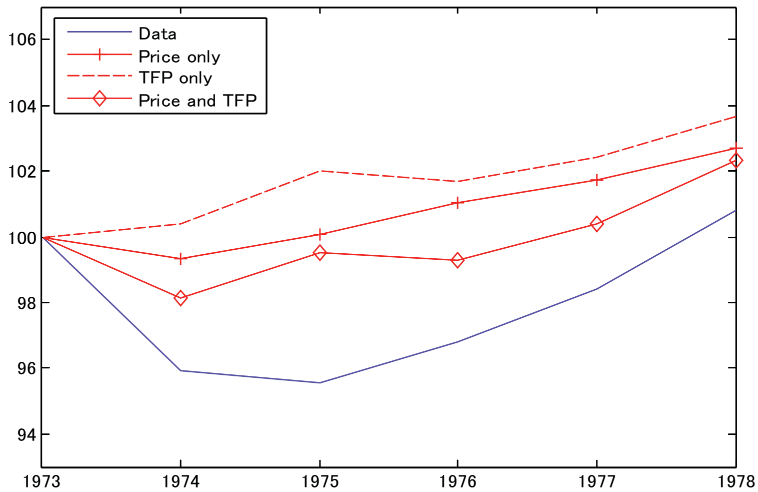

Figure 3.14: Detrended value added per working-age population (benchmark model vs. data) normalized to 100 in 1973.

As in the studies by Hayashi and Prescott (2002, 2008) and Chen et al. (2006), it is assumed that agents have perfect foresight about the sequence of four exogenous variables: the relative price of energy (p_t), the growth rate of TFP (γ_t), the level of energy-saving technology (z_t), and the growth rate of the working-age population (n_t). The model is then solved numerically by applying a shooting algorithm given the initial capital stock level and the path of the exogenous variables. The levels of the exogenous variables after the period 1973–1978 are assumed to take the average value for the period 1973–1978 except in the case of energy-saving technology. The level of energy-saving technology is assumed to continue to take the 1978 value after the period 1973–1978.

Figure 3.14 shows three simulation results for value added. The first is the simulated path with the actual time series for the relative price of energy only, labeled "Price only." The second is the simulated path with the actual time series for the TFP growth rate only, labeled "TFP only." Finally, the third is the simulated path with the actual time series for the relative price of energy and the TFP growth rate, labeled "Price and TFP." To generate the path labeled "Price only," the TFP growth rate is set to its geometric mean over the period 1973–1978, while to obtain the path labeled "TFP only" the relative price of energy is set to its mean over the same period.[21] A notable feature in Figure 3.14 is that the upsurge in the relative price of energy alone fails to account for the drop in value added in 1974. In the "Price only" simulation, value added in 1974 declines by only 0.7%, while in the actual data it falls by about 4%. Finally, in the "Price and TFP" simulation, the sluggish growth rate of TFP adds to the negative effect on value added, but this is insufficient to account for the severe recession following the first oil shock in 1973. Next, Figure 3.15 displays the simulated paths for other aggregate variables. As can be seen, the simulated path for energy use reproduces the downward trend in energy use well because of the improvements in energy-saving technology.[22]

In sum, the simulation analysis using the benchmark model shows that the sharp rise in the relative price of energy plays a limited role in accounting for the decline in value added. In addition, the analysis suggests that sluggish TFP growth also does not appear to have played an important role in the recession following the first oil crisis, which contrasts with the findings by Hayashi and Prescott (2002) and Chen et al. (2006) that trends in TFP growth provide a good explanation of developments in macroeconomic variables in Japan. A likely reason why the relative price of energy in the benchmark model only plays a limited role in explaining the drop in value added is

[21]Since the main focus of this chapter is the impact of the relative price of energy and the growth rate of TFP on value added, it is assumed that the other two exogenous variables always take the actual values.

[22]The simulation without energy-saving technological change (not shown in Figure 3.15) generates a path that substantially overpredicts energy use even with the upsurge in the relative price of energy. Thus, incorporating energy-saving technological change into the model is essential to reproducing the energy use actually observed in the data.

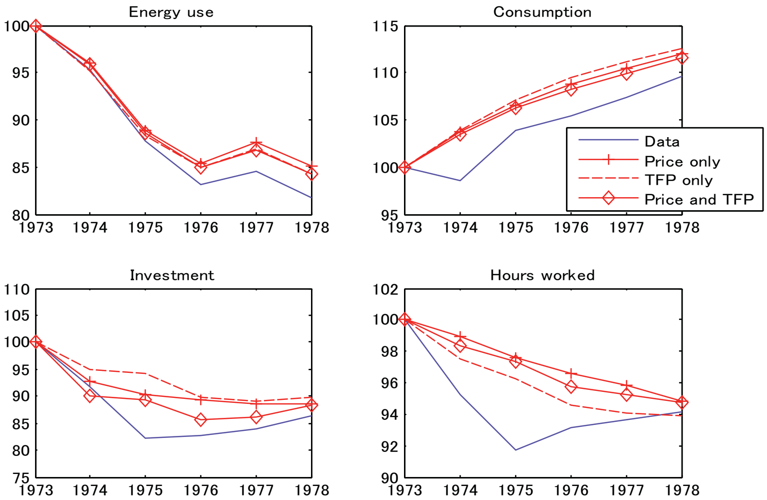

Figure 3.15: Other aggregate variables per working-age population (benchmark model vs. data) normalized to 100 in 1973.

the small ratio of real energy use to real value added ($p_t E_t / V_t$). In Japan, the average value of this ratio is only 3.7% during the period 1973–1978. That is, the relative price of energy does not play an important role in accounting for recessions simply because only a small amount of energy is needed for production.

In the next subsection, therefore, following Aguiar–Conraria and Wen (2007) and Finn (2000), endogenous capacity utilization is incorporated into the benchmark model as an amplification mechanism in order to examine whether this can help to explain the actually observed impact of the jump in the relative price of energy.

3.2.4 Simulation results with endogenous capacity utilization

Figure 3.16 shows the simulation result for value added with endogenous capacity utilization. First of all, the sharp rise in the relative price of energy now has a large depressing effect on value added.

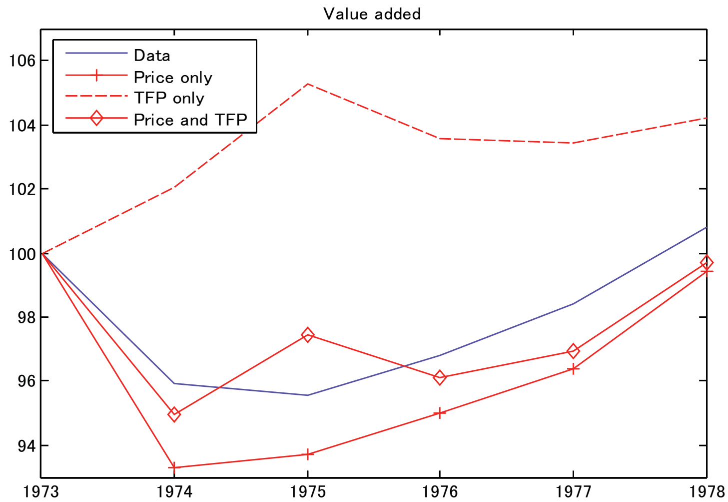

Figure 3.16: Detrended value added per working-age population (capacity utilization model vs. data) normalized to 100 in 1973.

The driving force of this large depressing effect is the endogenous capacity utilization rate. When the relative price of energy rises, energy input decreases, leading to a reduction in value added. This is the direct effect and the simulation result from the benchmark model shows that this effect is very small due to the small ratio of real energy use to real value added. Once capacity utilization is endogenized, however, another effect emerges. That is, the declining capacity utilization rate generated in the capacity utilization model (observed in Figure 3.17) generates a further drop in value added. This decrease in the simulated path of capacity utilization is due to two different effects. The first effect is the surge in the relative price of energy. When the relative price of energy increases, energy use declines, leading to a decrease in the marginal product of capacity utilization, which, in turn, leads firms to decrease their capacity utilization. The second effect comes from the fact that the initial capital stock is below the steady state. Since the marginal product of capacity utilization is a decreasing function of capital stock and the marginal cost of capacity utilization is an increasing function of capital stock, the lower initial capital stock results in a higher marginal product and lower marginal cost of capacity utilization than in the steady state (see Equation (2.18)). Therefore, the initial capacity utilization rate is higher than its steady state. As capital stock is accumulated over time, the marginal product of capacity utilization decreases and the marginal cost of capacity utilization increases, leading to a reduction in capacity utilization over time.

The second salient feature in Figure 3.16 is that the simulated path generated by "TFP only" in the capacity utilization model shows steady economic growth even after the first oil shock. This indicates that the Japanese economy would have enjoyed stable growth if the first oil crisis had not occurred. In other words, the capacity utilization model shows that the main cause of the economic recession in the wake of the first oil shock was the upsurge in the relative price of energy, which is consistent with conventional wisdom. Lastly, feeding the actual time series for the relative price of energy and the growth rate of TFP into the capacity utilization model now generates a good fit with the data.

Figure 3.17 displays the simulation results for other aggregate variables generated by the capacity utilization model. As in Figure 3.16, the simulation results labeled "Price only" actually underpredict the data for energy use, investment, and capacity utilization due to the large amplification mechanism driven by endogenous capacity utilization. However, the steady growth of purified TFP shifts up those simulated paths, leading to a reasonable fit with the data in the simulation labeled "Price and TFP." Figure 3.18 compares the simulation results in the benchmark model with the ones in the capacity utilization model. Both simulation results are derived by feeding the actual values of the relative price of energy and the growth rate of TFP into the model. As can be seen, although the simulated hours worked still substantially overpredict the

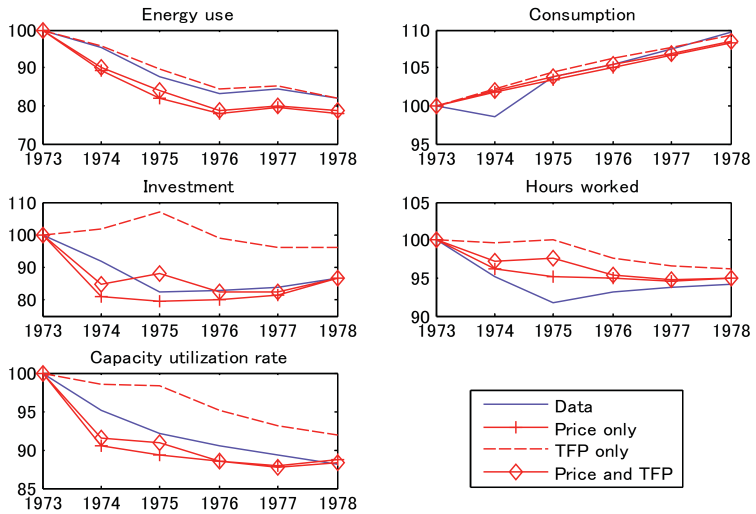

Figure 3.17: Other aggregate variables per working-age population (capacity utilization model vs. data) normalized to 100 in 1973.

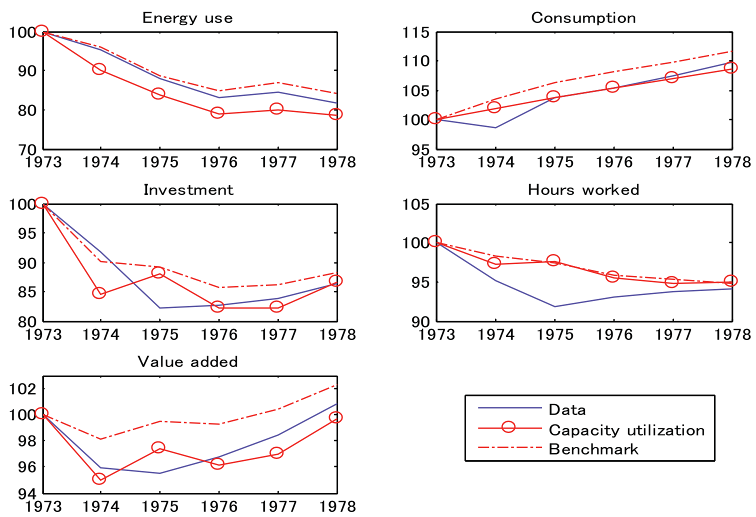

Figure 3.18: Comparison of the simulation results (benchmark vs. capacity utilization).

data for 1975, the capacity utilization model performs better than the benchmark model overall except with regard to energy use.

To sum up, in this subsection, a simple neoclassical growth model with energy as an input for production is constructed, calibrated to the Japanese economy, and used to examine the role of two key exogenous variables (the relative price of energy and the growth rate of TFP) to account for the severe recession following the first oil shock. In line with previous studies, the benchmark model shows that the relative price of energy has a limited role in accounting for the slump in value added due to the small ratio of real energy use to real value added. This means that to model the kind of drop in value added observed in the data it is necessary to incorporate a mechanism that amplifies the effect of the upsurge in the relative price of energy.

To this end, the present study proposed incorporating endogenous capacity utilization as such an amplification mechanism in the benchmark model. This capacity utilization model successfully generated a large negative effect of the sharp rise in the relative price of energy. In addition, the analysis also showed that the stagnation in TFP growth in the benchmark model was spurious due to the declining capacity utilization rate, and that the purified TFP series, in which the effect of time-varying capacity utilization is removed from the TFP in the benchmark model, shows steady growth steadily even after the first oil shock.

Appendix 3: Validity of the imputed capacity utilization rate

Figure 2.4 showed that the imputed capacity utilization rate for the entire economy is less volatile than the "Operating Ratio," which covers only selected industries in the manufacturing sector. In this Appendix, it is argued that this is probably due to the tendency that the capacity utilization rate in the manufacturing sector is more volatile than that in the non-manufacturing sector.

Note that in Japan there are no official statistics for the capacity utilization rate in the non-manufacturing sector. Therefore, in this Appendix, a proxy variable for the capacity utilization rate in the non-manufacturing sector following the methodology employed by the Cabinet Office, Government of Japan, is constructed. It is then shown that this is much less volatile than the "Operating Ratio."

To this end, first of all, the series of output divided by capital stock in the non-manufacturing sector is computed. The data for output and capital stock in the non-manufacturing sector are taken from the "Indices of Tertiary Industry Activity" published by the Ministry of Economy, Trade and Industry and the "Gross Capital Stock of Private Enterprises" published by the Cabinet Office, respectively. Then the cyclical component of this ratio extracted by applying the Hodrick–Prescott filter is used as a proxy for the capacity utilization rate in the non-manufacturing sector. Data for the period 1988–2005 are used, because the "Indices of Tertiary Industry Activity" are not available for years before 1988.

The imputed capacity utilization rate in the non-manufacturing sector is plotted with the "Operating Ratio" for comparison in Figure 3.19. As can be seen, the "Operating Ratio" fell substantially during the 1990s, which is probably due to the severe economic conditions during the period, the so-called "Lost Decade." In contrast, the imputed capacity utilization rate in the non-manufacturing sector declined only somewhat, providing indirect evidence for the validity of the

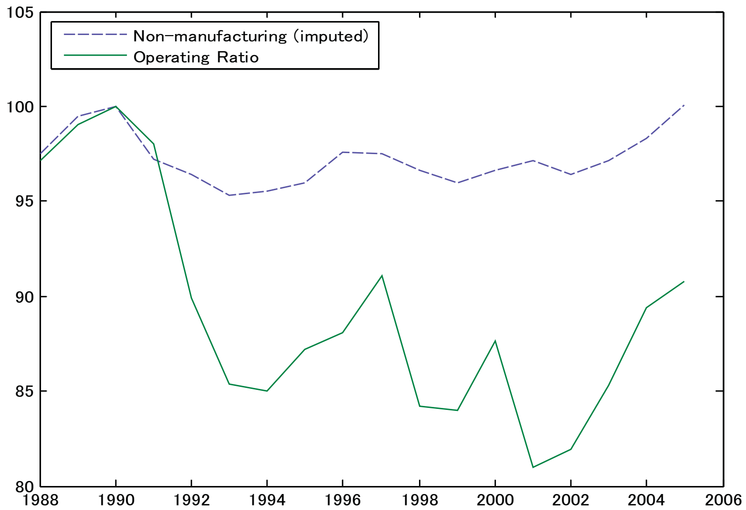

Figure 3.19: The imputed capacity utilization rate in non-manufacturing and Operating Ratio, both normalized to 100 in 1990.

imputed capacity utilization rate in Figure 2.4. One might still argue that the “Operating Ratio” is the appropriate capacity utilization rate for the economy as a whole since the manufacturing sector is generally more capital-intensive than the non-manufacturing sector. That is, if most of the capital stock is used in the manufacturing sector, using the “Operating Ratio” as a proxy for the capacity utilization rate of the economy as a whole would be the correct choice. According to the “Gross Capital Stock of Private Enterprises” provided by the Cabinet Office, the gross capital stock share of the manufacturing sector in the economy ranges from 44.3% in 1980 to 37.0% in 2009. Although this share is not available for the 1970s due to a lack of data, simple linear extrapolation implies a share of around 50%. Since the real GDP share of the manufacturing sector in the Japanese economy has been about 25% since 1970, the manufacturing sector is indeed more capital-intensive than the non-manufacturing sector. Nevertheless, this does not mean that the capacity utilization rate in the non-manufacturing sector can be ignored in the process of imputing the capacity utilization rate for the economy as a whole. In sum, the imputed capacity utilization rate in Figure 2.4 likely is not far from the true capacity utilization rate in the economy as a whole.

Appendix 4: First oil crisis as an unanticipated event

Throughout the thesis, it is assumed that agents have perfect foresight about the future path of exogenous variables for simplicity. Since the dramatic rise in relative price of energy in the beginning of the 1970s was doubtlessly triggered by a purely exogenous event, the Yom Kippur War, to Japan, it is hard to justify the perfect foresight assumption, and the robustness check must be conducted. In this Appendix, the first oil crisis is treated as a surprising event for agents and it is examined to what extent the simulation results with perfect foresight assumption would alter in this environment.

To achieve our goal, it is assumed that agents first believe that the relative price of energy indefinitely remains constant at its 1973 level; thus, no first oil crisis occurs. Given the intial level of capital stock in 1973, solve the optimization problem, store the optimal levels of consumption, hours worked, energy use in 1973 and capital stock in 1974. Then, given the optimal level of capital stock in 1974 derived in the above simulation, solve the optimization problem again as if the economy restarts in 1974, but this time with the actual path of relative price of energy. By this, the first oil crisis is set as an unexpected event to agents, and the point is that it is impossible for them to change the level of capital stock in 1974 since it has been already determined under the assumption that no oil crisis occurs.[23]

Figure 3.20 displays the comparison between the simulation results with perfect foresight and those in the environment where the first oil crisis is treated as an unanticipated event. In order to focus on the difference in the impacts of the rise in relative price of energy in the deterministic and unanticipated environments, it is assumed that the TFP growth rates remain constant at the averages over the period 1973–1978. As can be seen, investment declines less severely in the model

[23] In the second part of the simulation starting in 1974, it is assumed that the relative price of energy after 1978 is the same as the averages over the period 1974–1978.

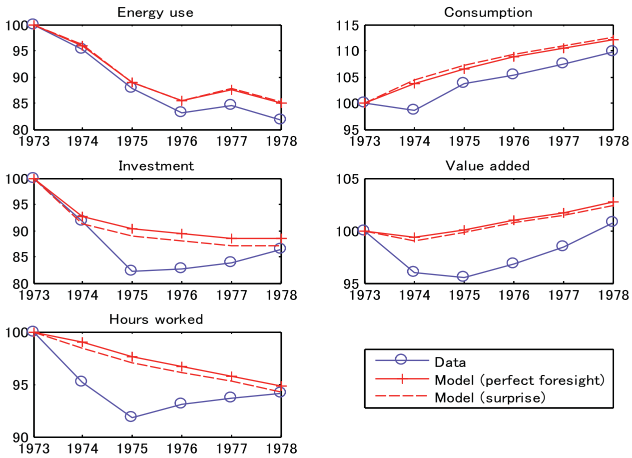

Figure 3.20: Comparison of simulation results (perfect foresight vs. surprise).

with perfect foresight, and this is probably because the household already reduces investment in 1973 to some extent in anticipation of the dramatic rise in relative price of energy next year. However, the discrepancies between simulation results generated by the the deterministic model and the stochastic model are not so significant, which is caused by the fact that energy in our model is treated as a flow, instead of a stock variable.[24] If energy is defined as a stock variable, the firm in the perfect foresight environment is able to import more energy when it is inexpensive, stockpile it, and unpile stored energy when it is expensive. On the other hand, this strategic behavior is impossible in the stochastic environment, resulting in the possible large discrepancy between the simulation results in the perfect foresight and unanticipated environments. This is not the case in our model in which energy is defined as a flow variable. In sum, this exercise demonstrates that the model with perfect foresight assumption can be used as a simplifed version of more realistic stochastic model.

[24]See Chapter 2 for the justification for defining energy as a flow variable.

Appendix 5: The capacity utilization model with Greenwood, Hercowitz, and Huffmann preference

In Section 3.2.4, it is shown that the simulated path of hours worked overpredicts the actual data even after the inclusion of endogenous capacity utlization rate. This might be caused by the negative income effect driven by the incresed energy imports cost. In this Appendix, Greenwood, Hercowitz, and Huffman (GHH) preference is introduced to the capacity utilization model to examine to what extent the negative income effect is attributed to the overprediction of hours worked. GHH preference, first introduced in Greenwood et al. (1988), is known to have no income effects on labor supply and widely used in the open economy models.

The household preference is now defined as follows,

$$U(C_t, H_t) = \ln\left(C_t - \frac{1}{\nu}H_t^{\nu}\right). \tag{3.10}$$

Note that the GHH preference is not an admissible preference to assure the existence of balanced growth path (See King et al (1988) for the types of utility function which guarantee the existence of balanced growth path in a neoclassical growth model). Therefore, it is simply assumed that all variables have no trend in this Appendix. The curvature parameter (ν) is calibrated so that the hours worked at the steady state is one third. All else settings are identical to the capacity utilization model.

Figure 3.21 shows the simulation results with GHH preference. Note that the only time-varying exogenous variable is the relative price of energy (and the level of energy-saving technology) in these simulations. Against our expectations, the introduction of GHH preference worsens the model prediction about hours worked. It quickly recovers right after the first oil crisis and continues to

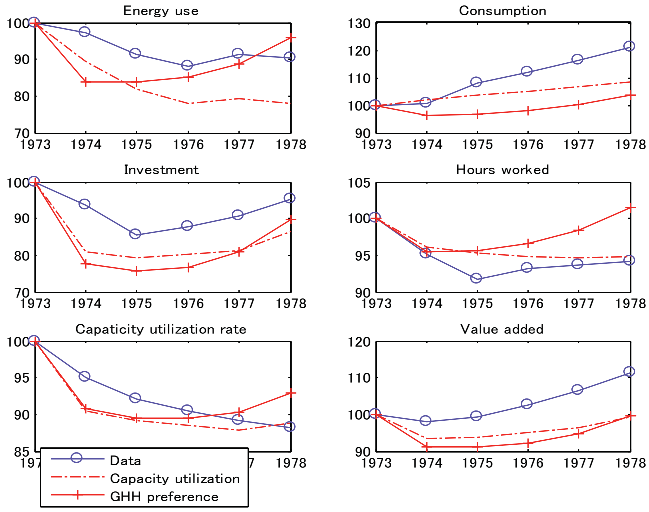

Figure 3.21: Comparison of the simulation results (capacity utilization vs. GHH preference)

increase afterward.

The key to understand this failure lies in the fact that the current analysis is conducted along the transition path, not on the balanced growth path, so that the initial capital stock is lower than its steady state level. As discussed at length in King et al. (1988), the lower level of initial capital stock has two implications for the model. First, lower capital stock induces the lower marginal product of labor than its steady state level, shifting the labor demand curve to the left. This causes the decline in wage, leading to the decrease in labor. Second, lower capital stock generates the higher marginal product of capital than its steady state level, shifting the capital demand curve to the right. This causes the rise in rental rate of capital, which increases the labor supply since the representative household can enjoy more income from capital if it works more. In the standard neoclassical growth model with endogenous labor supply like our capacity utilization model, the latter factor dominates the former, leading to the downward-sloping path for hours

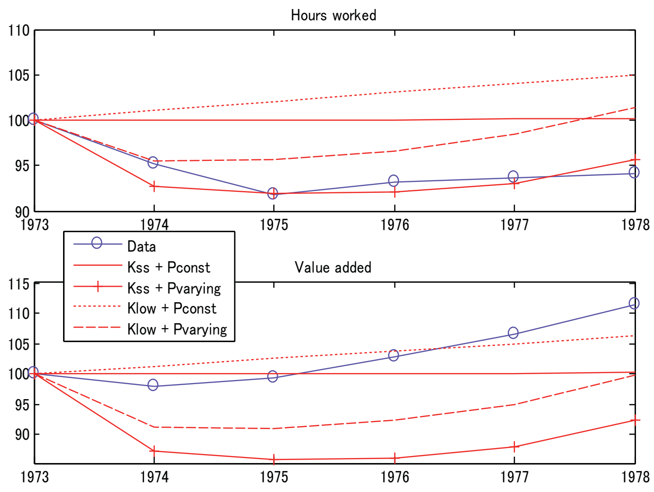

Figure 3.22: Simulation results with GHH preference.

worked along the transition dynamics. In the model with GHH preference, however, the latter factor, a strong income effect triggered by the high rental rate of capital, does not work, resulting in the upward-sloping path for hours worked.

To further investigate the mechanism behind the model with GHH preference, Figure 3.22 displays the simulation results for hours worked and value added in a variety of setting. The baseline case is that the initial capital stock is set at the steady state level and the relative price of energy is set at the constant level ("Kss+'Pconst'). Since there is no exogenous chnage and any transitional effect induced by the low initial capital stock, the simulated paths are just horizontal lines. If we feed the actual time series for relative price of energy on this environment, we obtain the simulation results labeled "Kss+Pvarying." In this case, while the model predicts the decline in hours worked quite well, the simulated path for value added substantially underpredicts the actual path. This is because the initial capital stock is set at the steady state so that there is no capital accumulation on the transition. Once the initial capital stock is set to the actual level which is lower than the steady state, we end up with the simulated paths, labeled "Klow+Pvarying," which is the simulation results shown in Figure 3.21.

In sum, the inclusion of GHH preference to our capacity utilization model is not suitable for filling in the discrepancy between the simulated path and the actual data for hours worked. Addressing this issue is left for future research.

3.3 Case3: Energy-Saving Technological Change and the Great Moderation

The mitigated volatility of output and other aggregate variables, so called the "Great Moderation" is observed in the mid 1980s in the United States. Table 3.4 displays the cyclical behavior of the U.S. economy over 1949–83, 1984–2009, and the full sample. The break point is followed by previous studies such as Kim and Nelson (1999) and McConnell and Perez–Quiros (2000). All data are logged and detrended using the Hodrick–Prescott filter.[25] Energy use is defined as unweighted sum of energy consumption of coal, natural gas, and petroleum in each three sector (commercial, industrial, and transportation) and energy price is calculated by dividing fossil fuel energy price by GNP deflator.[26] As can be seen, the volatility of all variables except energy price declines over the two sample periods. In particular, the volatility of real GNP reduces by 32% even if the late period includes the sharp drop in output triggered by financial crisis in 2008.

A number of possible candidates are discussed in previous studies and these can be broadly divided into two groups. The first group claims the importance of reduced volatility of exogenous shocks. For instance, Arias, Hansen, and Ohanian (2007) show that the volatility of output declines simply because the volatility of total factor productivity (TFP) becomes about half. Another group focuses on structural changes. Jaimovich and Siu (2009) claim that the demographical change can be an important factor to account for the great moderation. McConnell and Perez-Quiros (2000) emphasize on the role of better inventory management whereas Clarida, Gali, and Gertler (2000) underscore an improvement in monetary policy.

In this chapter, the role of energy-saving technological progress is examined on explaining the

[25] Time interval is annual because energy-related data are available only annually.
[26] See Section 3.3.1 for details of the data construction.

Variable	1949–2009 (Total) SD(%)	1949–83 (Early) SD(%)	1984–2009 (Late) SD(%)	ratio (Late/Early)
GNP($\hat{v}_t$)	2.19	2.52	1.71	0.68
Consumption($\hat{c}_t$)	1.79	2.00	1.51	0.75
Investment($\hat{x}_t$)	6.99	7.83	5.88	0.75
Hours worked($\hat{h}_t * e\hat{m}_t$)	1.95	2.07	1.83	0.88
Hours($\hat{h}_t$)	0.64	0.67	0.61	0.92
Employment($e\hat{m}_t$)	1.41	1.51	1.29	0.85
Capacity utilization($\hat{u}_t$)	1.00	1.13	0.84	0.74
Energy use($\hat{e}_t$)	2.88	3.17	2.49	0.79
Energy price($\hat{p}_t$)	9.91	9.21	10.84	1.18

Table 3.4: Cyclical behavior of the U.S. economy

Note: We use annual data from 1949 to 2009. All data are logged and detrended using the Hodrick–Prescott filter. Since annual data are used, the smoothing parameter in the Hodrick–Prescott filter is set to 100.

great moderation. Our focus on energy is based on the following two reasons. First, as mentioned repeatedly throughout this thesis, a number of studies show that fluctuations in relative price of energy (or oil) can be a source of business cycles. While Kim and Lougani (1992), for example, show that energy price shocks account for only a small fraction of output volatility (16–35%), Finn (2000) and Aguiar-Conraria and Wen (2007) indicate that the effects of energy price shocks in standard RBC models with energy such as that in Kim and Lougani (1992) are amplified by incorporating an endogenous capacity utilization and that this modification generates the output volatility close to what is observed in the United States data. Second, several authors show that the effects of volatile fluctuations in energy price on aggregate variables are mitigated in the last several decades. For instance, Blanchard and Gali (2008) show that the negative impulse response of output to oil price shock is muted after the mid 1980s due to the combination of following four factors: (i) good luck, (ii) smaller share of oil in production, and (iii) more flexible labor markets, and (iv) improvements in montary policy. Combining these two reasons, it is reasonable to argue

Parameters	Description	Value
ε	Elasticity of subst. btw. capital/labor and energy	0.100
θ	Capital share in income	0.333
δ	Depreciation rate of capital	0.100
β	Discount factor	0.960
α	Leisure weight in preferences	0.640
$\bar{H}$	Fixed hours worked	0.530
μ	Share of energy in production	0.002
ρ_A	Persistence parameter for technology	0.851
ρ_p	Persistence parameter for energy price	0.495

Table 3.5: Parameter values

that energy has at least a non-negligible impact on the Great Moderation.

Our conjecture is that the output response to oil price shock has been weakened because of the improvements in energy-saving technology.[27] To examine this hypothesis, the time series of energy-saving technology are estimated followed by Hasser et al. (2011) and fed into a standard real business cycle model with energy as a production input. Then the impulse responses of aggregate variables driven by an energy price shock are compared over the two sample periods. The simulation results show that energy-saving technological progress accounts for the great moderation, at least in part.

3.3.1 Calibration

The parameter values are set in a standard fashion and summarized in Table 3.5. The fixed hours worked ($\bar{H}$) is taken from Hansen (1985) and the share of energy in production (μ) is chosen by the same methodology shown in Section 3.1. The most important parameter in this analysis, ε (the elasticity of substitution between capital stock and energy use) is set to 0.1 as in Section

[27]Put differently, we emphasize the role of second factor (smaller share of oil in production) put forward by Blanchard and Gali (2008) since the improvements in energy-saving technology economize the amount of energy needed for production.

3.1 and 3.2. The persistent parameters of technology and energy price shocks are obtained by conducting ordinary least square (OLS) estimation of Equations (2.24) and (2.25). Finally, the curvature parameter in the depreciation function, ϕ, is calibrated in the same manner shown in Chapter 2 and set at 2.46.

3.3.2 Results

The level of energy-saving technology is estimated via the methdology employed in Chapter 2. Figure 3.23 shows how the level of energy-saving technology evolved over time. The annual mean growth rate of the level of energy-saving technology is 0.63% over 1949-1973, whereas 1.76% over 1974-2009, which are similar to those obtained in Hassler et al. (2012). They employed slighy different methodology and production function and concluded that the annual mean growth rate of the level of energy-saving technology is 0.15% over 1949–1973 and 2.44% over 1974–2009.

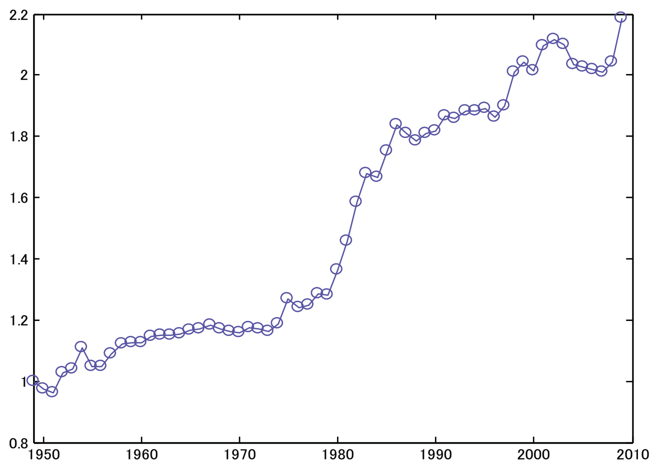

Figure 3.23: Level of energy-saving technology

Now the question is to what extent the energy-saving technological progress, shown in Figure 3.23, can be the source of the great moderation. Before answering the question, let us discuss the role of energy-saving technological progress on aggregate variables in our model. That is, it is examined how energy-saving technological progress affects the aggregate variables in our model. To do so, it is assumed for simplicity that the level of energy-saving technology follows an AR(1) process as shown below:

$$\ln z_{t+1} = \rho_z \ln z_t + \epsilon_{t+1} \tag{3.11}$$

where ϵ_{t+1} is an independent and identically distributed normal random variable.

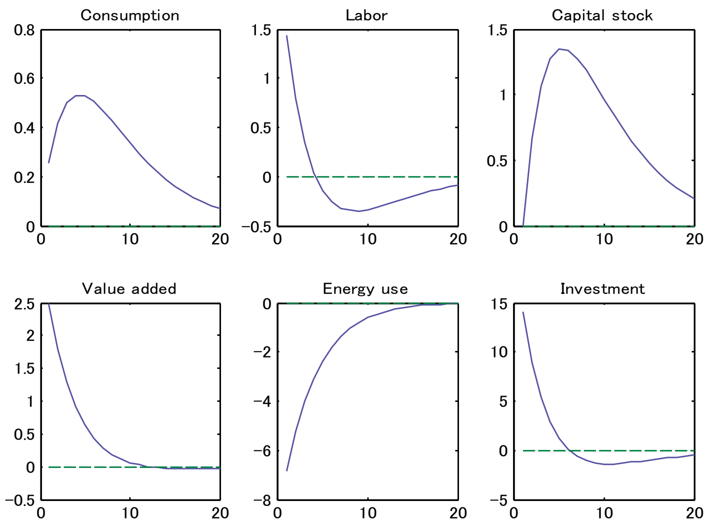

Figure 3.24: Impulse responses of the aggregate variables to a 10% positive energy-saving technology shock.

Figure 3.24 displays the impact of a 10% positive energy-saving technological shock on the aggregate variables.[28] The shock decreases the marginal product of energy, resulting in a decline in energy use. It, however, raises the marginal products of capital and labor and therefore stimulates investment and labor. Considering these effects, a 10% energy-saving technological shock increases the value added by 2.49%.

We then examine the extent to which energy-saving technological change contributes to the Great Moderation by investigating the impulse responses of the aggregate variables to a positive energy-price shock. This time, the level of energy-saving technology (z_t) takes the sample means for each sample. That is, z_t is 0.51 for the period from 1949 to 1983 and 0.84 for the period from 1984 to 2009. We then generate and compare two impulse responses to a 10% energy price shock under the different levels of energy-saving technology. The stochastic process for energy price is outlined in Equation (2.25).

Note that the only difference between the impulse responses in the different samples is the level of energy-saving technology. Figure 3.25 presents the simulation results. As discussed in Kim and Loungani (1992), an energy price shock affects both labor demand and labor supply. The labor demand curve shifts to the left because of the dampened marginal product of labor. The labor supply curve shifts to the right because of the negative income effect from the increased cost of energy imports. Under the current parameter settings, the labor demand effect dominates the labor supply effect, resulting in a decrease in labor at equilibrium.[29] An energy price shock also diminishes the marginal product of capital, leading to a reduction in investment. In total, value added declines.

All impulse responses, as shown in Figure 3.25, are mitigated due to energy-saving technological progress. In particular, while the value added declines 2.47% because of a relatively low level of

[28] For simplicity, it is assumed that the persistence parameter (ρ_z) is 0.8.

[29] Another aspect of an energy price shock is that it plays an important role in reducing the high correlation between wages and hours worked in standard real business cycle models. See Kim and Loungani (1992) for details.

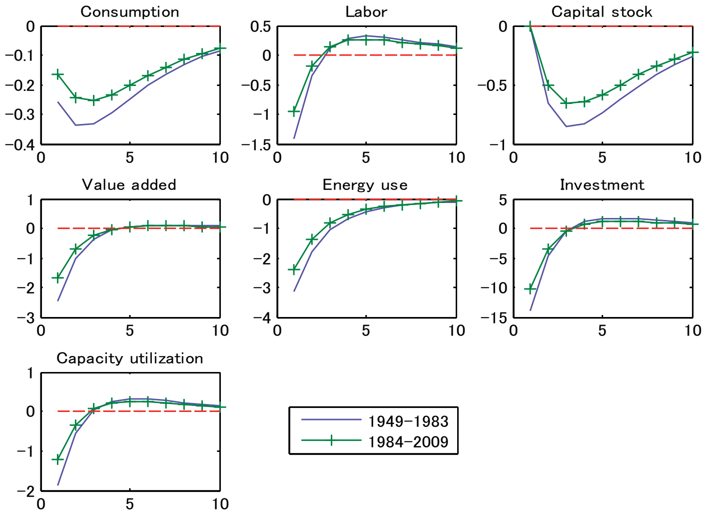

Figure 3.25: Impulse responses of the aggregate variables to a 10% positive energy price shock. *Note*: The 1949-1983 period represents the impulse responses with a low level of energy-saving technology, whereas the 1984-2009 period represents the impulse responses with a high level of energy-saving technology.

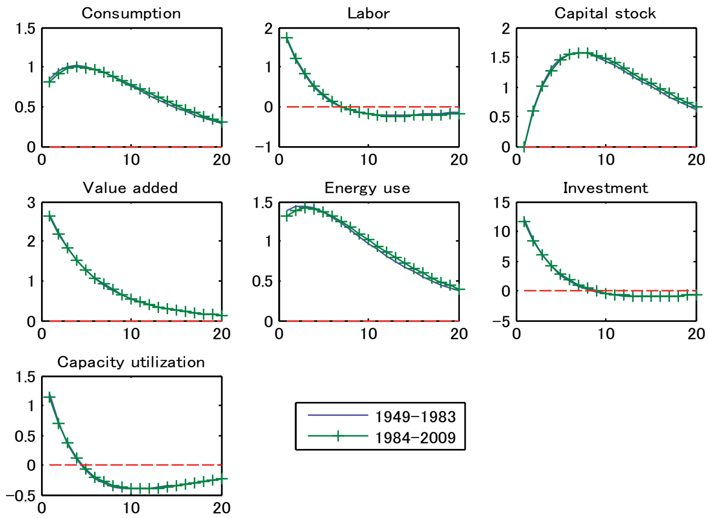

Figure 3.26: Impulse responses of the aggregate variables to a 10% positive technology shock.

energy-saving technology, it decreases only 1.66% with a high level of energy-saving technology. That is, the impact of an energy price shock on value added is mitigated by 32.8%. To check the possibility that the improvements in energy-saving technology affect the impact of technology shocks on aggregate variables, Figure 3.26 displays the impulse responses to a 1% positive technology shock under the two different levels of energy-saving technology. As can be seen, the impulse responses are almost identical, indicating that the improvements in energy-saving technology have a negligible impact on the dynamics of aggregate variables driven by technology shocks.

To compare the simulation results with the counterpart in the data, Table 3.6 shows the stochastic simulation results in our model. The simulated second moments are obtained as follows. First, draw a random number a thousand times from the error term in the stochastic process for relative price of energy, which is assumed to be normally distributed with mean zero and variance

Variable	1949–83 (Early) SD(%)	1984–2009 (Late) SD(%)	ratio (Late/Early)
GNP ($\hat{v}_t$)	1.26 (2.52)	0.94 (1.71)	0.75 (0.68)
Consumption($\hat{c}_t$)	0.18 (2.00)	0.13 (1.51)	0.72 (0.75)
Investment($\hat{x}_t$)	8.14 (7.83)	5.97 (5.88)	0.84 (0.75)
Hours worked($\hat{h}_t * \hat{em}_t$)	1.00 (2.07)	0.70 (1.83)	0.70 (0.88)
Capacity utilization($\hat{u}_t$)	1.27 (1.13)	0.86 (0.84)	0.67 (0.74)
Energy use($\hat{e}_t$)	1.72 (3.17)	1.31 (2.49)	0.76 (0.79)

Table 3.6: Cyclical behavior of the model

Note: Second moments in the data are shown in parentheses for comparison.

σ_p^2. Using the artifical series of relative price of energy generated in each iteration, calculate the standard deviations of each macroeconomic variable and average them to obtained the simulated second moments. Table 3.6 shows some interesting features. First, the energy price shocks account for around 50% and 55% of GNP volatility over 1949–1983 and 1984–2009, respectively. These numbers are higher than those reported in Kim and Loungani (1992), 16–35% depending on the elasticity of substitution between energy and capital stock. This is simply because our model includes an endogenous capacity utilization rate to amplify the effect of energy price shocks on aggregate variables while Kim and Loungani (1992) employ the standard RBC model with energy.

The second feature in Table 3.6 is that the simulated standard deviation of GNP in the model declines from 1.26% to 0.94%, indicating that the volativity in GNP is mitigated by about one quarter due to the improvements in energy-saving technology. Given that our model with energy price shocks account for arount half of the volativity in GNP, it is concluded that the energy-saving technological progress observed after the first oil crisis has , at least, a non-negligible effect on the Great Moderation.

To sum up, in this subsection, we investigate the impact of energy-saving technological progress on the Great Moderation using a standard real business cycle model with energy use as an input.

As in Hassler et al. (2011), we observe improvements in energy-saving technology following the first oil crisis. We subsequently incorporate into our model the actual sample averages of energy-saving technology from 1949 to 1983 and 1984 to 2009 and quantify the influence of this technological improvement on the Great Moderation. Our impulse response analysis of a 10% energy price shock shows that the value added declines by 2.47% in the 1949–1983 period but only 1.66% in the 1984–2009 period. Our stochastic simulation also shows that the volatility of GNP decreases by about 25 percentage points in response to energy price shocks due to the improvements in energy-saving technology. Given that about a half of volatility of GNP is attributed to energy price shocks in our model, the role of energy-saving technological change on the Great Moderation is not negligible.

Appendix 6: The different elasticities of substitution

Throughout the thesis, it is assumed that the elasticity of substitution between (effective) capital stock and energy (ε) is 0.1. In this Appendix, it is examined to what extent our simulation results depend on the elasticity of substitution. In particular, once an endogenous capacity utilization is incorporated, it is reasonable to presume that the elasticity of substitution between *effective* capital stock ($u_t K_t$) and energy use (E_t) is lower than that between capital stock (K_t) and energy use (E_t).

Figure 3.27 displays the impulse responses to a 10% energy price shock in the capacity utilization model with low ($\varepsilon = 0.05$) and high ($\varepsilon = 0.50$) elasticity of substitution.[30] Though the decline in value added is more significant in the low substitution environment, the discrepancy is very limited; value added declines by 2.10% and 2.02% in the low and high elasticity environments, respectively, in response to a 10% energy price shock. This indicates that lowering the elasticity of substitution from 0.50 to 0.05 induces only about 4 percentage points additional drop in value added. Thus, it is concluded that the simulation results are at least robust to the elasticities of substitution between capital and energy, ranging from 0.05 to 0.50.

[30]The simulation results in even lower elasticity environments ($\varepsilon < 0.05$) could not be obtained since some eigenvalues for the coefficient matrix in the first-order conditions became imaginary numbers.

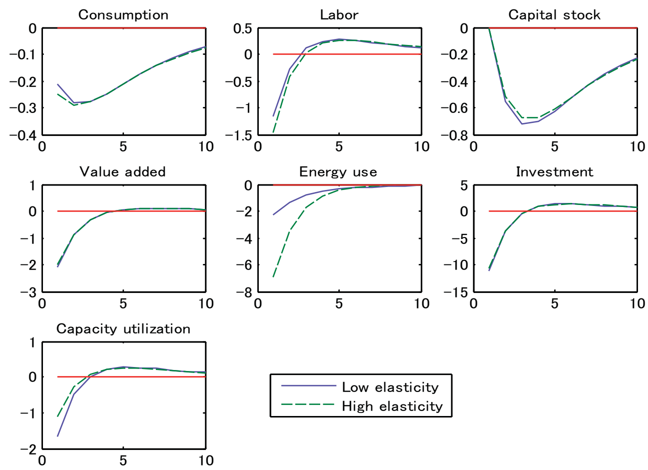

Figure 3.27: Simulation results with low ($\varepsilon = 0.05$) and high ($\varepsilon = 0.50$) elasticity of substitution bewteen effective capital stock and energy in the capacity utilization model.

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