JETEM

Journal of Economic Theory and Econometrics

The Journal of the Korean Econometric Society

(계 량 경 제 학 보)

December 2011

Volume 22. Issue 4. pp.47-75

Oil Price and Total Factor Productivity of Korean Manufacturing Industries[*]

Wonho Song[†] **Sinuk Park**[‡]

Abstract This paper estimates the effects of oil price change on the productivity changes of Korean manufacturing industry. We applied a stochastic frontier production model to estimate the changes of total factor productivity. The model is estimated by the recently developed KSS panel data estimator (Kneip et al, 2012) which allows for arbitrary patterns of time-varying individual effects. We decompose the sources of total factor productivity (TFP) growth into technical progress, technical efficiency change, scale effects change and allocation efficiency change following Kumbhakar (2000). Empirical results based on data from 2001–2010 show that productivity growth was driven mainly by declining technical progress together with improving technical efficiency. Scale effects and allocation efficiency exert marginal impacts on TFP growth. For the derived TFP components, the impacts of oil price have been analyzed. The effects of oil price change were different across the sample period. When the oil price is low and moves smoothly during 2001-2006, only scale effects are marginally affected. When the oil price is high and fluctuated greatly during 2007-2010, however, all the components were significantly affected, thus technical progress and scale effects increased, and technical efficiency and allocation efficiency decreased.

Keywords Total Factor Productivity, Stochastic Frontier Model, Technical Efficiency, Oil Price

JEL Classification C23, D24, O47

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[*] We thank three anonymous referees for their insightful comments and criticisms that substantially improved the paper.

[†] Corresponding author. Address correspondence to Wonho Song, School of Economics, Chung-Ang University, 221 Heuk Seok-Dong, Dong Jak-Gu, Seoul, Korea, or to whsong@cau.ac.kr Song gratefully acknowledges the financial support by Chung-Ang University

[‡] Analyst, Korea Asset Pricing, E-mail: ntmesinuk@hanmail.net

Received October 12, 2011, Revised November 14, 2011, Accepted December 2, 2011

1. Introduction

Crude oil price stayed stable around $20/barrel until 2000, but it has continued to rise since. From 2003, the price steadily increased and in 2008, the pace of increase of oil prices steepened sharply, with the nominal price reaching $145 a barrel on July 3, 2008, followed by an abrupt price collapse. Pressures on inflation rates and current account balance became heavier and national economies, particularly industrial production, suffered significantly from record-high oil prices.

There have been many studies that analyze the determinants of oil prices (Hamilton, 2009a, b), measure the impacts of the oil price on national economy (Lee and Ni, 2002; Hamilton, 2003; IEA, 2004; Blanchard and Gali, 2007; Kim and Yun, 2009), develop models that forecast oil prices (Ye et al, 2005; Knetsch, 2007), and analyze the relations between the oil price and monetary policy (Bernanke, Gertler, and Watson, 1997**;** Leduc and Sill, 2007; Lim, 2009). The impact of oil price on productivity is one of the important issues.

It was believed that oil shock was the main culprit of the productivity slowdown in 1970s and 1980s. However, Olson (1988) measures the impacts of oil shock on productivity and shows that the impacts are of minor importance. Dhawan, Jeske, and Silos (2010) investigate the linkage of total factor productivity (TFP) and energy price, and establish that the negative relationship between energy price and TFP that existed until around 1982 has disappeared since then. Kavand and Shahmoradi (2011) estimate a dynamic stochastic general equilibrium model for 1988-2008, and show that there is a positive correlation between oil price changes and the estimated technological fluctuations.

These studies imply that the issue on the linkage between oil price change and productivity has not been settled yet, and the results depend on estimation methods and sample periods. This paper tries to tackle this issue by analyzing the episode of record-high oil price in 2008 and by decomposing the TFP into four factors, i.e., technical progress, technical efficiency change, scale effects change, and allocation efficiency change, following Kumbhakar (2000). To our knowledge, there have been a few studies that decompose the total factor productivity into its components, but no such studies analyzed the impacts of oil price on them.

This paper analyzes the productivity of Korean manufacturing industry. There have been many studies on the total factor productivity of Korean economy. For example, Oh (2011) estimates the effects of foreign direct investment on the productivity of Korean manufacturing industry. Lee et al (2010) and Nam and Lee (2005) examine the relations between trade and productivity, and Joo et al (2009) investigate the effects of R&D on productivity. But there has been no study that considers the relations between the oil price and productivity although oil price is a very important production factor in Korean economy. Hence, this paper contributes to the literature in that it analyzes the effects of oil price change on the productivity change of Korean manufacturing industry.

As a productivity measure, we employ the TFP measure, and estimate it by utilizing a stochastic frontier production model in a panel data setup. To measure the productivity changes over time, we need to model the individual effects of panel data as time-varying. To do so, we use the panel data estimator recently developed by Kneip, Sickles, and Song (2012; called KSS hereafter). Their method extends the usual random and fixed effects model in such a way that we do not impose any explicit restrictions on the temporal pattern of individual effects. With the estimated productivity measures, we run the panel data regression to find out the impacts of oil price change on the TFP growth and its components.

Empirical results for ten manufacturing industries show that total factor productivity overall declined over the sample period (2001-2010) and that technical progress was the main contributor to the declining TFP. Technical efficiency and scale effects increased over the same period and the change of allocation efficiency was overall insignificant. When we estimate the effects of oil price change to productivity, the results depend on the sample period. When we split the sample into two, we have different pictures. In the first period where oil price is low and moves smoothly, there are almost no effects on all the productivity measures. But in the second period where oil price is high and fluctuates greatly, the effects of oil price change become very strong. Thus, due to high oil price, TFP, technical progress, and scale effects increased, and technical efficiency and allocation efficiency deteriorated.

The rest of the paper is organized as follows. Section 2 provides an overview of the methodology employed in the paper. TFP growth is decomposed into technical progress, technical efficiency change, scale effects, and allocation efficiency, and the KSS estimator which is a panel data model with time-varying individual effects is introduced. Section 3 briefly introduces the construction of the data used for our analysis. Section 4 presents empirical results. Concluding remarks are found in Section 5.

2. Model

2.1 Decomposition of TFP Change

In the "Solow" residual approach, technical progress is usually considered to be the unique source of TFP growth. Recent developments acknowledge that along with technical progress, changes in technical efficiency - the gap between frontier technology and a firm's actual production - can also contribute to productivity growth. Stochastic frontier production models assume that firms do not fully utilize existing technology because of various non-price and organizational factors that lead to inevitable technical inefficiencies in production. Under these circumstances, TFP growth may arise from improvements in technical efficiency (TE), without technical progress (TP).[1]

We introduce the production function as follows:

$$y_{it} = f(x_{it}, t)\exp(-u_{it}) \tag{1}$$

where y_{it} is the output of the ith firm ($i = 1, \ldots, N$) in period t ($t = 1, \ldots, T$), $f(\cdot)$ is the production technology, x_{it} is a vector of J inputs, and $u_{it} \geq 0$ is output-oriented technical inefficiency. Technical inefficiency, u_{it}, measures the proportion by which actual output (y_{it}) falls short of maximum possible output (labeled as frontier output $f(x_{it}, t)$). Technical efficiency is then defined by

$$TE_{it} = y_{it} / f(x_{it}, t) = \exp(-u_{it}) \leq 1$$

Note that the technical efficiency is assumed to be time-varying in our specification. Technical progress, which is known as exogenous technical change, is measured by the log derivative of the production frontier with respect to time. That is, technical progress is defined as

[1] For the decomposition of TFP growth into four components in this paper, refer to Kumbhakar (2000) and Nishimizu and Page (1982).

$$TP_t = \frac{\partial \ln f(x_{it}, t)}{\partial t}$$

The production frontier, $f(\cdot)$, is totally differentiated with respect to time to get

$$\frac{d \ln f(x_{it}, t)}{dt} = \frac{\partial \ln f(x_{it}, t)}{\partial t} + \sum_j \frac{\partial \ln f(x_{it}, t)}{\partial x_{itj}} \frac{dx_{itj}}{dt} \tag{2}$$

The first and second terms on the right-hand side measure the change in frontier output caused by TP and by change in input use, respectively. From the output elasticity of input j, $\varepsilon_{itj} = \partial \ln f / \partial \ln x_{itj}$, of the best practice firm, the second term can be expressed as $\sum_j \varepsilon_{itj} \dot{x}_{itj}$, where a dot over a variable indicates its rate of change. Thus, (2) is rewritten as

$$\frac{d \ln f(x_{it}, t)}{dt} = TP_t + \sum_j \varepsilon_{itj} \dot{x}_{itj} \tag{3}$$

Totally differentiating the logarithm of y in (1) with respect to time and using equation (3), the change in production can be represented as

$$\frac{d \ln y_{it}}{dt} = \frac{d \ln f(x_{it}, t)}{dt} - \frac{du_{it}}{dt} = TP_t - \frac{du_{it}}{dt} + \sum_j \varepsilon_{itj} \dot{x}_{itj} = TP_t + TEC_{it} + \sum_j \varepsilon_{itj} \dot{x}_{itj} \tag{4}$$

Thus, we note that the overall productivity change is not only affected by TP and changes in input use, but also by the change in technical inefficiency ($TEC_{it} = -du_{it} / dt$). TP_t is positive if the exogenous technical change shifts the production frontier upward, given the inputs. Similarly, TEC_{it} is positive if technical efficiency increases (technical inefficiency decreases) over time. TEC_{it} can be interpreted as the rate at which an inefficient producer moves towards the production frontier, everything else being constant.

Now, the total factor productivity change is defined as output growth unexplained by input:

$$T\dot{F}P_{it} = \dot{y}_{it} - \sum_j S_{itj} \dot{x}_{itj} \tag{5}$$

where S_j is input j's share in production cost, i.e, $S_j = \omega_j x_j / \sum_l \omega_l x_l$, ω_j being the price of input x_j.[2]

[2] We use the factor cost shares, instead of output elasticity for input of 'interior' firms because the latter is, in general, not

By substituting (4) into (5), equation (5) is rewritten as

$$
\begin{aligned}
T\dot{F}P_{it} &= TP_t + TEC_{it} + \sum_j (\varepsilon_{itj} - S_{itj})\dot{x}_{itj} \\
&= TP_t + TEC_{it} + (RTS_{it} - 1)\sum_j \lambda_{itj}\dot{x}_{itj} + \sum_j (\lambda_{itj} - S_{itj})\dot{x}_{itj}
\end{aligned} \tag{6}
$$

where $RTS(=\sum_j \varepsilon_j)$ denotes the measurement of returns to scale, and

$$\lambda_{itj} = f_{itj}x_{itj} / \sum_l f_{itl}x_{itl} = \varepsilon_{itj} / \sum_l \varepsilon_{itl} = \varepsilon_{itj} / RTS_{it}$$

Scale effects change, which measures the effects of input changes on output growth, are zero if *RTS* is constant, or are greater (less) than zero if *RTS* is increasing (decreasing), assuming positive input growth. At any given level of inputs, an interior firm's effort to reach its potential output may entail changes in output elasticities. The last component of observed total factor productivity change in (6) represents this. Thus, it measures inefficiency in resource allocation resulting from deviations of input prices from the value of their marginal product, i.e., $\omega_j = pf_j$, or output elasticity differences between the frontier and the interior. Thus, in (6), TFP growth can be decomposed into *TP*, the technical efficiency change, scale effects change ($SEC = (RTS-1)\sum_j \lambda_j \dot{x}_j$) and the allocation efficiency change ($AEC = \sum_j (\lambda_j - S_j)\dot{x}_j$).

2.2 Components of TFP Growth in Regression Form

The components of productivity change can be estimated within a stochastic frontier production framework, and the time-varying frontier production can be specified in translog form as:

$$
\begin{aligned}
\ln y_{it} &= \alpha_t + \alpha_L \ln L_{it} + \alpha_K \ln K_{it} + \alpha_M \ln M_{it} \\
&\quad + 1/2\beta_{LL}(\ln L_{it})^2 + 1/2\beta_{KK}(\ln K_{it})^2 + 1/2\beta_{MM}(\ln M_{it})^2 \\
&\quad + \beta_{LK}\ln L_{it}\ln K_{it} + \beta_{KM}\ln K_{it}\ln M_{it} + \beta_{LM}\ln L_{it}\ln M_{it} + e_{it} - u_{it}
\end{aligned} \tag{7}
$$

where y_{it} is the observed output, L_{it}, K_{it}, and M_{it} are labor, capital, and material, respectively.[3] The in-

directly measurable. For this, refer to Nishimizu and Page (1982) and Serot (1993).

[3] Here, we impose symmetry restriction on parameters. Thus, $\beta_{jl} = \beta_{lj}$ where j,l = *L*, *K*, and *M*.

efficiency term u_{it} represents production loss due to firm-specific inefficiency, α_t nonlinear time trend, and the error e_{it} is assumed to be iid $N(0,\sigma_e^2)$. The above model assumes input-neutral technical progress.[4] If all β s are equal to zero ($\beta_{LL} = \beta_{KK} = \beta_{MM} = \beta_{LK} = \beta_{KM} = \beta_{LM} = 0$), the production function reduces to the Cobb-Douglas function with neutral TP.

Given the estimates of (7), the technical progress can be calculated by

$$TP_t = \frac{\partial \ln f(x_{it}, t)}{\partial t} = \alpha_t - \alpha_{t-1}$$

The technical efficiency change is defined by

$$TEC_{it} = -\frac{du_{it}}{dt} = -u_{it} + u_{t-1}$$

The output elasticity of input j is

$$\varepsilon_{itj} = \frac{\partial \ln f(x_{it}, t)}{\partial \ln x_{itj}} = \alpha_j + \beta_{jj} \ln x_{itj} + \sum_{l \neq j} \beta_{jl} \ln x_{itl}$$

where $j, l = L, K, M$. Then, the scale effects change and the allocation efficiency change can be calculated, respectively, by

$$SEC_{it} = (RTS_{it} - 1)\sum_j \lambda_{itj} (\ln x_{itj} - \ln x_{i,t-1,j})$$
$$AEC_{it} = \sum_j (\lambda_{itj} - S_{itj})(\ln x_{itj} - \ln x_{i,t-1,j})$$

Here *RTS* decreases, is constant, and increase if *RTS<1, RTS=1,* and *RTS>1*, respectively.

For the translog production function in (7), we may test whether the function shows constant returns to scale. Thus, we may test the following joint hypothesis:

$$\begin{aligned} \alpha_L + \alpha_K + \alpha_M &= 1 \\ \beta_{LL} + \beta_{LK} + \beta_{LM} &= 0 \\ \beta_{KK} + \beta_{KL} + \beta_{KM} &= 0 \\ \beta_{MM} + \beta_{ML} + \beta_{MK} &= 0 \end{aligned} \tag{8}$$

[4] In the KSS estimator we consider in the paper, identifiability of (7) requires that all variables possess considerable variation over *t*. Since linear time trend has small variation over t, we do not use it and, instead, employ arbitrary nonlinear time trend α_t. We thus have to assume input-neutral technology.

For the Cobb-Douglas function we consider only the first equation $\alpha_L + \alpha_K + \alpha_M = 1$.

2.3 Estimation of Time-varying Individual Effects

For the estimation of u_{it} in equation (7), many attempts have been made, and Kumbhakar (1990) and Battese and Coelli (1992) are among them. Kumbhakar (1990) assumed $u_{it} = \gamma_i[1+\exp(at+bt^2)]^{-1}$, and Battese and Coelli (1992) used $u_{it} = \gamma_i \exp(-\eta(t-T))$. These models are estimated using the maximum likelihood estimation. Another approach that has been made is to use the usual panel data model. Thus, we consider the following panel data model with time-varying individual effects:

$$\ln y_{it} = \beta_0(t) + \sum_j \beta_j \ln x_{itj} + v_{it} + e_{it} \tag{9}$$

where $\beta_0(t)$ is the general average function, v_{it} is the time-varying individual effects and e_{it} is the error term. Then, Cornwell, Schmidt, and Sickles (1990) modeled $v_{it} = \theta_0 + \theta_1 t + \theta_2 t^2$, and Bai (2009), using the factor structure, assumed $v_{it} = \lambda_1 F_1 + \lambda_2 F_2 + \cdots + \lambda_l F_l$ where F_l is the arbitrary form of time functions. Ahn, Lee, and Schmidt (2007) developed GMM estimation method for the factor model of Bai (2003). Then, once the v_{it} is estimated, we follow Schmidt and Sickles (1984) to calculate $u_{it} = \max_i v_{it} - v_{it}$. Then, this u_{it} is non-negative, and measures the relative technical efficiency of the production function.[5] Also, we let $\alpha_t = \beta_0(t) + \max_i v_{it}$, then (9) becomes

$$\begin{aligned}\ln y_{it} &= \beta_0(t) + \max_i v_{it} + \sum_j \beta_j \ln x_{itj} + e_{it} - (\max_i v_{it} - v_{it}) \\ &= \alpha_t + \sum_j \beta_j \ln x_{itj} + e_{it} - u_{it}\end{aligned}$$

as in equation (7).

In this paper, we apply the new estimation method for arbitrary time functional of v_{it} recently developed by Kneip, Sickles, and Song (2012). As shown in KSS (2012), the failure to correctly model

[5] This type of relative measure of technical inefficiency may suffer from outlier problem. Thus, we trimmed upper and lower 5% of v_{it} estimates except for nonmetal and wood industry where 10% is used due to lack of observations.

the time-varying effects caused serious distortions in the estimates of coefficients and individual effects. For this purpose, they provide a semiparametric method for estimating general patterns of cross-sectional specific time trends. The approach is based on a factor model, where time-varying individual effects are represented by linear combinations of a small number of unknown basis functions, with coefficients varying across cross-sectional units. Main difference from previously developed factor models such as Bai (2009) is the use of nonparametric smoothing techniques as an inherent part of the estimation procedure. KSS (2012) showed that by incorporating smoothing procedures in the estimation of the individual effects, one may achieve dramatically improved rates of convergence when estimating common factors, compared to standard results. [6]

The smoothing procedure adopted is the cubic spline smoothing method. Thus, smoothed time function of v_{it} is estimated by minimizing the following criterion:

$$\sum_i \frac{1}{T}\sum_t (\ln y_{it} - \sum_j \beta_j \ln x_{itj} - v_{it})^2 + \sum_i \kappa \frac{1}{T}\int_1^T (v_{it}^{(m)}(s))^2 ds$$

where $v_{it}^{(m)}$ is the m-th derivative of v_{it} and κ is the smoothing parameter that governs the tradeoff between smoothness and goodness-of-fit. In the cubic spline smoothing method, we use $m = 2$. Then, $v_{it}^{(2)}$ measures the second order derivative of v_{it}. If this value is large, v_{it} changes roughly. If it is small, v_{it} moves smoothly. Thus, the penalty function measures the smoothness (or roughness) of the v_{it} function. The smoothness is controlled by the parameter κ. If κ is infinite, the estimated v_{it} is a linear function. If κ is 0, then v_{it} is simply the residual from the regression of $\ln y_{it}$ on $\ln x_{itj}$. Then, the optimal value of κ is needed to be chosen, and it is selected using the 'leave-one-individual-out' cross validation for the grid from 0.001 to 0.999. To the estimated $\hat{v}_{it}$, we apply the factor model to find common factors. Due to the smoothing procedure, this method performs very well for small number of time series and cross section dimensions. The optimal number of factors is chosen using the dimensionality test suggested in the section 3.3 of KSS (2012).

2.4 Estimation of the Impacts of Oil Price Change

[6] The approach of the KSS estimator is similar to that of Bai (2009) in that factor model is employed to estimate individual effects. However, the KSS estimator is more suitable for our case because the dimension of times series T is only 10. Indeed, Bai and Ng mention in their 2002 paper (page 203) that their methods work well only when $\min\{n, T\}$ is 40 or larger. However, the KSS estimator works very well even for as small as T=10.

Second issue of the paper is to estimate the effects of oil price change on productivity change. For this purpose we use the panel data estimator. Thus, we estimate the following regression equation:

$$q_{it} = \mu + \gamma \Delta \ln oil_{i,t-1} + \beta_0' \Delta \ln z_{it} + \beta_1' \Delta \ln z_{i,t-1} + v_{it} + e_{it}$$

where q_{it} is the productivity change such as TFP growth, technical progress and so on, $\Delta \ln oil_{i,t-1}$ the lagged difference of log oil price, z_{it} is the explanatory variables of productivity change, v_{it} represents the individual effects, and e_{it} is the error term. In this model, we assume that all the right hand side variables are exogenous, and we use the panel fixed effects model with panel corrected standard errors as suggested by Beck and Katz (1995).

The change of oil price may be safely regarded as exogenous. However, the other variables may not be, as argued in many studies of endogenous productivity such as Griliches (1995), and Heshimati and Kim (2011) among others. Heshimati and Kim showed that there are feedback effects between R&D investment and labor productivity. Hence, it would be better to model z_{it} as predetermined and to estimate the model by dynamic panel estimator. We thus use the system GMM estimator developed by Blundell and Bond (1998).

$$q_{it} = \mu + \alpha q_{i,t-1} + \gamma \Delta \ln oil_{i,t-1} + \beta_0' \Delta \ln z_{it} + \beta_1' \Delta \ln z_{i,t-1} + v_{it} + e_{it}$$

The moment conditions of the above estimator are valid only if there is no serial correlation in the idiosyncratic errors. Because the first difference of independently and identically distributed idiosyncratic errors will be autocorrelated, rejecting the null hypothesis of no serial correlation at order one in the first-differenced errors does not imply that the model is misspecified. Rejecting the null hypothesis at higher orders implies that the moment conditions are not valid. Thus, we report the Arellano–Bond test for serial correlation in the first-differenced errors in the table. The standard errors of the coefficient are calculated using the Arellano-Bond robust estimator. In the table, we omitted the constant and the coefficient of the lagged dependent variable because they are not of our interest.

3 Data

The data used in this paper is a balanced panel consisting of annual time-series for 708 Korean manufacturing firms during 2000–2010, with a total of 7,788 observations. The sample covers all manufacturing firms whose stocks are listed on the Korean Stock Exchange. The enlisted firms are required to report their financial statements. All firms' data are taken from their financial reports of the dataset in the Korea Investors Service (KIS). The firms we consider are the ones existed in the market for the entire sample period.[7] For individual industry estimation, this study classifies sample firms into double-digit industries according to the International Standard Industry Classification (SIC).

We have used the adjusted sales with inventories as output. For labor input we have used the number of employees of firms. For capital stock, we have considered building and structure, machinery and equipment, and transportation equipment without land among tangible fixed assets of firm. The measure of capital input is the book value of the capital stock of the firm.[8] For material input, we used 'cost of sales' plus 'sales and general administration expenses' minus 'personnel expenses' and 'cost of depreciation' from financial statement. Output, labor, and material input are deflated by Producer Price Index (PPI) and capital stocks are deflated by the PPI of each industry obtained from the Bank of Korea. Table 1 shows average values of logarithms of the variables.

As a measure of shares, we have adopted production cost shares. The total cost is the sum of labor cost, capital cost, and material cost. Labor cost is measured by personnel expenses, the capital cost by the user cost of capital multiplied by capital stock, and material cost by material input. For the calculation of the user cost of capital, equity rate data is not available, thus, we used 3 years corporate bond rate, 5% of depreciation rate (estimates used in Pyo (2003) for manufacturing industry), and PPI-based inflation rates. The factor shares S_j are calculated as the factor's share out of the total costs.

For the estimation of the impact of oil price change on productivity change, we use Dubai oil price. As determinants of TFP, we also consider education and R&D investment data from financial statements, interest rate (3 year corporate bond rate), and unit labor cost index by industry from the Bank

[7] We do not consider the effects of entry and exit firms on the productivity change. They are carefully examined in Rhee and Pyo (2010). We consider only the staying firms because the KSS estimator assumes balanced panel.

[8] Capital stock is often measured by the Perpetual Inventory Method (PIM). For PIM, however, we need long time series of investment and depreciation rates. Thus, this method is not suitable given the short period of time series of our dataset.

of Korea. The first two variables are widely known as determinants of TFP growth, and the latter three variables are considered as the proxy for the price of input variables. The changes in input prices affect production process, thereby causing productivity change.

4 Estimation

In this section, a stochastic frontier production function model is applied to decompose total factor productivity growth in Korean manufacturing industry into technical progress, technical efficiency change, scale effects change and allocation efficiency change. First of all, we perform hypothesis tests for the specification of the model (7).

4.1 Hypothesis Tests

We first test whether the individual effects are better modeled as constant fixed effects or time-varying effects. The second column of the Table 2 shows that all the industries have time-varying individual effects. The null hypothesis of constant individual effects is strongly rejected for all the industries. Thus, it would cause biased estimates if usual constant effect panel data models are used. Among the various time-varying individual effect models, we use the KSS estimator introduced in Section 2 since this estimator is known to capture arbitrary patterns of individual effects.

Next, we test whether the data is better fitted by Cobb-Douglas function or translog function. For this, we need to test the joint significance of the coefficients β_{ij} $(i, j = L, K, M)$ in (7). The third column of Table 2 shows the test results. As seen in the table, the null hypothesis of joint significance of the coefficients is strongly rejected for all industries except nonmetal industry. This means that the coefficients are not jointly zero, and that all the industries except nonmetal industry are better fitted by the translog production function. Hence, in the following, we estimate the translog function for all the industries except the nonmetal industry, and the Cobb-Douglas function for the nonmetal industry.

From the equation (7), we may also test whether the production function shows constant returns to scale (CRTS) or not. The F-test for the constraints in (8) shows that the null of constant returns to scale is rejected in all the industries except the nonmetal industry, meaning that all the industries except the nonmetal industry show non-CRTS technology. The last column of table 2 specifically shows the estimates of returns to scale (RTS) which is obtained by the sum of input elasticities. It shows that six industries show decreasing returns to scale while three industries show increasing returns to scale. The paper industry has the lowest RTS of 0.66 and the machine industry has the highest RTS of 1.22.

The total manufacturing industry including all the firms is better fitted by the translog production function with time-varying individual effects. Also, it shows increasing returns to scale. It is interesting that six industries show decreasing RTS and three industries increasing RTS, but total industry shows increasing RTS. This may be because the machine industry, which has the highest RTS, is about one third of the manufacturing industry. This result is in contrast to the ones obtained in Oh et al (2008), where the RTS was estimated for 1993-2003 to be 0.967.

4.2 Estimation Results

In this subsection, we estimate the regression model in (7) for each industry and total industry, and calculate the TFP growth and its components using the formulae defined in subsection 2.2. For the comparison of TFP growth of Korean manufacturing industry across time, we consider the results from Kim and Han (2001) and Oh et al (2008). Cautions are required, however, when we interpret the results because these studies are different from the current paper in the sample period, composition of firms, assumption on the individual effects, and estimation methods.[9] Now, the estimation results for total industry are found in Table 3, and Table 4 shows the results for each industry.

Table 3 shows that the TFP change for total industry was -0.78% for the sample period 2001-2010. Although there have been fluctuations over the period, negative changes were dominant and overall change was also negative. Particularly, the TFP change is -10.3% in 2009 when the world economy was suffering from the sub-prime crisis. It recovered partly in 2010 by 5.2%, but it was not enough.

[9] Kim and Han (2001) examine 1980s, include all the firms that entered, exited, and survived over the period, assume the same pattern of time-varying individual effects, and estimate using the maximum likelihood method. Oh et al. (2008) examine 1990s, include all the firms that entered, exited, and survived over the period, assume constant individual effects, and estimates using the panel fixed effects estimator. On the other hand, the current paper examines 2000s, includes only staying firms over the period, assumes arbitrarily time-varying effects, and estimates the recently developed KSS estimator. Therefore, the results shown in the paper must be compared considering these differences.

The estimates of TFP growth is also observed in Oh et al (2008) for the period 1993-2003, and they showed positive rates of TFP growth. This implies that after the year 2000, the contribution of the TFP growth to output growth is less apparent than previous decades.

Next, we turn to the components of TFP growth. First, the technical progress is overall negative, and its size is the largest among the other three components. Thus, we can see that negative technical progress of -3.45% is the main cause of the negative TFP growth. Technical efficiency change follows next with the estimates of 2.02%, scale component is estimated as 0.6%, and allocation efficiency is 0.04%. Thus, attributing all changes in TFP to technical progress alone, as in previous growth accounting studies, may be misleading and possibly over- or underestimates actual technical progress.

Specifically, the technical progress explains large proportions of the TFP growth, and the decline in 2009 was influential. This means that exogenous technical progress did not happen in 2000s which is in contrast to 1980s and 1990s. Kim and Han (2001) and Oh et al (2008) both showed that the technical progress was positive and it was the main driver of positive TFP growth in 1980s and 1990s, respectively.

Technical efficiency overall shows positive growth and the absolute size of it is as large as that of technical progress. This means that technological catch-up of technically inefficient firms was also the main contributor to TFP growth, and it should not be ignored or omitted in the study of TFP growth. Thus, the seventh column of the Table 3 shows that the level of technical efficiency steadily increased over the sample period from about 64% to 75%.

Scale component has been positive over the sample period. It is negative only in 2009. The last column of the table shows that RTS was larger than 1 with declining trend. This declining trend is in contrast to the results from Oh et al (2008). The years of 2001-2003 of this study overlaps with the sample period of their study. The estimates of RTS for 2001-2003 by Oh et al (2008) were below 1.0 and the trend was increasing, whereas those of RTS in our study are larger than 1.0 and the trend is declining. As mentioned above, these estimates of RTS came from different assumptions and methods and do not permit direct comparison. This is left for future research.

Allocation efficiency takes the smallest portion of the TFP growth. This measure indicates the rate of inefficiency coming from the differences between marginal rates of substitution of inputs and input price ratios. This measure has been paid little attention relative to other measures, but this is important especially when we consider the impact of price shock on production process. The overall size of allocation efficiency is 0.04% over the period. The size of the allocation efficiency is very large during 2008-2009, in which years the oil price fluctuated widely. This sheds some light on measuring oil price change on allocation efficiency, where the movement of oil price change is important in determining the size of allocation efficiency. More detailed analysis follows in the next subsection.

Looking at the industry level estimates of TFP growth and its components provides slightly different pictures on the relative importance of the TFP components across periods and industries. For example, technical progress of total industry was negative but it was positive for textile, paper, chemicals, transport, and wood industries. TFP growth was mainly determined by TP, but for food, textile, paper, and wood industries, the other factors were more important than TP. The technical efficiency also showed large variations across industries. The magnitudes of technical efficiency are almost comparable to those of technical progress, but they are overall of secondary importance compared with technical progress. Scale efficiency was largest in the machine industry, but overall it explained small part of TFP growth. Although allocation efficiency is small in total industry, there are also large variations in the magnitudes across industries. Thus, it is estimated to be the largest in the textile industry among the industries, and it is actually largest among the four components unlike other industries.

4.3 Effects of Oil Price Change

In this subsection, we estimate the impact of oil price change on the TFP change and its components. As explanatory variables, we consider lagged values of Dubai oil price, current and lagged values of education, R&D investment, interest rate, and wage rate by industry. All the variables are used in log difference form. We provide two sets of results where the first set assume that the explanatory variables are strictly exogenous to TFP growth. In the second, we relax the assumption so that other variables except the oil price are assumed to be predetermined in the sense that current and past values of explanatory variables affect productivity growth, but only lagged values of productivity affect other explanatory variables. Oil price is always assumed to be exogenous to TFP growth. The first set of results is obtained by panel fixed effects estimator with panel corrected standard errors, and the second one is obtained by dynamic panel data estimator suggested by Blundell and Bond (1998).[10] In the results, we do not show the results for the constants and lagged dependent variable.

We divide the sample period into two according to the patterns of oil price movements. Figure 1 shows the time series of oil price, the trend generated by the Hodrick-Prescott filter, and its cycle. As shown in the figure, the oil price is low and slowly moving during the first half period, and it is high and greatly fluctuating during the second half. This evidence provides us with the insight that different patterns of oil price movements may have different effects on the productivity change. We investigate this hypothesis more carefully in the following. We use the F-test that tests the equality of variances to split the sample into two. Among the years 2006 and 2007, the latter one was finally chosen because the null hypothesis of equal variance was rejected at the 5% significance level while it was not for the former one.

We posit that high and volatile oil price force the firms to restructure their production system. Thus, for example, for low and smoothly moving oil price, firms do not adjust their production system and tolerate slightly falling profits. For high and volatilely moving oil price, however, firms begin to restructure production system. Thus, new technological innovation occurs by the best practice firms. Also, due to the similar reason, the scale effects increase as the best practice firm find a way to increase the output given the input uses. In contrasts, we may have negative impacts on technical efficiency and allocation efficiency. Due to the time for new technology to distribute to less efficient firms, the spread between the best practice firms and less efficient firms gets large, lowering technical efficiency. Similarly, it takes time to find the new optimal ratio of input uses under price distortions, hence allocation efficiency deteriorates. In all, we expect positive effects on technical progress and scale effects, and negative effects on technical efficiency and allocation efficiency.

[10] We examined the endogeneity of the variables using the Hausman-Wu-Durbin endogeneity test (Greene 2003, pp.80-83). The test results show that we cannot reject the null hypothesis of no endogeneity. Hence, the results in Table 5 are more reliable than those in Table 6.

Table 5 shows that the results of the first period. Most importantly, oil price change does not seem to be an important determinant of productivity except for the scale component. This is expected as noted above because it was assumed that firms hesitate to adjust their production system faced with low and slowly moving oil price. Also, the results show that different factors affect the TFP and its components in a variety way. Thus, education significantly affects only technical progress, technical efficiency, and scale effects. R&D affects only TFP, scale effects, and allocation efficiency. Interest rate affects technical progress and technical efficiency. Wage rate affects TFP and scale effects. These findings imply that it is important to investigate the effects of explanatory variables on individual components to develop policies that enhance total factor productivity.

In the second period, the oil price change becomes significant in explaining productivity changes. Due to the oil price change, technical progress advances and technical efficiency declines significantly. Scale effects become positive, and allocation efficiency deteriorates. This result is well predicted as we indicated above. Overall, TFP growth is positively affected by oil price change mainly due to positive growth of technical progress. This change of results indicates that the level and the volatility of oil price affect productivity in a different manner. Thus, in a lower and smoothly moving price, productivity components are not much affected, whereas, in a higher and rapidly changing price level, they are significantly affected. Regarding the differential impacts of oil price on economy, Hamilton (1996, 2003) showed that oil price increase has significantly negative impact on growth while oil price decrease has insignificant impact. Our results suggest a different property of the oil price effect that high and volatile movements of the oil price significantly affect the productivity while low and smooth movements do not. More formal economic modeling of this property is left as a future research topic.

The assumption of strictly exogenous explanatory variables may be too strong. Thus, we relax the assumption here and we estimate the equation using the system GMM method. The results of Arellano–Bond tests for serial correlation in the first-differenced errors in the last row of the Table 5 and 6 show that the model is not misspecified. The overall results in Tables 6 are very similar to those in Tables 5. Thus, signs and magnitudes of the coefficients are almost similar to those in previous table, but some of the variables lose significances. For example, in the first subsample, almost all the variables turned out to be insignificant. In the second subsample, we have still many significant variables including the oil price change. Now, oil price change loses significances for TFP growth, technical efficiency, and scale effects. But the technical efficiency and scale effects are marginally significant at about 20% and 15%, respectively.[11]

Our results are summarized as follows. First, the impact of oil price change depends on the level and the volatility of oil price change. Thus, for the first period where the oil price level is low and moves smoothly, we have less significant results. But for the second period where oil price is high and moves rapidly, the impacts of oil price change become quite significant. Second, in a period of abrupt oil price change, technical progress and scale effects are positively related to oil price change, and technical efficiency and allocation efficiency are negatively related to oil price change. These results point toward the direction where policy makers should put efforts to improve TFP growth in the face of oil price shock.

5 Concluding Remarks

This paper estimated the impacts of oil price change on TFP growth of Korean manufacturing industries. For this, we estimated the TFP growth and decomposed the TFP growth into four components using stochastic frontier production function model. The model is estimated by the KSS panel data estimator under the assumption that individual effects have arbitrary patters of time trend. For the estimated TFP growth and its components, we ran the regressions with oil price change and other explanatory variables as regressors. The results show that oil price change is an important determinant of TFP growth and its components when the oil price is high and fluctuates greatly. Also, the oil price change advances technical progress and scale effects, while it exerts harmful effects on technical efficiency and allocation efficiency.

The results of the paper provide important policy implications. From a policy perspective, the decomposition of TFP into various factors provides useful information in productivity analysis. Thus,

[11] It is well known that IV estimator suffers from efficiency loss compared with OLS (Wooldridge, 2009, pp.521-524). Hence, the less significant results in Table 6 may come from using the less efficient IV estimator.

policymakers can recommend policies that are more effective in improving the productivity of firms if they understand the sources of variation in productivity growth. For example, if low productivity growth results from slow TP, then a policy to induce technological innovation should be recommended to shift up the production frontier. In this paper, the oil price change in a period of high level and volatility was shown to exert large impact on productivity components. Due to the oil price, technical change and scale effects advanced but technical efficiency and allocation efficiency deteriorated. In response to these impacts, therefore, to promote the TFP growth, government may want to focus on improving technical efficiency and allocation efficiency by distributing known technology to technically inefficient firms and by promoting free markets and lessening government intervention, respectively.

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Table 1. Summary Statistics by Industry

	No. of Firms	lnY	lnL	lnK	lnM
Food	57	14.1966	5.9079	12.4318	14.0346
Textile	52	13.3826	5.3917	11.4985	13.3050
Paper	32	13.7132	5.3196	12.6568	13.6186
Chemicals	113	13.6467	5.3745	12.0561	13.5190
Ceramic	31	14.0275	5.8196	12.6322	13.9151
Metal	61	14.1394	5.1985	12.2498	14.0475
Nonmetal	17	14.1252	5.5284	12.5145	14.0601
Machine	236	12.9601	5.0032	11.0703	12.8267
Transport	94	13.8755	5.8563	12.1321	13.7816
Wood	15	13.8731	5.6383	11.9153	13.7761
Average	708	13.7940	5.5038	12.1157	13.6884

Table 2. Results of Hypothesis Tests

	H_0: v_{it} = constant vs H_1: v_{it} = time-varying	H_0: CD vs H_1: Translog	H_0: CRTS vs H_1: Non CRTS	RTS
Food	4.6253***	143.8212***	3.5606***	0.9794
Textile	5.4763***	6.9273***	5.9158***	0.9819
Paper	3.5794***	2.6191**	8.3842***	0.6614
Chemicals	4.7917***	89.2533***	66.7057***	0.9509
Ceramic	4.2470***	15.0827***	8.4906***	0.9395
Metal	2.2279**	5.8672***	3.6294***	1.1052
Nonmetal	3.3037***	1.2734	0.3681	1.0153
Machine	14.9557***	28.9437***	122.4375***	1.2184
Transport	8.2105***	5.9814***	4.3748***	0.9994
Wood	3.6858***	12.4955***	15.1049***	1.0552
Total	24.1565***	136.6812***	86.5371***	1.0898

Note: ***, **, and * means the significance at the 1%, 5%, and 10% level, respectively.

Table 3. Decomposition of TFP Growth for Entire Manufacturing Industry

	TFP	TP	TEC	SEC	AEC	Efficiency	RTS
2001	-0.0540	-0.1016	0.0354	0.0146	-0.0024	0.6418	1.1092
2002	0.0061	-0.0285	0.0201	0.0152	-0.0007	0.6544	1.1025
2003	-0.0032	-0.0833	0.0719	0.0086	-0.0004	0.7021	1.0988
2004	0.0028	0.0092	-0.0182	0.0098	0.0020	0.6900	1.0931
2005	-0.0243	-0.0627	0.0326	0.0056	0.0002	0.7112	1.0892
2006	-0.0194	-0.0546	0.0336	0.0027	-0.0011	0.7351	1.0867
2007	0.0201	0.0204	-0.0035	0.0029	0.0003	0.7321	1.0827
2008	0.0448	0.0535	-0.0149	0.0008	0.0054	0.7228	1.0797
2009	-0.1030	-0.1384	0.0459	-0.0062	-0.0044	0.7555	1.0818
2010	0.0520	0.0410	-0.0009	0.0066	0.0053	0.7547	1.0741
Average	-0.0078	-0.0345	0.0202	0.0060	0.0004	0.7100	1.0898

Table 4. Decomposition of TFP Growth by Industry

Industry	Period	TFP	TP	TEC	SEC	AEC
Food	2001-2004	-0.0007	-0.0030	-0.0007	0.0005	0.0025
	2005-2007	0.0124	-0.0011	0.0107	-0.0002	0.0030
	2008-2010	0.0109	-0.0046	0.0074	-0.0028	0.0109
	Total	0.0067	-0.0029	0.0052	-0.0007	0.0051
Textile	2001-2004	-0.0311	-0.0034	-0.0097	-0.0020	-0.0160
	2005-2007	-0.0295	-0.0036	0.0000	0.0068	-0.0327
	2008-2010	-0.0188	0.0182	-0.0142	0.0045	-0.0273
	Total	-0.0269	0.0030	-0.0081	0.0026	-0.0244
Paper	2001-2004	-0.0252	-0.0180	-0.0055	-0.0011	-0.0007
	2005-2007	-0.0004	0.0205	-0.0174	-0.0072	0.0037
	2008-2010	0.0182	0.0673	-0.0307	-0.0327	0.0143
	Total	-0.0047	0.0192	-0.0166	-0.0124	0.0051
Chemicals	2001-2004	-0.0058	0.0331	-0.0271	-0.0120	0.0002
	2005-2007	0.0164	0.0723	-0.0497	-0.0115	0.0052
	2008-2010	0.0197	0.0319	-0.0302	-0.0285	0.0464
	Total	0.0085	0.0445	-0.0348	-0.0168	0.0156
Ceramic	2001-2004	-0.0139	-0.0488	0.0211	0.0022	0.0116
	2005-2007	-0.0272	-0.0769	0.0449	0.0034	0.0014
	2008-2010	0.0050	0.0104	-0.0029	-0.0006	-0.0019
	Total	-0.0122	-0.0395	0.0210	0.0017	0.0045
Metal	2001-2004	0.0034	0.0049	-0.0006	0.0098	-0.0108
	2005-2007	-0.0273	-0.0542	0.0225	0.0078	-0.0035
	2008-2010	-0.0330	-0.0236	-0.0033	0.0078	-0.0139
	Total	-0.0168	-0.0214	0.0055	0.0086	-0.0095
Nonmetal	2001-2004	-0.0068	-0.0239	0.0144	0.0004	0.0024
	2005-2007	-0.0010	-0.0053	-0.0039	0.0020	0.0064
	2008-2010	-0.0061	-0.0007	-0.0083	0.0015	0.0014
	Total	-0.0048	-0.0114	0.0021	0.0012	0.0033
Machine	2001-2004	-0.0513	-0.1772	0.0974	0.0382	-0.0097
	2005-2007	-0.0199	-0.0505	0.0239	0.0075	-0.0008
	2008-2010	-0.0199	-0.0320	0.0101	0.0081	-0.0061
	Total	-0.0325	-0.0956	0.0492	0.0200	-0.0060
Transport	2001-2004	0.0036	0.0135	-0.0047	-0.0004	-0.0048
	2005-2007	0.0040	0.0462	-0.0408	-0.0011	-0.0004
	2008-2010	-0.0068	-0.0238	0.0253	-0.0013	-0.0071
	Total	0.0006	0.0121	-0.0065	-0.0008	-0.0042
Wood	2001-2004	-0.0064	0.0133	-0.0156	-0.0010	-0.0031
	2005-2007	0.0418	0.0985	-0.0521	-0.0038	-0.0009
	2008-2010	-0.0580	-0.0859	0.0534	-0.0284	0.0028
	Total	-0.0074	0.0091	-0.0059	-0.0100	-0.0006

Table 5. Estimation of the Effects of Oil Price Change on Productivity by Period
: Panel Fixed Effects Estimation

2001-2006	TFP	TP	TEC	SEC	AEC
DOIL(-1)	-0.0117 (0.0208)	-0.0349 (0.0346)	0.0288 (0.0308)	-0.0216* (0.0111)	0.0160 (0.0142)
DEDU	0.0042 (0.0127)	0.0638*** (0.0221)	-0.0499*** (0.0143)	-0.0103* (0.0060)	0.0006 (0.0065)
DEDU(-1)	-0.0025 (0.0154)	0.0307 (0.0219)	-0.0300** (0.0134)	-0.0012 (0.0052)	-0.0021 (0.0076)
DRND	0.0090 (0.0055)	0.0064 (0.0091)	-0.0044 (0.0063)	0.0048** (0.0019)	0.0022 (0.0019)
DRND(-1)	0.0095** (0.0042)	0.0055 (0.0059)	-0.0033 (0.0048)	0.0036** (0.0017)	0.0037* (0.0021)
DINT	0.0089 (0.0206)	0.0747* (0.0380)	-0.0505 (0.0357)	0.0091 (0.0102)	-0.0244 (0.0204)
DINT(-1)	0.0185 (0.0179)	0.0641** (0.0251)	-0.0572* (0.0294)	0.0067 (0.0111)	0.0049 (0.0183)
DWAGE	-0.1688*** (0.0612)	-0.1326 (0.0940)	0.0699 (0.0579)	-0.0412* (0.0211)	-0.0649 (0.0408)
DWAGE(-1)	-0.1185** (0.0553)	-0.1007 (0.0933)	0.0198 (0.0653)	-0.0242 (0.0188)	-0.0134 (0.0393)
R-squared	0.4392	0.7345	0.7477	0.7215	0.4902
2007-2010	TFP	TP	TEC	SEC	AEC
DOIL(-1)	0.1245*** (0.0308)	0.3816*** (0.0457)	-0.2422*** (0.0381)	0.0368** (0.0147)	-0.0516*** (0.0097)
DEDU	0.0185 (0.0181)	0.0108 (0.0352)	0.0121 (0.0261)	0.0128* (0.0063)	-0.0172*** (0.0041)
DEDU(-1)	0.0351 (0.0297)	0.0651 (0.0583)	-0.0509 (0.0387)	0.0025 (0.0165)	0.0184** (0.0072)
DRND	0.0128 (0.0237)	-0.0193 (0.0269)	0.0297 (0.0205)	0.0063 (0.0094)	-0.0040 (0.0035)
DRND(-1)	-0.0614** (0.0289)	-0.1259*** (0.0392)	0.0771** (0.0296)	0.0025 (0.0126)	-0.0151** (0.0055)
DINT	0.0439*** (0.0073)	0.0636*** (0.0087)	-0.0245** (0.0091)	0.0075** (0.0032)	-0.0027 (0.0027)
DINT(-1)	-0.2623*** (0.0738)	-0.8924*** (0.0857)	0.6155*** (0.0629)	-0.0232 (0.0321)	0.0379 (0.0227)
DWAGE	-0.0321 (0.1013)	0.1576 (0.1247)	-0.1650 (0.1054)	-0.0762 (0.0445)	0.0516 (0.0358)
DWAGE(-1)	-0.0191 (0.1268)	0.4304*** (0.1471)	-0.4286*** (0.0712)	-0.0526 (0.0517)	0.0317 (0.0457)
R-squared	0.4147	0.5591	0.4795	0.5212	0.7086

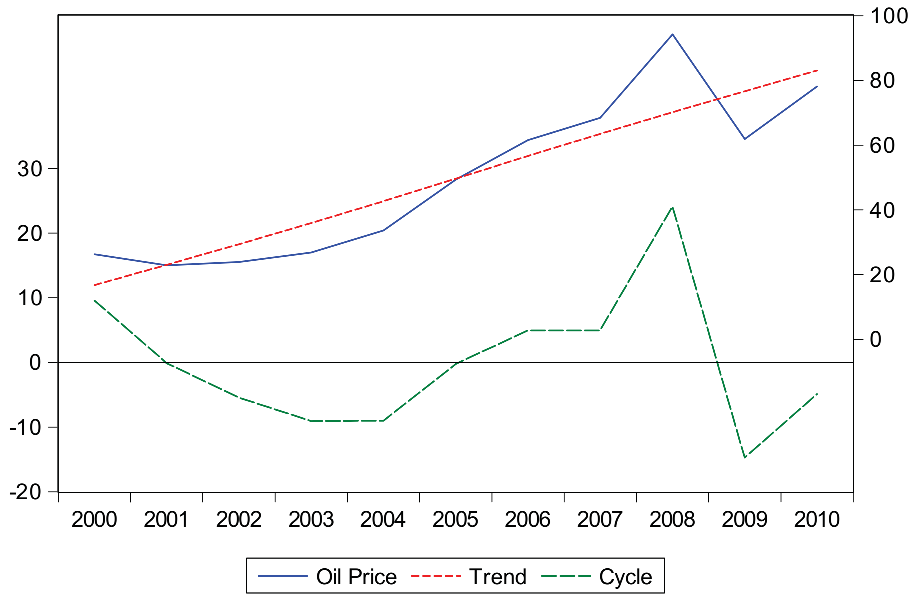
Note: Standard errors are in parenthesis. ***, **, and * means the significance at the 1%, 5%, and 10% level, respectively.

Table 6. Estimation of the Effects of Oil Price Change on Productivity by Period
: Dynamic Panel Estimation

2001-2006	TFP	TP	TEC	SEC	AEC
Doil_L	-0.0220 (0.0481)	-0.0949 (0.0908)	0.0475 (0.0697)	-0.0006 (0.0079)	0.0118 (0.0291)
DEDU	-0.0092 (0.0100)	0.0200 (0.0219)	-0.0370* (0.0198)	0.0052 (0.0065)	-0.0097 (0.0064)
DEDU_L	-0.0083 (0.0146)	-0.0040 (0.0104)	-0.0151 (0.0101)	0.0010 (0.0049)	0.0073 (0.0067)
DRND	0.0052 (0.0039)	0.0107 (0.0081)	-0.0084 (0.0073)	0.0008 (0.0025)	0.0003 (0.0015)
DRND_L	0.0042 (0.0031)	0.0027 (0.0041)	-0.0027 (0.0043)	0.0009 (0.0015)	-0.0004 (0.0018)
DINT	0.0110 (0.0311)	0.1366* (0.0754)	-0.0774 (0.0623)	-0.0052 (0.0198)	0.0090 (0.0203)
DINT_L	0.0516 (0.0595)	0.1135 (0.0755)	-0.0653 (0.0762)	-0.0085 (0.0233)	-0.0099 (0.0372)
DWAGE	-0.0917 (0.0980)	-0.0530 (0.1326)	0.0377 (0.0516)	-0.0312 (0.0303)	-0.0033 (0.0428)
DWAGE_L	-0.0142 (0.1008)	0.0536 (0.1225)	-0.0385 (0.0645)	-0.0142 (0.0179)	-0.0201 (0.0216)
Test	0.9817	0.5669	0.2359	0.9762	0.5781
2007-2010	TFP	TP	TEC	SEC	AEC
Doil_L	0.1127 (0.1183)	0.4176* (0.2169)	-0.2199 (0.1763)	0.0592 (0.0417)	-0.0890* (0.0465)
DEDU	0.0215 (0.0300)	0.0170 (0.0373)	0.0202 (0.0233)	-0.0030 (0.0119)	-0.0193** (0.0096)
DEDU_L	0.0408 (0.0355)	0.0659 (0.0736)	-0.0650 (0.0662)	0.0072 (0.0087)	0.0242658c (0.0128)
DRND	0.0159 (0.0327)	-0.0307 (0.0357)	0.0287 (0.0177)	0.0060 (0.0079)	-0.0102 (0.0075)
DRND_L	-0.0557*** (0.0161)	-0.1149** (0.0526)	0.0767 (0.0475)	0.0036 (0.0047)	-0.0162*** (0.0043)
DINT	0.0423 (0.0275)	0.0335 (0.0370)	-0.0168 (0.0348)	0.0162 (0.0146)	0.0084 (0.0125)
DINT_L	-0.2361 (0.1973)	-0.9885** (0.4602)	0.5886 (0.3737)	-0.0931 (0.0760)	0.1022 (0.0901)
DWAGE	0.0061 (0.0820)	0.2669 (0.1636)	-0.2100* (0.1224)	-0.0184 (0.0359)	-0.0143 (0.0366)
DWAGE_L	-0.0459 (0.0728)	0.4105 (0.2791)	-0.3913 (0.2391)	-0.0373* (0.0225)	0.0034 (0.0341)
Test	0.1717	0.2005	0.1198	0.2082	0.8160

Note: Standard errors are in parenthesis. The p-values of Arellano–Bond tests for serial correlation in the first-differenced errors are shown in the last row. ***, **, and * means the significance at the 1%, 5%, and 10% level, respectively.

Figure 1. Oil Price Movement



Note: The trend is estimated by the Hodrick-Prescott filter, and the cycle is the difference between the series and the trend.