ECONOMICS AND RESEARCH DEPARTMENT

ERD WORKING PAPER SERIES NO. 116

Productivity and Employment in a Developing Country:

Evidence from Republic of Korea

Sangho Kim, Hyunjoon Lim, and Donghyun Park

June 2008

Asian Development Bank

ERD Working Paper No. 116

Productivity and Employment in a Developing Country: Evidence from Republic of Korea

Sangho Kim, Hyunjoon Lim, and Donghyun Park

June 2008

Sangho Kim is professor at the College of Business, Honam University, Republic of Korea; Hyunjoon Lim is a Ph.D. student at the Department of Economics, University of Rochester, New York; and Donghyun Park is senior economist in the Macroeconomics and Finance Research Division, Asian Development Bank, Manila.

Asian Development Bank

Asian Development Bank
6 ADB Avenue, Mandaluyong City
1550 Metro Manila, Philippines
www.adb.org/economics

June 2008
ISSN 1655-5252

FOREWORD

The ERD Working Paper Series is a forum for ongoing and recently completed research and policy studies undertaken in the Asian Development Bank or on its behalf. The Series is a quick-disseminating, informal publication meant to stimulate discussion and elicit feedback. Papers published under this Series could subsequently be revised for publication as articles in professional journals or chapters in books.

CONTENTS

ABSTRACT

The paper empirically investigates the relationship between productivity and employment in Republic of Korea using structural vector autoregression (VAR) models. Productivity-enhancing technology shocks significantly increase hours worked, which lends support to the real business cycle theory. The results show that technology shocks can explain most elements of a business cycle both in the short and long run. On the other hand, demand shocks can only explain price fluctuations. The evidence thus suggests that Korean policymakers should give higher priority to supply-side policies that promote technological progress and innovation.

I. INTRODUCTION

Traditional Keynesian theory emphasizes the central role of demand-side factors such as monetary, fiscal, and investment shocks in macroeconomic fluctuations. In contrast, real business cycle (RBC) theory puts forth technology shocks as the main drivers of business cycles. A major prediction of the RBC theory is a high positive correlation between productivity and employment. The underlying idea is that a positive technology shock increases both productivity and demand for labor, which, in turn, increases employment. Unfortunately for RBC theorists, a well-known stylized fact from United States (US) data that shows no correlation and indeed often negative correlation between productivity and employment has led many economists to question the relevance of their theory. A substantial literature has recently emerged to empirically examine more rigorously the relationship between productivity and employment.

The pioneering paper by Gali (1999) finds that productivity-enhancing technology shocks reduced hours worked in the US as well as in all other G-7 economies except Japan. The substantial body of research that confirms and supports Gali's milestone findings include Basu et al. (2006), Francis and Ramey (2005), Francis et al. (2003), Gali (2004), Gali and Rabanal (2004), Shea (1999), and Kiley (1998). A number of studies have challenged the robustness of such evidence, primarily on methodological grounds. These include Christiano et al. (2003), Uhlig (2004), Dedola and Neri (2004), Peersman and Straub (2004), Chang and Hong (2006), and Chang et al. (2004). In any case, a negative effect of positive-enhancing technology shocks on employment cannot be reconciled with the RBC theory and is more consistent with the sticky prices of Keynesian models. The basic idea is that price rigidity prevents demand from changing in the face of lower marginal costs due to productivity gains, leading firms to produce the same output with less labor.

The central objective of the paper is to empirically investigate the effect of technological shocks on productivity and employment in Republic of Korea (henceforth Korea). The paper reexamines the relationship between productivity-enhancing technology shocks and employment using Korean data. The paper hopes to make a significant contribution by using data from a developing country to investigate this relationship and the broader issue of empirical validity of the RBC theory. The vast majority of the existing empirical literature on the relationship between productivity and employment looks at data from the US and other developed countries. This is also true for the broader literature testing the validity of the RBC theory. The limited number of studies on RBCs in developing countries includes Mendoza and Smith (2006), Carmichael et al. (1999), and Chyi (1998). Studies on RBC in Korea are similarly limited and includes Yoon (2006), Park (2000), and Masih and Masih (1995).

However, neither set of studies looks at the technology–employment relationship nor seeks to otherwise test the RBC theory. That is, those studies look at issues other than how technology shocks affect productivity and employment or, more generally, how such shocks drive the business cycle in developing countries. Yet there is no theoretical reason why technology shocks should have a smaller impact on productivity and employment or on the business cycle in developing countries than in developed countries. On the contrary, technological shocks are likely to have a bigger impact on developing countries, due to their relative technological backwardness and hence greater scope for technological progress. This is especially true for Korea, where imported foreign technology played a central role in the country's rapid industrialization and economic growth. While the role of technology in long-term economic development and growth has long been recognized and studied, there has been very little research on the role of technological shocks on the business cycle of developing countries, as noted above. This paper seeks to examine the effect of productivity-enhancing technology shocks on Korean employment as a way of testing the RBC theory, to help shed light on the sources of business cycles in developing countries, and thus contribute to the limited empirical literature on the topic.

The rest of the paper is organized as follows. In Section II, we describe the basic framework for our empirical analysis. More specifically, we describe the construction of our data, along with the bivariate structural vector autoregression (VAR) model of productivity and hours worked, which is used to identify the technology shocks. In Section III, we report and discuss the results of our estimation of the bivariate model. We also introduce the variable prices, to build a trivariate structural VAR model, estimate it, and report and discuss the results. In Section IV, we draw conclusions and policy implications from our main empirical findings.

II. BASIC EMPIRICAL FRAMEWORK

In this section, we explain why we choose total factor productivity (TFP) as our measure of productivity as well as how we construct our TFP data. We also describe how we plan to identify technology shocks using the bivariate structural VAR model.

A. Data Construction

Many empirical studies on the employment–productivity relationship use labor productivity as the measure of productivity, but this partial measure fails to take into account factor substitution between capital and labor. Such substitution is especially important for the Korean economy, which has continuously experienced capital deepening and adoption of new production technologies. Labor productivity generally depends on capital deepening as well as technological progress and structural efficiency changes. Furthermore, it is often argued that Korean economic growth has been driven mostly by factor accumulation rather than by productivity growth. In light of these facts, we use TFP, which incorporates the effects of both structural and technological changes, as well as labor productivity, as our productivity measures.[1]

The data for labor productivity, which is defined as the ratio of gross domestic product (GDP) to total hours worked, is compiled by the Bank of Korea. We constructed our TFP data from various sources in the Bank of Korea database and used the data to estimate Solow residuals for the period 1980Q1–2002Q4. The capital stock is the real amount of tangible fixed assets, adjusted for the capital utilization rate. Our measure of employment is hours worked, which we derived as the product of total number of employed workers and average hours worked per week (h_i). All variables are converted into constant 2000 prices.

[1] Chang and Hong (2006) and Chang et al. (2004) used TFP to investigate the dynamic relationship between technology shocks and employment in the US manufacturing sector.

The measured Solow residual is an imperfect measure of productivity growth in the absence of perfect competition, constant returns to scale technology, and full employment of labor and capital. This implies that the measured Solow residual may be affected by demand-side variables.[2] In the case of Korea, Kim and Lim (2004) find that the Solow residual is not a strictly exogenous variable but instead co-moves with demand shocks. If measured productivities are influenced by the business cycle, a correlation between productivity and employment may be spurious and due to a correlation between employment and the business cycle. For this reason, it is desirable to control for cyclical bias in the productivity measure.

To address this problem, we follow the method suggested by Basu and Kimball (1997) and Ball and Moffitt (2001). This first step in this method is to regress the log difference of measured labor productivity and Solow residual on the log difference of the capital utilization rate, which is a proxy for business cycles. The next step is to adjust the average of the regression error term so that it equals the original productivity measure when the productivity measure is adjusted for cyclical factors. Appendix Figure A.1 shows the growth rates of measured Solow residual and TFP estimates we obtained after eliminating the cyclical effects from the residual. TFP grew rapidly after the mid-1980s but slowed somewhat in the 1990s, and collapsed during the crisis of 1997–1998. TFP recovered from the crisis shortly thereafter but then fell again after 2000.

Table 1 below presents the lagged correlation coefficients between the variables used in our empirical analysis. Real GDP has coefficient values of 0.54 and 0.48 with hours worked and employment, respectively. TFP is highly correlated with hours worked and the GDP, leading the two variables by a quarter or showing simultaneous correlation. The correlation coefficients support the predictions of the RBC theory in the sense that productivity growth is closely related to macroeconomic fluctuations. Based on this observation, in the next section, we apply a structural VAR model to Korean data to investigate the dynamic relation between technology shocks and employment.

TABLE 1
LAG CORRELATION COEFFICIENTS BETWEEN KEY VARIABLES IN KOREA, 1980Q1–2003Q4

	–4Q	–3Q	–2Q	–1Q	0Q	+1Q	+2Q	+3Q	+4Q
Hours worked, GDP	–0.08	0.10	0.10	0.15	0.54	0.14	0.14	0.06	-0.06
Employment, GDP	0.06	0.12	0.26	0.28	0.48	0.20	0.13	0.07	-0.10
TFP, GDP	–0.18	–0.05	0.18	0.45	0.71	0.63	0.42	0.22	0.07
TFP, hours worked	–0.13	–0.03	0.14	0.31	0.43	0.43	0.30	0.14	–0.02

TFP = total factor productivity; GDP = gross domestic product.
Note: Lag correlation coefficients measure correlation between the former variable in the present period and the latter variable in the $t \pm i$ period.

[2] See Hall (1989) and Mankiw (1989) for more comprehensive discussions.

Prior to our empirical analysis, we carried out augmented Dickey-Fuller (ADF); Phillips-Peron (PP); and Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) unit root tests to examine whether the time-series of the variables follow stochastic trends. Appendix Table A.1 reports the test results for both levels and first differences. The tests unambiguously suggest the existence of one unit root for every variable, indicating that the time-series are integrated of order 1, I(1). We performed Johansen's cointegration test on various sets of variables to check for the existence of a long-run relationship among the variables. The results, which we report in Appendix Table A.2, indicate that there is no cointegration vector and thus no long-run time-series relationship among the variables.

B. Bivariate Structural VAR Model

In view of the absence of a cointegrating relationship among the variables, we specify a bivariate structural VAR model of TFP and hours worked to identify technology shocks in the Korean economy. While Shea (1999) used the number of patents and research and development expenditures as proxies for technology shocks, Gali (1999) used the long-run restriction that only technology shocks can affect productivity permanently in a structural VAR model. Although Shea's method may be able to solve some measurement problems, such as those associated with procyclical movements of productivity, it cannot replace Gali's identification method due to the low explanatory power of the proxies.[3]

Let z_t be a vector of TFP growth (x_t) and total hours worked growth (h_t), $z_t = [\Delta x_t, \Delta h_t]'$, and ε_t be a vector of log of technology shocks (ε_t^x) and log of nontechnology shocks (ε_t^h), $\varepsilon_t = [\varepsilon_t^x, \varepsilon_t^h]'$. Then, the *k*-lag VAR of TFP growth and hours growth can be written as

$$\Phi(L)z_t = \varepsilon_t \tag{1}$$

where $\Phi(L)$ is a *k*th-order matrix polynomial in the lag operator. The VAR can be rewritten in its moving average (MA) representation:

$$z_t = C(L)\varepsilon_t \tag{2}$$

where C(*L*) is an infinite polynominal matrix in the lag operator $\Phi(L) = C(L)^{-1}$. We can rewrite equation (2) as

$$z_t = \begin{bmatrix} C_{11}(L) & C_{12}(L) \\ C_{21}(L) & C_{22}(L) \end{bmatrix} \begin{bmatrix} \varepsilon_t^x \\ \varepsilon_t^h \end{bmatrix} \tag{3}$$

[3] To minimize the misspecification error, Peersman and Straub (2004) used sign restrictions, first suggested by Faust (1998), to identify structural shocks in VAR.

Each of the matrices is a polynominal in the lag operator. Two disturbances of technology and nontechnology shocks cause fluctuations in TFP and hours worked, and are assumed to be orthogonal to each other.[4] To identify the technology shock, ε_t^x, we assume that both technology and nontechnology shocks can have a permanent effect on hours worked, but only technology shocks can have a permanent effect on TFP. This assumption imposes the long-run restriction that the nontechnology shock's long-run impact on productivity be equal to zero and implies that $C_{12}(1)=0$, which restricts the unit root in TFP to originate solely from technology shocks.

III. EMPIRICAL RESULTS

We report and discuss the results of our estimation of the bivariate VAR model outlined in the preceding section. We also introduce an additional variable, prices, to specify a trivariate structural VAR model, estimate it, and report and discuss the results.

A. Results of the Bivariate Structural VAR Model

In this subsection, we report the results of our estimation of the bivariate model of productivity and hours worked. We chose the lag length of four to minimize the Akaike Information Criterion, Schwarz Criterion, or Bayesian Information Criterion. However, changing the lag length does not affect our results.[5] We first define productivity as labor productivity, as in Gali (1999), and report the coefficient estimates in equation (4) below.

$$\begin{bmatrix} \Delta lp_t \\ \Delta h_t \end{bmatrix} = \begin{bmatrix} \begin{matrix} 0.0083 \\ (0.0016) \end{matrix} & 0 \\ \begin{matrix} -0.0025 \\ (0.0024) \end{matrix} & \begin{matrix} 0.0085 \\ (0.0014) \end{matrix} \end{bmatrix} \begin{bmatrix} \varepsilon_t^t \\ \varepsilon_t^{nt} \end{bmatrix} \tag{4}$$

where Δlp_t and Δh_t denote labor productivity growth and hours worked growth, respectively, and ε_t^t and ε_t^{nt} denote technology and nontechnology shocks, respectively. The standard errors are in parentheses, and zero is the long-run restriction used to identify technology shocks. Our results show that the impact of positive technology shocks on hours worked is negative but statistically insignificant.

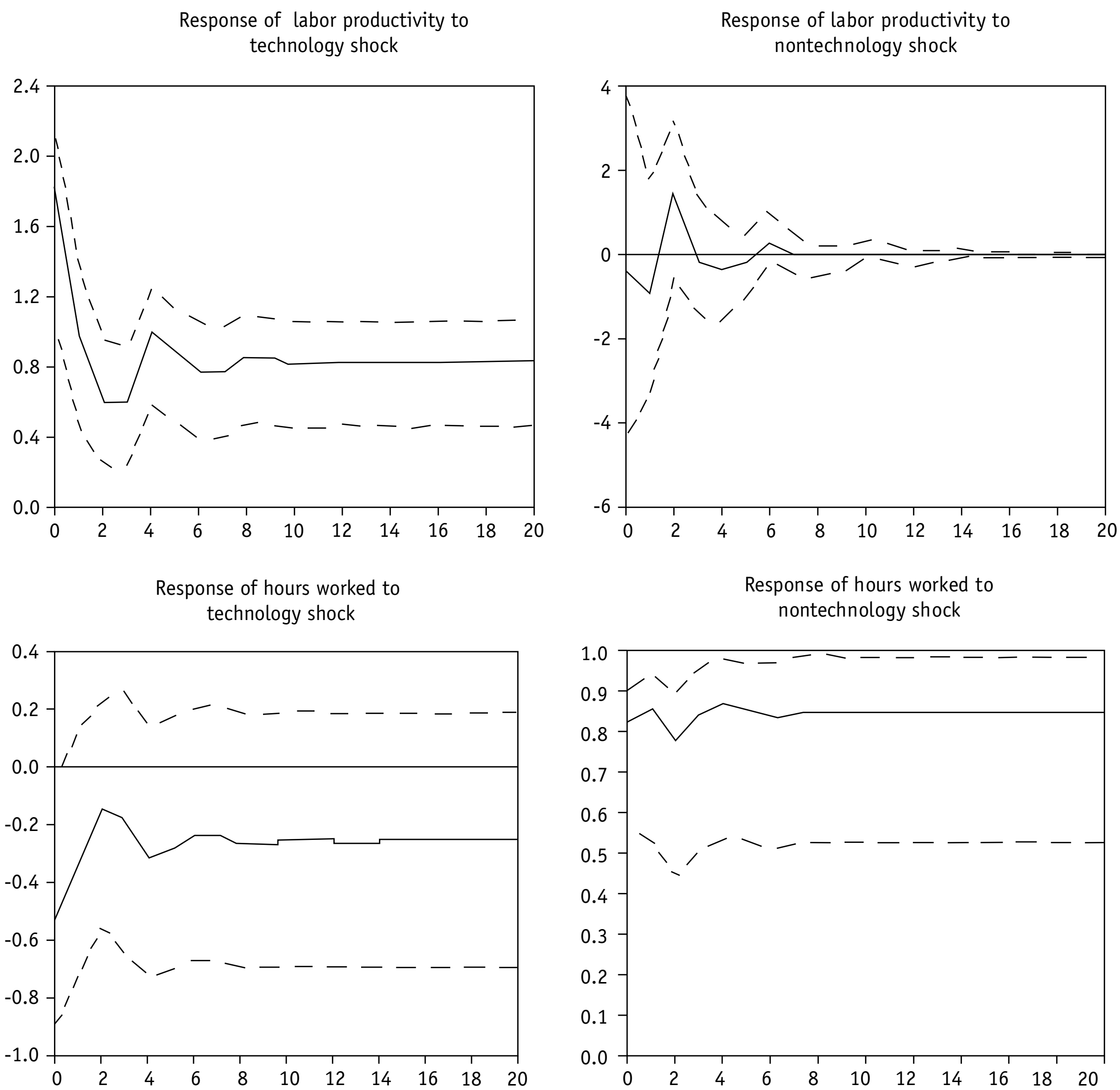
Figure 1 below shows the cumulative impulse response of labor productivity and hours worked to technology and nontechnology shocks in the bivariate model. The responses are defined in terms of the natural logs of the levels rather than growth rates of the endogenous variables.[6] Labor productivity rose permanently to higher levels after initial adjustments in response to a one-standard-deviation positive technology shock. Hours worked initially rose, then fluctuated and settled into a new steady-state level after six quarters, in response to the same shock. The response of hours worked to technology shock was negative but insignificant.

[4] Some studies, including McGrattan (2004) and Holzl and Reinstaller (2004) interpreted the two shocks in the structural VAR as technology shocks and demand shocks. However, many supply shocks other than technology shocks, such as shocks arising from fluctuations in production costs or labor supply, have no long-run impact on productivity. Therefore, it seems more appropriate to classify shocks as technology shocks and nontechnology shocks rather than as technology shocks and demand shocks.

[5] The Ljung-Box Q statistics cannot reject the nonexistence of cross- and auto-correlations between the estimated error terms, implying the nonexistence of autocorrelation and heteroskedasticity.

[6] We computed the standard errors by bootstrapping 1,000 random draws.

FIGURE 1
CUMULATIVE IMPULSE RESPONSES OF LABOR PRODUCTIVITY AND HOURS WORKED TO TECHNOLOGY AND NONTECHNOLOGY SHOCKS IN KOREA, 1985–2002



Our finding of negative but insignificant effect of productivity-enhancing technology shocks on hours worked is qualitatively very similar to Gali (1999). As noted earlier, it is possible to interpret such evidence as casting doubt on the validity of the RBC theory.

However, the negative correlation between hours worked and technology shock disappeared when we replaced labor productivity with TFP. The identified coefficients of the structural VAR of TFP and hours worked are:

$$\begin{bmatrix} \Delta S_t \\ \Delta h_t \end{bmatrix} = \begin{bmatrix} \begin{matrix} 0.0225 \\ (0.0063) \end{matrix} & 0 \\ \begin{matrix} 0.0073 \\ (0.0031) \end{matrix} & \begin{matrix} 0.0077 \\ (0.0019) \end{matrix} \end{bmatrix} \begin{bmatrix} \varepsilon_t^s \\ \varepsilon_t^h \end{bmatrix} \tag{5}$$

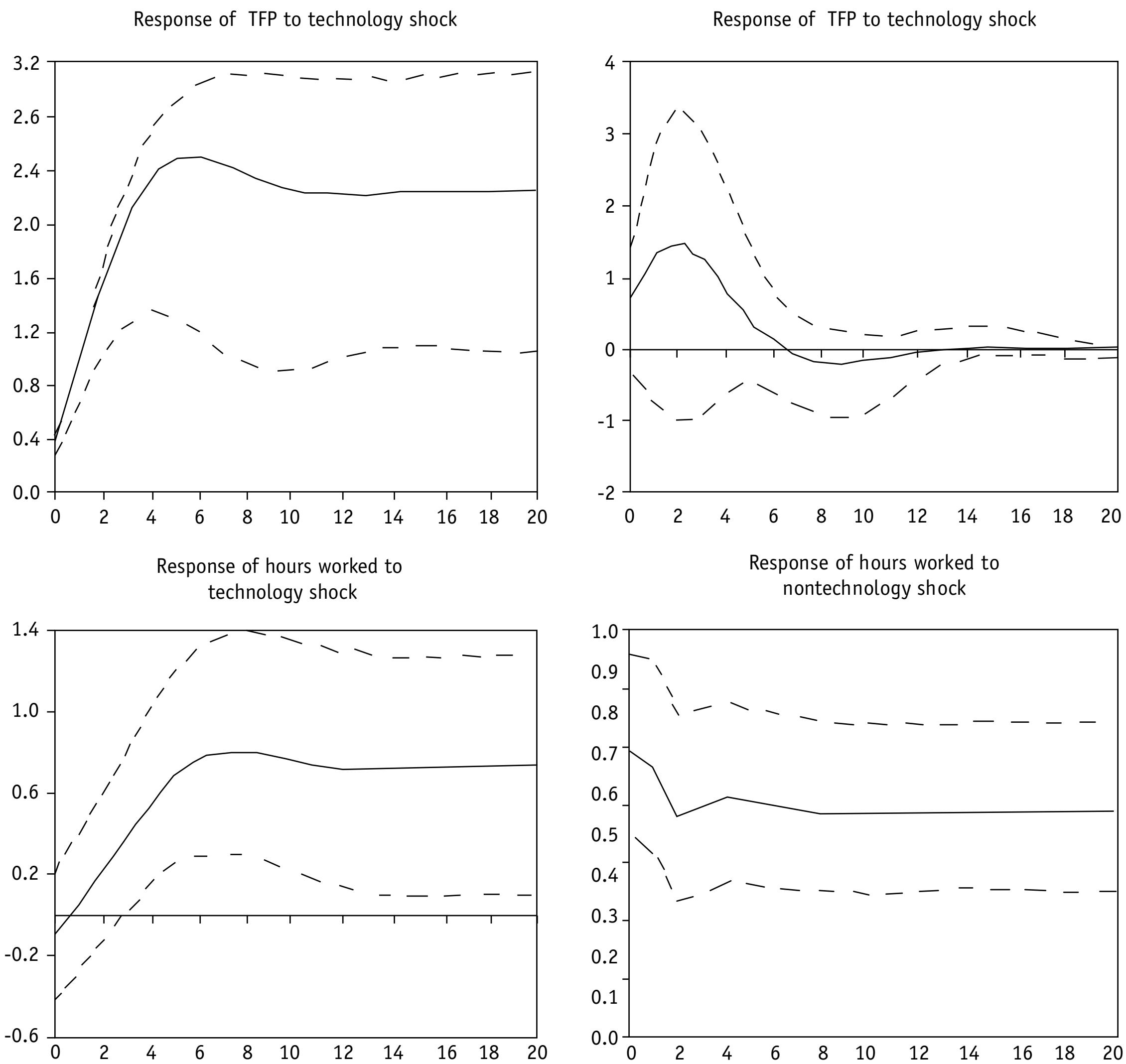
where ΔS_t and Δh_t denote TFP growth and hours worked growth, respectively, and ε_t^s and ε_t^h denote technology and nontechnology shocks, respectively. The standard errors are in parentheses, and zero is the restriction used to identify technology shocks.

The statistically significant and positive coefficients suggest that productivity and hours worked permanently increases under favorable technology shocks. The results also imply that hours worked increases in the long run under nontechnology shocks. Our finding of technology shocks permanently raising hours worked lends empirical support to the RBC argument that technology shocks play a major role in short-run business fluctuations by raising both output and employment.

Figure 2 shows the impulse response of the bivariate model after we replaced labor productivity with TFP as our measure of productivity. Hours worked did not show a positive and significant response to a positive technology shock until the second quarter, but increased steadily thereafter, peaking in the fifth quarter and settling into its new steady-state level after six quarters. The effect of positive nontechnology shock on TFP was statistically insignificant, even in the short run. This result is consistent with the assumption that TFP is statistically orthogonal with nontechnology shocks such as demand or mark-up shocks, even in the short run. All other results, including the permanent increase in TFP to higher levels, are qualitatively similar to the results we obtained using labor productivity instead, and consistent with economic theory.[7]

[7] Technology shocks can have a permanent effect on productivity because the level of the TFP is an unstable time series with a unit root.

Figure 2
Cumulative Impulse Responses of Total Factor Productivity and Hours Worked to Technology and Nontechnology Shocks in Korea, 1985–2002



The most striking difference between the two sets of results based on different productivity measures has to do with the response of hours worked to technology shocks. The response was positive and significant when we used TFP but negative and insignificant when we used labor productivity. It is possible to interpret the positive and significant response as empirical evidence supportive of real business cycles in Korea, since according to the RBC theory, technology shocks drive the business cycle through their positive impact on both output and employment.

As pointed out in the previous section, the estimated Solow residual may be an imperfect measure of TFP in the presence of cyclical effects. To eliminate the cyclical effects, we adjusted the Solow residual by using a composite index of business cycles and demand-related instrumental variables. We replaced the original Solow residual (TFP) with the adjusted Solow residual ($\overline{TFP}$), and reestimated the structural VAR. The identified coefficients are:

$$\begin{bmatrix} \Delta T_t \\ \Delta h_t \end{bmatrix} = \begin{bmatrix} \begin{matrix} 0.0146 \\ (0.0035) \end{matrix} & 0 \\ \begin{matrix} 0.0054 \\ (0.0024) \end{matrix} & \begin{matrix} 0.0076 \\ (0.0019) \end{matrix} \end{bmatrix} \begin{bmatrix} \varepsilon_t^T \\ \varepsilon_t^H \end{bmatrix} \tag{6}$$

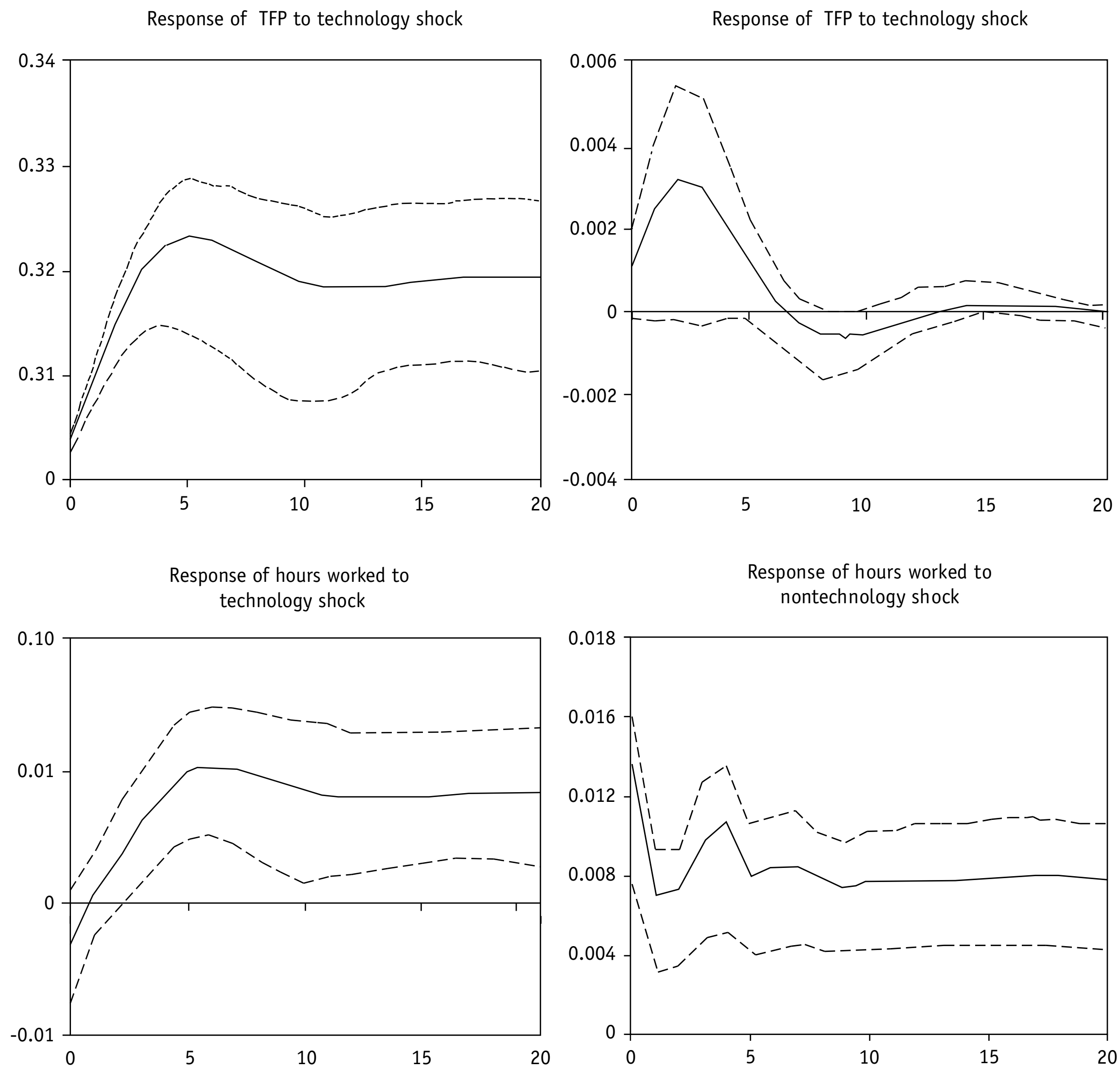
where ΔT_t and Δh_t denote $\overline{TFP}$ growth and hours worked growth, respectively, and ε_t^T and ε_t^H denote technology and nontechnology shocks, respectively.

Broadly speaking, the results for the adjusted $\overline{TFP}$ are qualitatively similar with the earlier results for the unadjusted TFP. Most significantly, the identified coefficients still imply a permanent rise in productivity and hours worked under positive technology shocks, and thus continue to provide evidence of a real business cycle. The results also suggest that hours worked increase permanently under a nontechnology shock.

Figure 3 shows the impulse responses of the bivariate model when we used the adjusted $\overline{TFP}$ as our measure of productivity. They are generally similar to the responses we obtained earlier when we used the unadjusted TFP as our productivity measure. Hours worked began to show a positive and significant response to positive technology shocks in the second quarter, and settled into its new steady-state level after ten quarters. We may interpret our results, which show the co-movement of output and employment, as lending support to the empirical validity of the RBC theory in the context of the Korean economy.[8]

[8] To check for the robustness of our structural VAR results, we also used impulse responses from the standard VAR with Cholesky factorization to construct the innovations. The estimation results are very similar to those from our structural VAR models.

Figure 3
Cumulative Impulse Responses of Adjusted Total Factor Productivity and Hours Worked to Technology and Nontechnology Shocks in Korea, 1985–2002



B. Trivariate Structural VAR Model and Its Results

So far we have used the bivariate structural VAR model of productivity and hours worked to investigate the impact of technology shock on employment in Korea. Our estimation results indicate that positive technology shocks raise both output and employment, and are thus consistent with the predictions of the RBC theory. The bivariate model lumped together all shocks other than technology shocks as nontechnology shocks. These include demand shocks such as monetary policy, fiscal policy or shifts in business confidence, mark-up shocks associated with changes in oil prices, other input prices or terms of trade, and labor supply shocks. Since it is unlikely that any of these diverse shocks affect productivity in the long run, the long-run restriction we use in our model remains appropriate.

Nevertheless, decomposing nontechnology shocks may be helpful for a more in-depth analysis. For example, dividing nontechnology shocks into labor supply shocks and price shocks allows us to analyze their effects on employment, output, and prices. Price shocks generally reflect demand shocks. We now expand our bivariate model into the following trivariate model:

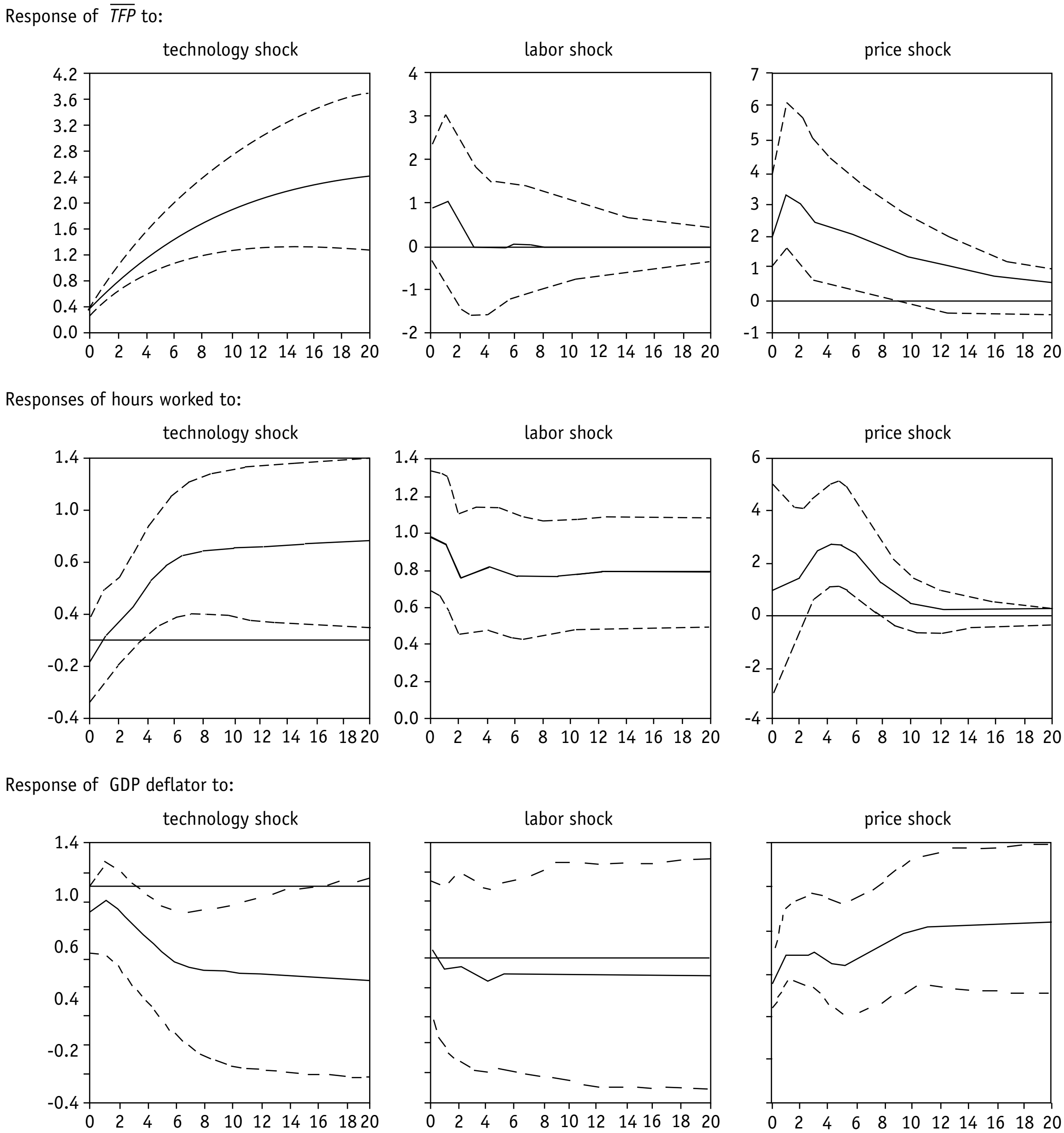
$$\begin{bmatrix} \Delta T_t \\ \Delta h_t \\ \Delta p_t \end{bmatrix} = \begin{bmatrix} C_{11}(1) & C_{12}(1) & C_{13}(1) \\ C_{21}(1) & C_{22}(1) & C_{23}(1) \\ C_{31}(1) & C_{32}(1) & C_{33}(1) \end{bmatrix} \begin{bmatrix} \varepsilon_t^T \\ \varepsilon_t^H \\ \varepsilon_t^P \end{bmatrix} \tag{7}$$

where ΔT_t, Δh_t, and Δp_t denote adjusted $\overline{TFP}$ growth, hours worked growth, and GDP deflator growth, respectively, and $\Delta\varepsilon_t^T$, $\Delta\varepsilon_t^H$, and $\Delta\varepsilon_t^P$ denote technology shock, labor supply shock, and price shock, respectively. $C(1)$ represents the long-run multipliers of the shocks on the endogenous variables.

Identifying the trivariate structural VAR model requires three additional restrictions, along with symmetry and normalization conditions of the covariance matrix of error terms, $\Omega = Var(\varepsilon_t)$. We adopted the long-run restrictions of Blanchard and Quah (1989). First, we retain our earlier restriction that only technology shock can affect productivity in the long run. This means that labor supply shock and price shock have no impact on long-run productivity, i.e., $C_{12}(1)=C_{13}(1)=0$. Second, demand or price shocks do not affect hours worked in the long run, implying the long-run restriction of $C_{23}(1)=0$.

Figure 4 below shows the impulse responses in the trivariate structural VAR model. In response to a positive technology shock, hours worked slightly fell at first, then started to rise within a quarter, peaking in the sixth quarter, and settling into its new steady-state level after ten quarters. In response to a positive labor supply shock, hours worked rose by about 1.5% at first, then fell before reaching its new equilibrium, about 0.8% higher than initially, after ten quarters. In response to a positive demand or price shock, which was assumed to have no long-run effect on hours worked and productivity, hours worked rose slightly at first but returned to its initial level after 2 years.

Figure 4
Cumulative Impulse Responses of Adjusted Total Factor Productivity ($\overline{TFP}$), Hours Worked, and Prices to Technology and Nontechnology Shocks in Korea, 1985–2002



GDP = gross domestic product.

In response to a positive demand shock, the GDP deflator increased rapidly for 12 quarters and kept increasing modestly thereafter. In contrast, the deflator fell in response to positive technology and labor supply shocks. Those who are skeptical about the empirical validity of real business cycles, including Gali (1999), have argued that technology and labor supply shock cannot affect the business cycle because nominal rigidity limits their impact on demand. However, our analysis of Korean data strongly suggests that technology and labor supply shocks affect prices, which supports the empirical relevance of the RBC theory for Korea.

Table 2 below reports the decomposition results of forecast error variances of the trivariate structural VAR model of adjusted TFP, hours worked and GDP deflator. For hours worked, labor supply shock explained about 40% of the forecast error variance in the early periods, but its impact gradually fell afterward, until it explained less than 10% of the variance. The proportion of variance in hours worked explained by technology shock was initially around 30%, but rose to more than 80% two years after the shock. Demand or price shock explained about 25% of the forecast error variance until one year after the shock, but the proportion rapidly fell thereafter, and almost disappeared after 5 years. Labor supply shock had a bigger impact than the price shock, even in the short run. For the GDP deflator, the price shock explained about 50–60% of the forecast error variance until 5 years after the shock. The labor supply and technology shocks jointly explain about 40% of the variance throughout.

Table 2
Decomposition of Forecast Error Variance of Adjusted Total Factor Productivity ($\overline{TFP}$), Hours Worked, and GDP Deflator for Korea, 1985–2002

	Horizon (Quarters)	Technology Shock	Labor Supply Shock	Price Shock
Total hours worked	0	24.2	50.1	25.7
	1	33.4	42.8	23.8
	2	42.7	35.6	21.7
	4	60.7	22.7	16.7
	8	86.4	7.4	6.2
	12	92.6	6.2	1.1
	20	92.4	6.6	1.0
$\overline{TFP}$	0	31.0	43.5	25.5
	1	47.1	39.6	13.3
	2	63.2	26.7	10.1
	4	66.9	23.4	9.7
	8	78.5	12.9	8.6
	12	83.9	8.8	7.2
	20	86.3	8.3	5.4
GDP deflator	0	13.1	24.9	62.1
	1	14.2	25.8	60.0
	2	15.4	26.7	57.8
	4	18.5	27.7	53.8
	8	25.1	25.3	49.6
	12	28.0	20.6	51.4

GDP = gross domestic product.

All in all, our results indicate that labor supply and technology shocks can explain much of the Korean business cycle, both in the short run and the long run. This is because our results indicate that the two supply-side shocks jointly account for a large part of both output and price fluctuations in Korea. On the other hand, our evidence indicates that demand shocks affect prices but have only a limited impact on output.

IV. CONCLUDING REMARKS

According to the real business cycle theory, the business cycle is driven largely by technology shocks rather than the traditional Keynesian demand shocks associated with macroeconomic policy or business confidence. A major empirically testable prediction of the RBC theory is a positive relationship between productivity and employment. A substantial empirical literature initiated by Gali (1999) finds that productivity-enhancing technology shocks reduced employment in the US and other developed countries. Although a number of studies challenge the robustness of this literature, the balance of evidence seems more supportive of a negative relationship than a positive relationship. This has cast serious doubt on the empirical validity of the RBC theory among many economists.

In this paper, we reexamined the relationship between productivity-enhancing technology shocks and employment using quarterly Korean data. More specifically, we used a bivariate structural VAR model of productivity and hours worked with two types of shocks, technology and nontechnology, along with the long-run restriction that nontechnology shocks cannot permanently affect productivity. Our empirical results show a negative but insignificant effect of positive technology shocks on hours worked when we used labor productivity as the measure of productivity. However, when we used TFP instead of labor productivity as our productivity measure, we found that technology shocks had a significant positive effect on hours worked, which lends support to the presence of a real business cycle. We were able to replicate this finding when we adjusted our measure of TFP, the Solow residual, to control for cyclical effects. Significantly, in a study of the US manufacturing sector, which produced qualitatively similar results as our study, Chang and Hong (2006) also use TFP rather than labor productivity and find that positive TFP shocks increase employment.

We then added another variable, overall price level, to expand our bivariate model to a trivariate model of productivity, hours worked, and GDP deflator. We divide nontechnology shocks into labor supply shocks and demand or price shocks. Our empirical results reconfirm a positive effect of productivity-enhancing technology shocks on hours worked. They also suggest that the two supply-side shocks (technology shocks and labor supply shocks) jointly account for a large part of the fluctuations in both output and prices, both in the short run and long run, and thus help to explain much of the Korean business cycle. On the other hand, while demand shocks seem to have a big impact on prices, their impact on output is very limited. All in all, in the case of Korea, our findings lend support to the RBC notion that supply-side shocks drive the business cycle.

A significant contribution of our study to the literature is the use of data from a developing country to look at the relationship between productivity-enhancing technology shocks and employment, and the broader issue of the empirical validity of the RBC theory. The overwhelming majority of the literature on these issues is based on data from the US and other developed countries. This is perfectly understandable in light of the fact that developing countries typically accord a much higher priority to achieving higher long-run growth rather than smoothening out the business cycle.

However, in the wake of the Asian crisis, understanding the sources of macroeconomic fluctuations has become more relevant for developing countries. Furthermore, there is no theoretical reason why technology shocks should have a smaller impact on the business cycle in developing countries than in developed countries. On the contrary, technology shocks may be relatively more important for developing countries due to their technological backwardness. The short-run and long-run impact of the information technology revolution on the Indian economy is a well-known case in point.

We hope that the analysis in this paper will contribute meaningfully to the very limited literature on the empirical validity of the RBC theory in developing countries, and inspire researchers to pursue the same topic with data from other developing countries in the future. At a broader level, such studies will help developing-country policymakers better understand the forces behind the business cycles of their respective countries and thus provide useful policy guidance. For example, in the case of Korea, our results imply that policymakers should give higher priority to institutional and structural supply-side policies that promote technological progress and innovation. Further, our findings, along with those of Chang and Hong (2006), suggest that future studies that look at the impact of productivity-enhancing technology shocks on employment should use TFP as well as labor productivity for a more comprehensive and robust empirical analysis of the productivity–employment relationship.

APPENDIX

APPENDIX TABLE A.1
UNIT ROOT TESTS OF KEY VARIABLES

	ADF		PHILLIPS-PERRON		KPSS	
	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)
ln(LPD)	-1.72	6.35***	-1.26	-13.63***	1.29***	0.19
ln(TFP)	-2.59*	-5.74***	-2.28	-3.15**	1.25***	0.43*
ln(hour)	-1.45	-14.03***	-1.01	-22.64***	1.24***	0.20
ln(GDP)	-1.53	-9.58***	-1.46	-9.62***	1.29***	0.30
ln(DEF)	-1.59	-7.28***	-1.76	-7.21***	1.30***	0.10

***, **, and * denote rejection of the null hypothesis at the 1%, 5%, and 10% significance level, respectively.
ADF = augmented Dickey-Fuller; KPSS = Kwiatkowski, Phillips, Schmidt, and Shin.
Note: Test regressions contain a constant and a linear time trend, and lags of the dependent variable are chosen by Akaike Information Criterion, Schwarz Criterion, and Bayesian Information Criterion. The null hypothesis is the existence of unit root for ADF and Phillips-Perron tests, and the nonexistence of unit root for KPSS test.

APPENDIX TABLE A.2
JOHANSEN'S LOG LIKELIHOOD TEST FOR COINTEGRATION

Labor productivity, hours worked

NUMBER OF CE(S)	EIGENVALUE	TRACE ST.	5% CRITICAL	MAX-EIGEN ST.	5% CRITICAL
None	0.149	19.72	25.32	14.18	18.96
At most 1	0.061	5.55	12.25	5.546	12.25

Total factor productivity, hours worked

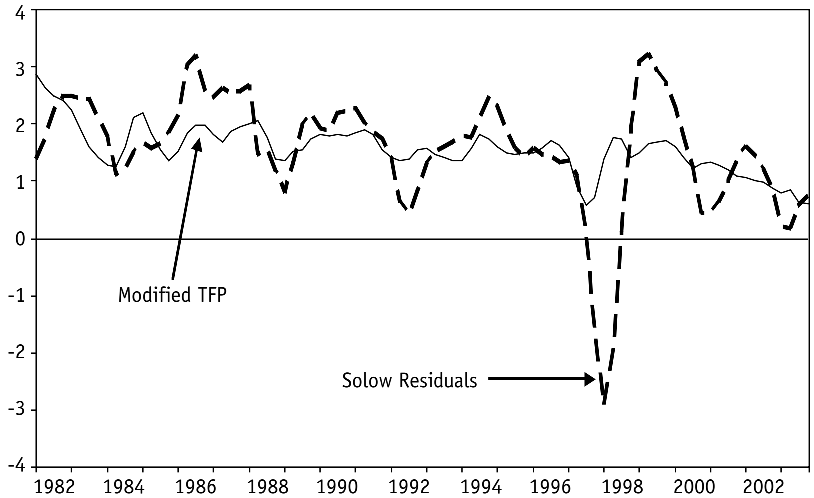
NUMBER OF CE(S)	EIGENVALUE	TRACE ST.	5% CRITICAL	MAX-EIGEN ST.	5% CRITICAL
None	0.116	17.19	25.32	11.93	18.96
At most 1	0.063	5.96	12.25	5.96	12.25

Total factor productivity, hours worked, GDP deflator

NUMBER OF CE(S)	EIGENVALUE	TRACE ST.	5% CRITICAL	MAX-EIGEN ST.	5% CRITICAL
None	0.227	36.70	42.44	23.39	25.54
At most 1	0.091	13.31	25.32	8.71	18.96
At most 2	0.049	4.60	12.25	4.60	12.25

Note: Test regression includes a constant and a linear deterministic trend in the data. The test indicates zero cointegrating equation at the 5% significance level for each set of variables.

Appendix Figure A.1
Growth of the Solow Residual and Cyclically Adjusted TFP (percent)



TFP = total factor productivity.
Note: To eliminate cyclical effects from the measured Solow residual, we regressed the log differences of the measured Solow residual on the log differences of the composite index (CI) for business cycles. We then adjusted the averages of the regression error terms to equal the original productivity measures, after controlling for cyclical effects. To address the endogeneity problem, we used the generalized method of moments with 1- and 2-period-lagged CI as well as M2 and 1-period-lagged M2 growth as instruments.

REFERENCES

Ball, L., and R. Moffitt. 2001. Productivity Growth and the Phillips Curve. NBER Working Paper No. 8421, National Bureau of Economic Research, Massachusetts.

Basu, S., and M. Kimball. 1997. Cyclical Productivity with Unobserved Input Variation. NBER Working Paper No. 5915, National Bureau of Economic Research, Massachusetts.

Basu, S., J. Fernald, and M. Kimball. 2006. "Are Technology Improvements Contractionary?" *American Economic Review* 96:1418–48.

Blanchard, O., and D. Quah. 1989. "The Dynamic Effects of Aggregate Demand and Supply Disturbances." *American Economic Review* 79(4):655–73.

Carmichael, B., S. Keita, and L. Samson. 1999. "Liquidity Constraints and Business Cycles in Developing Economies." *Review of Economic Dynamics* 2(2):370–402.

Chang, Y., and J. Hong. 2006. "Do Technological Improvements in the Manufacturing Sector Raise or Lower Employment?" *American Economic Review* 96(1):352–68.

Chang, Y., A. Hornstein, and P. Sarte. 2006. Understanding How Employment Responds to Productivity Shocks in a Model with Inventories. Federal Reserve Bank of Richmond Working Paper 06-06, Richmond, VA.

Christiano, L., M. Eichenbaum, and R. Vigfusson. 2003. What Happens After a Technology Shock? NBER Working Paper No. 9819, National Bureau of Economic Research, Massachusetts.

Chyi, Y. 1998. "Business Cycles Between Developed and Developing Economies." *Review of International Economics* 6(1):90–104.

Dedola, L., and S. Neri. 2004. What Does A Technology Shock Do? A VAR Analysis with Model-based Sign Restrictions. CEPR Discussion Paper No. 4537, Centre for Economic Policy Research, London.

Faust, J. 1998. The Robustness of Identified VAR Conclusions about Money. International Finance Discussion Paper 610, Board of Governors of the Federal Reserve System, Washington, DC.

Francis, N., and V. A. Ramey. 2005. "Is the Technology-Driven Real Business Cycle Hypothesis Dead? Shocks and Aggregate Fluctuations Revisited." *Journal of Monetary Economics* 52:1379–99.

Francis, N., M. Owyang, and A. Theodorou. 2003. "The Use of Long-run Restrictions for the Identification of Technology Shocks." *Federal Reserve Bank of St. Louis Review* 85:53–66.

Gali, J. 1999. "Technology, Employment and the Business Cycle: Do Technology Shocks Explain Aggregate Fluctuations?" *American Economic Review* 89:249–71.

———. 2004. "On the Role of Technology Shocks as a Source of Business Cycles: Some New Evidence." *Journal of the European Economic Association* 2:372–80.

Gali, J., and P. Rabanal. 2004. Technology Shocks and Aggregate Fluctuations: How Well Does the RBC Model Fit Postwar U.S. Data? NBER Working Paper No. 10636, National Bureau of Economic Research, Massachusetts.

Hall, R. 1989. Invariance Properties of Solow's Productivity Residual. NBER Working Paper No. 3034, National Bureau of Economic Research, Massachusetts.

Holzl, W., and A. Reinstaller. 2004. The Impact of Technology and Demand Shocks on Structural Dynamics: Evidence from Austrian Manufacturing. MERIT-Infonomics Research Memorandum Series 2004-015, The Netherlands.

Kiley, M. 1998. "Labor Productivity in U.S. Manufacturing: Does Sectoral Comovement Reflect Technology Shocks?" Board of Governors of the US Federal Reserve System, Washington, DC. Unpublished.

Kim, S., and H. Lim. 2004. "Does Solow Residual for Korea Reflect Pure Technology Shocks?" Paper presented at the Far Eastern Meeting of the Econometric Society, 1 July, Seoul.

Mankiw, N. 1989. "Real Business Cycles: A New Keynesian Perspective." *Journal of Economic Perspectives* 3:79–90.

Masih, A., and R. Masih. 1995. "Temporal Causality and the Dynamic Interactions among Macroeconomic Activity within a Multivariate Cointegrated System: Evidence from Singapore and Korea." *Weltwirtschaftliches Archiv* 131(2):265–85.

McGrattan, E. 2004. Comments on Gali and Rabanal's "Technology Shocks and Aggregate Fluctuations: How Well Does the RBC Model Fit Postwar US Data?" Federal Reserve Bank of Minneapolis Staff Report 338, Minnesota.

Mendoza, E., and K. Smith. 2006. "Quantitative Implications of a Debt-Deflation Theory of Sudden Stops and Asset Prices." *Journal of International Economics* 70(1):82–114.

Park, H. 2000. "Trade and Real Business Cycles in a Small Open Economy: The Case of Korea." *Bank of Korea Economic Papers* 3(2):135–63.

Peersman, G., and R. Straub. 2004. Technology Shocks and Robust Sign Restrictions in a Euro Area Structural VAR. European Central Bank Working Paper No. 373, Frankfurt.

Shea, J. 1999. "What Do Technology Shocks Do?" In *NBER Macroeconomics Annual 1998*. Cambridge: MIT Press.

Uhlig, H. 2004. "Do Technology Shocks Lead to a Fall in Total Hours Worked?" *Journal of the European Economic Association* 2(2–3):361–71.

Yoon, J. 2006. "International Real Business Cycle Model with Human Capital and Skill Acquisition Activities." *Journal of the Korean Economy* 7(2):253–76.

About the Paper

Sangho Kim, Hyunjoon Lim, and Donghyun Park find that productivity-enhancing technology shocks have a significant positve effect on employment in the Republic of Korea. Their evidence also indicates that technology shocks can explain fluctuations in output and prices, both in the short run and long run, but demand shocks can only explain price fluctuations. This suggests an expanded role for supply-side policies that promote technological progress and innovation.

About the Asian Development Bank

ADB's vision is an Asia and Pacific region free of poverty. Its mission is to help its developing member countries substantially reduce poverty and improve the quality of life of their people. Despite the region's many successes, it remains home to two thirds of the world's poor. Nearly 1.7 billion people in the region live on $2 or less a day. ADB is committed to reducing poverty through inclusive economic growth, environmentally sustainable growth, and regional integration.

Based in Manila, ADB is owned by 67 members, including 48 from the region. Its main instruments for helping its developing member countries are policy dialogue, loans, equity investments, guarantees, grants, and technical assistance. In 2007, it approved $10.1 billion of loans, $673 million of grant projects, and technical assistance amounting to $243 million.

Asian Development Bank
6 ADB Avenue, Mandaluyong City
1550 Metro Manila, Philippines
www.adb.org/economics
ISSN: 1655-5252
Publication Stock No.

Printed in the Philippines