Structural Change in the Trend and Cycle in Korea

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On the basis of regression of consumption on output, we develop a new approach to identify a structural break in business cycles. Using this approach, we find that a structural change in the trend and cycle in Korea occurred in 1993 and that the business cycles in Korea started to show the regularities of emerging market business cycles beginning in 1993. To explain these, we estimate the parameters of the productivity process in Korea, using data on Solow residuals. Our estimates show that the relative importance of trend growth shocks in the post-break period increased by a factor of 2.56 from that in the pre-break period.

Keywords: Structural change, Consumption volatility, Trend growth shocks

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I. Introduction

Since the beginning of the 21st century, economists have paid close attention to differences in business cycle regularities observed between emerging markets and developed countries (Neumeyer and Perri 2005; Aguiar and Gopinath 2007). Emerging market business cycles have two key features: consumption being more volatile than output and strongly countercyclical net exports. Specifically, Aguiar and Gopinath (2007) report that business cycles in Korea showed these features over the period 1980-2003.

The less well-known fact regarding Korea is that business cycle regularities observed in emerging markets have stood out in Korea since the early 1990s. Figure 1 depicts this experience by showing consumption volatility relative to output volatility. Fluctuations in consumption have become greater than or equal to those in output since the early 1990s. The actual historical experience is also revealed in Figure 2, which shows Hodrick-Prescott (HP)-filtered real GDP and net exports over GDP from the first quarter of 1980 to the last quarter of 2016. During this period, net exports were countercyclical; however, net exports have become strongly countercyclical since the early 1990s. In mid-1990s, Korea became a developed country with the World Bank high-income classification in 1995 and membership in the Organization for Economic Cooperation and Development (OECD) in 1996. As such, Korean business cycles showing key features as in developing countries over the same period is puzzling. Thus, the goals of this study are to detect exactly when the business cycle regularities of emerging markets began to appear in Korea and to explain the reason for this change.

The first contribution of this study is the development of a regression-based approach to identify a structural break using changing patterns of relative volatility of consumption to output. As consumption becomes more volatile than output, net exports tend to be more countercyclical, because consumption is procyclical, and net exports are equal to output minus consumption, investment, and government spending. Since these two key features of emerging market business cycles are connected, we can identify a structural break using a sudden change in the relative volatility of consumption to output. We consider a simple regression of HP-filtered consumption on HP-filtered output, which helps us express the relative volatility of consumption to output as the ratio of the regression coefficient to the square root of the coefficient of determination, R-squared. If this ratio becomes greater than unity, it means that the consumption is more volatile than output. Since the coefficient of determination is between zero and one, we can capture a structural break using an abrupt increase in the regression coefficient. This is indeed what happened in Korea in the early 1990s. We then use Bai (1997)'s method to find a structural break date in the sample period 1980–2016. Our finding suggests that HP-filtered consumption started to be more volatile than output in 1993.

The second contribution of this study is in showing that the structural break in 1993 is due to the rising importance of shocks to the trend growth of the total factor productivity (TFP) in Korea. Following Aguiar and Gopinath (2007), we propose that the rising volatility in trend growth drives the increase in the relative consumption volatility of Korea since 1993. To confirm this, we estimate the parameters of the productivity process in Korea, using data on Solow residuals. We find that variations in trend growth explain roughly 70% of the fluctuations in TFP growth after 1993, more than double the percentage before that year.

This study first relates to the literature that explains the difference in business cycle regularities between developed and developing countries. Aguiar and Gopinath (2007) show that compared with that of developed countries, the greater importance of trend growth shocks to productivity in developing countries causes the greater volatility of consumption relative to that of output. Neumeyer and Perri (2005) find that the countercyclical borrowing premium shocks and financial frictions in developing economies raise the volatilities of consumption and output. Alvarez-Parra *et al.* (2013) claim that countercyclical borrowing premium shocks raise the volatility of durable goods consumption, which increases the relative consumption volatility in emerging markets. Restrepo-Echavarria (2014) and Chen *et al.* (2018) focus on the greater importance of the informal economy or home production in developing countries relative to developed economies. In emerging markets, consumers can substitute goods produced in the informal economy or at home for those produced in the formal economy or markets, raising the relative volatility of consumption to output. This study focuses on business cycles in Korea, which experienced a rapid transition from a developing country to a developed one. We first develop a new method to identify a structural break in business cycles. Using this method, we find that there was a structural change in the trend and cycle in Korea in 1993. Then, we show that the importance of trend growth shocks to productivity increased since 1993 and that this raised the relative volatility of consumption to output in Korea.

This study also contributes to the literature on business cycles in Korea. Using data before the mid-1990s, Kim and Choi (1997), and Kim and Ahn (2005) find that business cycles in Korea resemble those in developed countries. On the other hand, using data from 1987 to 2013, Rhee (2017) shows that the business cycles in Korea are similar to those in developing countries. Unlike the previous studies, we find that Korean business cycles have featured the business cycle regularities observed in developing countries since 1993 and that there was a structural change in the trend and cycle in Korea in 1993.

The paper is organized as follows. In the next section, we describe the data sources and variable construction and then present stylized facts about business cycles in Korea. Section III presents our main results on the structural break in the trend and cycle of productivity in Korea, while Section IV concludes.

II. Korean Business Cycles

This section begins our analysis by documenting the Korean business cycle from the first quarter of 1980 to the last quarter of 2016 and by introducing a new method to identify the timing of a structural break in the relative consumption volatility. With this method, we show how the economic fluctuations of the two neighboring regimes surrounding the break differ.

To document the stylized facts of Korean business cycles, we obtain data from OECD national accounts.[1] Each series in 2010 U.S. dollars is quarterly and spans the period from the first quarter of 1980 to the fourth quarter of 2016. After implementing the Census Bureau's X-12 ARIMA program to deseasonalize the series, we use both the HP-filtered series with a smoothing parameter value of 1,600 and the first

[1] Due to the measurement issues associated with a currency unit and a seasonal adjustment program, we calculate the same set of business cycle moments using data from the Bank of Korea (BOK). Each series in 2015 Korean won is seasonally adjusted by the BOK-X-12 ARIMA program, which considers Korean holidays. Results in Appendix 2 show that the empirical regularities are robust.

difference of the unfiltered series (growth rates) to compute business cycle moments.

The three features of business cycle regularities in emerging market economies are consumption being more volatile than output, strongly countercyclical net exports, and sudden stops (Aguiar and Gopinath 2007; Neumeyer and Perri 2005). Table 1 and Figure 2 illustrate that Korean business cycles have these features during the period from the first quarter of 1980 to the fourth quarter of 2016.

The first column of Table 1 reports business cycle moments in the full sample period (1980–2016), and two of the features are noticeable. First, in the data, consumption volatility exceeds output volatility at business cycle frequencies (1.36). Second, the data suggest that Korea has experienced a negative contemporaneous correlation of net exports and output; however, the correlation is moderate, with correlations of −0.26 in filtered log output and of −0.35 in the growth rate of output.

The sudden stop phenomenon is associated with a dramatic and large reversal in net capital inflows. Figure 2 plots the ratio of net exports to output and filtered log output. The most striking feature is the abrupt and large increases in the ratio in 1997 and 2008. This reflects the Asian financial crisis and the global financial crisis, respectively.

A. Structural Change in Relative Consumption Volatility

We start with looking at patterns in relative consumption volatility over time. The top panel of Figure 1 plots HP-filtered log consumption and log output. A brief glance at the figure suggests that consumption is more volatile than output in the period after the early 1990s.[2]

Before we develop an approach to capture the structural break in relative consumption volatility, let's step back and ask a fundamental question: Why is consumption volatility greater than that of output in the past two decades? The permanent income hypothesis (PIH) provides an answer to this question. According to the PIH, changes in consumption depend primarily on changes in permanent income. If a large fraction of fluctuations in income came from changes in

[2] Lee (2009) reports that output and consumption were both more volatile in the 1970s than in the 1980s. However, the relative volatility of consumption to output was below unity (0.66) in the 1970s.

permanent income, consumption would respond strongly to changes in income. On the other hand, if income fluctuations came from changes in transitory income, consumers would spread out these income changes over time by adjusting savings to smooth consumption. This logic can explain the small consumption volatility relative to output volatility before the early 1990s.

Motivated by the prediction of the PIH, we consider the following regression to detect more precisely when the pattern in volatility of consumption relative to output changes:

$$\tilde{c}_t = \alpha + \beta \tilde{y}_t + e_t, \tag{1}$$

where $\tilde{c}_t$ and $\tilde{y}_t$ denote HP-filtered log consumption and log output, respectively. If this structure is not a bad approximation, relative consumption volatility can be represented by the regression coefficient β and the square root of R-squared as follows:[3]

$$\frac{\sigma(\tilde{c}_t)}{\sigma(\tilde{y}_t)} = \frac{\beta}{R}. \tag{2}$$

Equation (2) gives us an idea about how to detect a structural break in relative consumption volatility. Values of β, greater (less) than those of R, imply consumption volatility being greater (less) than output volatility. When β is greater than unity, it is a special case. If this is the case, consumption is always more volatile than output because R is limited to an upper bound of unity and changes in the same direction as β.

The special case is useful to identify a structural break in relative consumption volatility in our case. It is generally difficult to detect an abrupt change in the ratio of β to R; however, Table 2 shows that it would be enough to see whether there was an abrupt shift in β to determine a structural break at an unknown point in the early 1990s. The estimated β over R is 0.45 in the 1980s with a regression coefficient of 0.21; it rises to 1.50 in the 1990s with a sharp rise in the estimated

[3] Equation (2) is directly derived from the regression considered. Taking the variance on both sides of the regression equation (1), $\sigma^2(\tilde{c}_t) = \beta^2\sigma^2(\tilde{y}_t) + \sigma^2(e_t)$. Since $R^2 = 1 - \sigma^2(e_t)/\sigma^2(\tilde{c}_t)$, $\sigma^2(\tilde{c}_t)(1 - \sigma^2(e_t)/\sigma^2(\tilde{c}_t)) = \beta^2\sigma^2(\tilde{y}_t)$ becomes $\sigma^2(\tilde{c}_t)R^2 = \beta^2\sigma^2(\tilde{y}_t)$. Dividing both sides by $\sigma^2(\tilde{y}_t)R^2$ and taking the square root, we have $\sigma(\tilde{c}_t)/\sigma(\tilde{y}_t) = \beta/R$.

regression coefficient (1.45).

To utilize this idea, we adopt Bai (1997)'s method to identify a structural break at an unknown point in the sample period 1980–2016 based on the following model:

$$\tilde{c}_t = (\alpha_1 + \beta_1 \tilde{y}_t)1(t \le m) + (\alpha_2 + \beta_2 \tilde{y}_t)1(t > m) + e_t, \tag{3}$$

where $1(t \le m)$ and $1(t > m)$ are the dummy variables that take values equal to one for dates until and after a specific date m, respectively. We first trim the top and bottom 10% of the sample. For each possible break date, we split the sample in line with the break date, estimate the regression coefficients, and compute the sum of squared residuals. The procedure is terminated by finding the break date that minimizes the sum of squared residuals. The break date is defined as follows:

$$\hat{m} = \arg \min_{t_1 \le m \le t_2} S(m),$$

where t_1 and t_2 are trimmed dates and $S(m) = (1/\mathrm{T})\sum_{t=1}^{T} \hat{e}_t(m)^2$.[4] Bai (1997) provides two kinds of asymptotic distributions of the estimated break date: when regressors and errors are homogeneous for the whole sample and when their distributions change at the estimated break date.[5] We consider both cases in this study.

We report results for equation (3) (labeled "HP-filtered series") for the full sample period 1980–2016 and for growth rates (labeled "Growth rates") over the same period. Table 3 presents parameter estimates,

[4] One of the modern approaches to determine a break date is to carry out a Sup test, also known as the Quandt Likelihood Ratio (QLR) test (Andrews 1993). Andrews (1993)'s idea is to find the break date at which the Wald statistics are maximized. The QLR estimate is equivalent to that obtained by minimizing the sum of squared residuals. The problem of the QLR test is that the asymptotic critical values are computed under the assumption that regressors are strictly stationary, which excludes structural changes. Hansen (2000) overcomes the problem by proposing the fixed regressor bootstrap, but this method is relevant only when errors are serially uncorrelated. We, therefore, follow Bai (1997)'s method for estimating a structural break because it provides the asymptotic distribution for the estimated break date even when regressors are not strictly stationary and errors are serially correlated.

[5] The confidence intervals for the estimated break dates are described in detail in Appendix 1.

R-squared, and implied relative consumption volatility (β/R) for these two models. For each parameter estimate, we also report two types 90% confidence intervals using the Newey–West (1987) covariance estimators: symmetric and skewed confidence intervals. The symmetric confidence interval comes from the assumption that regressors and errors have homogenous distributions for the whole sample, while the skewed confidence interval is derived from the assumption that regressors and errors have non-homogenous distributions.

For the HP-filtered series, we identify the first quarter of 1993 as the most likely date for the structural break associated with relative consumption volatility. Assuming non-homogenous data, the lower boundary of the skewed confidence interval is found to be the first quarter of 1992, and the upper boundary is the third quarter of 1994. The estimated break date straddles the lower and upper boundaries of the skewed confidence interval for the estimated break date in the "Growth rates" regression model (the fourth quarter of 1990 and the second quarter of 1995, respectively). On the other hand, the break date in the "Growth rates" model that we estimate is the fourth quarter of 1994, which is outside the 90% confidence interval for the break date in the "HP-filtered series" model. Hence, we choose the first quarter of 1993 as the structural break date at which the full sample is split into two sub-samples in this study.

We find evidence for non-homogenous responses of consumption to income. In the pre-break period from the first quarter of 1980 to the first quarter of 1993, the 90% confidence interval for the estimated slope coefficient lies far below unity, with a point estimate of 0.26. The number sharply rises to 1.44, with the 90% confidence interval lying well above unity, in the post-break period from the second quarter of 1993 to the last quarter of 2016. This result implies that consumption responded more strongly to changes in income in the post-break period than in the pre-break period; hence, consumption became more volatile than income after the break date. Our finding of non-homogenous responses of consumption still holds when we use growth rates instead of the HP-filtered series. The estimate of the slope coefficient is 0.09, and zero is inside the 90% confidence interval in the first sub-sample period. The estimate, on the other hand, is large—around 1.28 in the second sub-sample period.

B. Changes in Business Cycles

This subsection presents changes in Korean business cycle moments. In order to look into changes in the business cycle moments in Korea, we divide the dataset into two sub-periods based on the structural break date obtained from the previous subsection. The first sub-sample ranges from the first quarter of 1980 to the first quarter of 1993. The period of the crisis and its aftermath is captured through the second sub-sample period spanning from the second quarter of 1993 to the fourth quarter of 2016.

The second column of Table 1 reports results for the first sub-sample. We find that business cycles in Korea show the empirical regularities of those in developed economies in the pre-break period. The data suggest that consumption is less volatile than output (0.51) and that net exports are acyclical, with a correlation of -0.03. These features stand in contrast with the well-documented regularities of business cycles in emerging market countries.

The third column of Table 1 presents that the Korean economy experiences relatively volatile consumption at business cycle frequencies as compared to output (1.55). It also shows that the Korean economy exhibits strongly countercyclical trade balances in the post-break period (-0.36). These features do not change when we compute the same moments using growth rates.

These distinct patterns of business cycles between the two sub-samples indicate that a structural change may exist in the trend and cycle in Korea. Aguiar and Gopinath (2007) highlight the role of trend growth shocks to productivity in explaining the characteristics of emerging market business cycles. In line with the literature, we focus on a change in the importance of trend growth shocks to productivity over time as a source of the different patterns of economic fluctuations in Korea.

III. Trend and Cycle in Productivity

This section begins by describing the data sources used for the construction of Solow residuals. We then present empirical findings on how the importance of trend growth shocks to productivity has changed over time.

A. Construction of Solow Residuals

In order to calculate the Solow residuals, we measure labor input as the total number of employed workers (employed population aged 15 and over), reported in the OECD Main Economic Indicator (MEI) database. The available labor series start from the first quarter of 1983.

The log of Solow residuals at time t is constructed as follows:

$$a_t = \log Y_t - \alpha \log L_t - (1 - \alpha)\log K_t,$$

where Y_t denotes output, K_t is capital input, and L_t is labor input. The labor share α is set at 0.68, which is a standard value from the literature. To construct the capital stock series, we use the perpetual inventory method. The capital stock series are obtained according to the following recursion:

$$K_{t+1} = (1 - \delta)K_t + I_t,$$

where the depreciation rate of capital stock, $\delta = 0.05$. The initial capital stock for the first quarter of 1980 is calculated as $I_{1980Q1}/(\delta + \mu_I)$, where μ_I is the quarterly average growth rate of investment for 1980-2016. For the labor input series, we remove a seasonal component using X-12 ARMA. The resulting Solow residuals are the quarterly series spanning the period from the first quarter of 1983 to the last quarter of 2016.

B. Empirical Model and Estimation

Following Aguiar and Gopinath (2007), we assume that the log of Solow residuals a_t has two independent stochastic components: cycle z_t and trend x_t components,

$$a_t = x_t + z_t \tag{4}$$

The persistence of the effect of a transitory shock on the cycle component is governed by an AR(1) process

$$z_t = \rho_z z_{t-1} + \varepsilon_{z,t},$$

where $|\rho_z| < 1$.

The stochastic trend component x_t is non-stationary, and its growth

s_t evolves according to an AR(1) process. In particular,

$$x_t = \mu + x_{t-1} + s_t,$$

$$s_t = \rho_s s_{t-1} + \varepsilon_{s,t},$$

where μ is its unconditional mean and $|\rho_s| < 1$. If $\rho_s = 0$, a trend growth shock $\varepsilon_{s,t}$ has a one-time effect on productivity growth, while it has a persistent effect on productivity growth if $\rho_s > 0$.

We assume the following distributions for the transitory and permanent shocks:

$$\begin{bmatrix} \varepsilon_{z,t} \\ \varepsilon_{s,t} \end{bmatrix} \sim i.i.d.\ N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_z^2 & 0 \\ 0 & \sigma_s^2 \end{bmatrix}\right),$$

where $\sigma_z > 0$ and $\sigma_s > 0$ for all t.

To estimate the structural parameters, μ, ρ_s, ρ_z, σ_s, and σ_z, we first take the first differences on both sides of equation (4) and then cast the model in state–space form. The state–space representation is given by

$$\Delta a_t = \mu + [1 \quad -1 \quad 1] \begin{bmatrix} z_t \\ z_{t-1} \\ s_t \end{bmatrix},$$

$$\begin{bmatrix} z_t \\ z_{t-1} \\ s_t \end{bmatrix} = \begin{bmatrix} \rho_z & 0 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & \rho_s \end{bmatrix} \begin{bmatrix} z_{t-1} \\ z_{t-2} \\ s_{t-1} \end{bmatrix} + \begin{bmatrix} 1 & 0 \\ 0 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \varepsilon_{z,t} \\ \varepsilon_{s,t} \end{bmatrix}.$$

Since the state vector $[z_t \quad z_{t-1} \quad s_t]'$ is stationary, the Kalman filter is initiated by setting the initial mean squared error matrix of the state vector equal to its unconditional covariance matrix. We then evaluate the log-likelihood function based on the prediction error decomposition. To find the parameters that maximize the log-likelihood function, the Broyden–Fletcher–Goldfarb-Shanno (BFGS) algorithm is conducted.

C. Empirical Results

We document how trend and cycle dynamics changed since 1983. Motivated by the PIH, we propose that trend growth shocks have grown in importance. Specifically, we argue that this substantial importance of trend growth shocks causes the relative consumption volatility to be greater than unity after 1993.

Table 4 presents parameter estimates and a measure of the relative importance of trend growth shocks for the pre-and post-break periods alongside the full sample period. As in Aguiar and Gopinath (2007), we determine the relative importance of the random walk component of the Solow residuals according to the following expression:[6]

$$\frac{\sigma_{\Delta x}^2}{\sigma_{\Delta a}^2} = \frac{\dfrac{\sigma_s^2}{1-\rho_s^2}}{\dfrac{\sigma_s^2}{1-\rho_s^2} + \dfrac{2\sigma_z^2}{1+\rho_z}}.$$

We find evidence for the distinct importance of trend growth shocks between the two sub-samples. Based on the estimates, the above ratio is 0.27 in the pre-break period but more than doubled at 0.69 in the post-break period.

In order to illustrate the change in the importance of trend growth shocks, we plot our estimates of the evolution of the trend growth and cycle process from each sample (Figure 3). The first feature of the figure is that cycle served an important role in explaining fluctuations in productivity in the first sub-sample; however, its importance declined after 1993, and trend growth dominated its counterpart. Second, trend growth on average remained high in the first sub-sample (0.93% per quarter) but then declined to 0.55% in the second sub-sample. Our estimates attribute much of the declined trend growth to large drops in trend during the Asian financial crisis of 1997 and the global financial crisis of 2008 and to the sluggish economy since 2010.

Both trend and cycle show different time-series patterns for the two sub-samples. In the pre-break period, we identify large but purely transitory variation in cycle and small variation in trend growth, which is consistent with the estimates of cycle and trend growth shocks in

[6] $var(\Delta a_t) = var(\Delta x_t) + var(\Delta z_t)$, where $var(\Delta x_t) = var(s_t) = \dfrac{\sigma_s^2}{1-\rho_s^2}$ and $var(\Delta z_t) = (\rho_z - 1)^2 var(z_{t-1}) + \sigma_z^2$. As $var(s_t) = \dfrac{\sigma_s^2}{1-\rho_s^2}$ and $var(z_{t-1}) = \dfrac{\sigma_z^2}{1-\rho_z^2}$, $var(\Delta x_t) = \dfrac{\sigma_s^2}{1-\rho_s^2}$ and $var(\Delta z_t) = \sigma_z^2\left(\dfrac{(\rho_z-1)^2}{1-\rho_z^2}+1\right) = \dfrac{2\sigma_z^2}{1+\rho_z}$. Hence, $var(\Delta a_t) = \dfrac{\sigma_s^2}{1-\rho_s^2} + \dfrac{2\sigma_z^2}{1+\rho_z}$.

Table 4. In the case of cycle, its persistence is estimated at almost zero, which means productivity reverts to trend following a transitory shock in a quarter. Such a positive, purely transitory shock acts as an incentive for households to increase savings to smooth consumption over time, whereas households consume more following a positive trend shock. The contribution of cycle to variation in productivity growth was larger by a factor of 2.70 than that of trend in the pre-break period, which explains why relative consumption volatility is less than unity.

The dominant role of the cycle component in explaining variation in productivity growth would also imply the negative autocorrelation of productivity growth in the pre-break period. This is because positive shifts in productivity caused by purely transitory shocks should be followed by negative shifts in productivity growth.[7] Table 5, which illustrates the variance ratio for productivity growth, confirms this assumption. The variance ratio is a simple way to quantify the persistence of time-series of interest. Cochrane (1998) defines it as the ratio of the variance of k-period productivity growth to one-period productivity growth divided by k:

$$VR_k = \frac{var(\Sigma_{j=0}^{k-1} \Delta a_{t-j})}{k \cdot var(\Delta a_t)}.$$

The second column of Table 5 reports variance ratios for the pre-break period. The variance ratio for productivity growth for 24 quarters is 0.71, below one, which indicates evidence for the negative autocorrelation of productivity growth.

We next examine the properties of trend and cycle in the post-break period. Trend growth is more volatile than cycle; however, cycle is more persistent than its counterpart. The fact that variation in trend growth explains roughly two-thirds of the movement of productivity growth is associated with the positive autocorrelation of productivity growth in the post-break period. The third column of Table 5 shows that the

[7] This assumption comes directly from the Wold representation of the empirical model considered: $\Delta a_t = \mu + (\varepsilon_{s,t} + \rho_s \varepsilon_{s,t-1} + \rho_s^2 \varepsilon_{s,t-2} + \dots) + (\varepsilon_{z,t} + (\rho_z - 1)\varepsilon_{z,t-1} + (\rho_z - 1)\rho_z \varepsilon_{z,t-2} + (\rho_z - 1)\rho_z^2 \varepsilon_{z,t-3} \dots)$. For simplicity, ignore trend growth shocks and assume $\rho_z = 0$ and $\mu = 0$. Then $\Delta a_t = \varepsilon_{z,t} - \varepsilon_{z,t-1}$, which implies that a positive, transitory shock at time $t - 1$ ($\varepsilon_{z,t-1} > 0$) results in a negative value of expected productivity growth at time t ($E_{t-1}[\Delta a_t] < 0$).

variance ratio for productivity growth for 24 quarters is 1.14, above one. If we choose a small lag length (*e.g.*, 2 quarters) to obtain a good approximation, the ratio is statistically significant and substantially above unity (1.27). These properties of productivity growth provide a key explanation as to why households make a considerable consumption change in response to output.

D. Remarks

In this subsection, we provide two possible explanations as to why permanent shocks to productivity have grown in prominence since 1993. For this purpose, we first focus on the openness of the economy. Figure 4 depicts trade openness and reported cases of foreign investment. Trade openness is measured as the sum of exports and imports as a share of GDP. Figure 4a shows that the trade-to-GDP ratio has been on a sharp rise since 1993. In addition, the Korean government launched a series of campaigns to open the capital market to foreign investors in 1992 and 1993, which facilitated foreign investment thereafter. This is illustrated in Figure 4b, which plots the reported cases of foreign investment from the U.S. and European countries. In 1993, there were 127 (108) reported cases of foreign investment from the U.S. (European countries). However, after 1993, investment from U.S. and European investors began to grow rapidly, and those figures reached 263 (183) in 1995, roughly double those in 1993.

Increasing openness seems to have contributed to the increasing importance of the trend growth shocks in Korea. The trade-to-GDP ratio, which has been on an upward trend since 1993, appears to have permanent impacts on productivity in Korea. Lileeva and Trefler (2010) show that high openness stimulates persistent competition and facilitates effective access to production inputs, which leads to productivity growth. On the other hand, higher openness seems to make the Korean economy more vulnerable to external shocks. Two major examples are the 1997 Asian financial crisis and the global financial crisis of 2008, which led to a massive outflow of foreign capital. The negative shocks had permanent impacts on the income level in Korea. We, therefore, attribute a structural change in the trend, more precisely the increasing importance of the trend growth shocks, to the consequence of increasing the openness of the Korean economy.

A second reason for this may be political polarization.[8] Azzimonti and Talbert (2014) argue that shifts in political philosophy tend to give rise to economic policy uncertainty, which is pronounced in emerging market countries. Indeed, Koreans directly elected the civilian president Young-Sam Kim in 1993, which brought 32 years of military rule to a close. Since the Presidential Election Act of 1987 was established, presidents have been directly elected to a single five-year term, and Korea has experienced higher levels of political polarization than it had before. Switches of policy ideology between left-wing and right-wing governments in Korea may change policies, for example, about the accumulation of both physical and human capital stocks on a regular basis, which affect the trend in productivity. These switches may have amplified variations in permanent shocks in Korea since 1993.

IV. Conclusion

We developed a regression identification approach to estimate the structural break in the relative consumption volatility in Korea, and the first quarter of 1993 was identified as the break point. Empirical evidence suggested that Korean business cycles featured the business cycle regularities observed in emerging markets in the post-break period. Motivated by Aguiar and Gopinath (2007), we quantified the importance of the trend component in productivity in both the pre- and post-break periods. Our finding was that time-series patterns of trend and cycle behaviors changed at the break point. Specifically, the cycle component played a dominant role in explaining fluctuations in productivity in the pre-break period, whereas the variations in productivity were largely attributed to the trend component in the post-break period.

We looked at two possible explanations for the finding, the openness of the economy and political polarization in Korea, but did not perform an in-depth analysis of them. It would be interesting to uncover the underlying reasons for the break in the trend and cycle. We leave this as a future research topic.

[8] Soh (1994) provides a review of the literature on the impacts of political frictions on business cycles.

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TABLE 1
KOREAN BUSINESS CYCLE MOMENTS

	Full sample 1980Q1–2016Q4	Pre-break 1980Q1–1993Q1	Post-break 1993Q2–2016Q4
Volatility of GDP			
$\sigma(\tilde{y})$	1.99	1.70	2.14
$\sigma(\Delta y)$	1.50	1.60	1.31
Relative volatility of consumption, investment, and net exports			
$\sigma(\tilde{c}) / \sigma(\tilde{y})$	1.36	0.51	1.55
$\sigma(\Delta c) / \sigma(\Delta y)$	1.12	0.42	1.47
$\sigma(\tilde{i}) / \sigma(\tilde{y})$	2.48	2.77	2.37
$\sigma(\Delta i) / \sigma(\Delta y)$	2.12	2.19	2.14
$\sigma(NX / Y)$	5.94	2.59	6.26
Correlation of net exports with GDP			
$p(NX / Y, \tilde{y})$	-0.26	-0.03	-0.36
$p(NX / Y, \Delta y)$	-0.35	0.19	-0.38

Note: Data are derived from the OECD. Lowercase letters denote logarithms of variables. Tildes denote HP-filtered series using smoothing parameter of 1,600. Δ denotes difference operator; that is, $\Delta y_t = y_t - y_{t-1}$.

TABLE 2
OLS REGRESSIONS OF FILTERED CONSUMPTION ON FILTERED OUTPUT

Period	α	β	R^2	β/R	$\hat{\sigma}(\tilde{c}_t)/\hat{\sigma}(\tilde{y}_t)$
1980-1989	-0.14	0.21	0.21	0.45	0.45
	(0.18)	(0.13)			
1990-1999	0.09	1.45	0.94	1.50	1.50
	(0.23)	(0.06)			
2000-2009	0.17	1.21	0.55	1.62	1.62
	(0.42)	(0.24)			
2010-2016	-0.01	0.55	0.27	1.06	1.06
	(0.11)	(0.19)			

Note: Newey-West (1987) standard errors are in parentheses. β/R denotes implied relative consumption volatility.

TABLE 3

ESTIMATED PARAMETERS AND CONFIDENCE INTERVALS

	HP-filtered series		Growth rates	
	Estimate	90% C.I.	Estimate	90% C.I.
m	1993Q1	[1992Q1, 1994Q3][a] [1992Q1, 1993Q4][b]	1994Q4	[1990Q4 1995Q2][a] [1992Q3 1997Q1][b]
	1980Q1–1993Q1		1980Q1–1994Q4	
α_1	-0.06	[-0.34, 0.23]	0.61	[0.38, 0.83]
β_1	0.26	[0.06, 0.45]	0.09	[-0.02, 0.20]
R_1^2	0.26		0.05	
β_1/R_1	0.51		0.43	
	1993Q2–2016Q4		1995Q1–2016Q4	
α_2	0.02	[-0.31, 0.35]	0.13	[-0.07, 0.33]
β_2	1.44	[1.33, 1.56]	1.28	[0.90, 1.66]
R_2^2	0.87		0.71	
β_2/R_2	1.55		1.52	

Note: "HP-filtered series" column reports parameter estimates of the following model: $\tilde{c}_t = (\alpha_1 + \beta_1 \tilde{y}_t)1(t \le m) + (\alpha_2 + \beta_2 \tilde{y}_t)1(t > m) + e_t$. "Growth rates" column is based on $(\Delta c_t - \hat{\mu}_c) = (\alpha_1 + \beta_1)(\Delta y_t - \hat{\mu}_y)1(t \le m) + (\alpha_2 + \beta_2)(\Delta y_t - \hat{\mu}_y)1(t > m) + e_t$. Confidence intervals for break date estimates $\hat{m}$ are constructed according to Bai (1997)'s method. We trim the top and bottom 10% from the data and employ Newey–West (1987) covariance estimators allowing for a lag of up to 4 (Bartlett kernel with bandwidth of 5).
[a] The skewed confidence interval is calculated on the assumption that distributions of ($\tilde{y}_t$, Δy_t, e_t) change at the estimated break date.
[b] The symmetric confidence interval is based on the assumption that ($\tilde{y}_t$, Δy_t, e_t) have homogeneous distributions for the entire sample.

TABLE 4
ESTIMATED PARAMETERS

	Full sample 1983Q1–2016Q4	Pre-break 1983Q1–1993Q1	Post-break 1993Q2–2016Q4
Parameter estimates			
μ	0.67	0.93	0.55
	(0.11)	(0.25)	(0.12)
ρ_s	0.33	0.62	0.36
	(0.24)	(0.28)	(0.20)
ρ_z	-0.33	-0.09	0.80
	(0.38)	(0.29)	(0.30)
σ_s	0.89	0.61	0.75
	(0.23)	(0.25)	(0.27)
σ_z	0.48	0.85	0.52
	(0.23)	(0.18)	(0.32)
Log likelihood			
LL	409.22	112.38	303.28
Relative importance of trend			
$\sigma^2_{\Delta x} / \sigma^2_{\Delta a}$	0.65	0.27	0.69

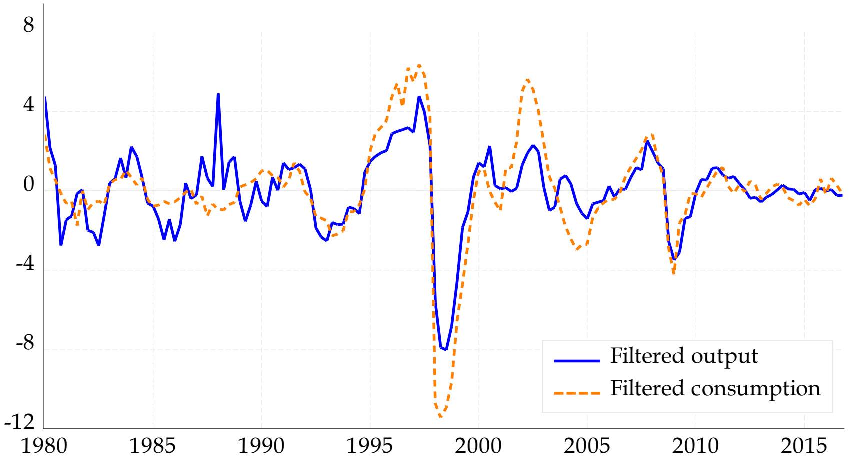
Note: Estimates of mean and standard deviations are reported in percentage terms. Numbers in parentheses are standard errors.

TABLE 5
VARIANCE RATIO TEST

	Full sample 1983Q1–2016Q4	Pre-break 1983Q1–1993Q1	Post-break 1993Q2–2016Q4
VR(2)	1.05	0.82	1.27
	(0.12)	(0.22)	(0.12)
VR(4)	1.16	0.90	1.45
	(0.21)	(0.36)	(0.23)
VR(8)	0.98	0.75	1.23
	(0.33)	(0.54)	(0.41)
VR(12)	0.94	0.90	1.04
	(0.40)	(0.64)	(0.51)
VR(24)	0.84	0.71	1.14
	(0.52)	(0.83)	(0.67)

Note: Heteroskedasticity robust standard errors are reported in parentheses.

A. HP-filtered output and consumption



B. Growth rates of output and consumption

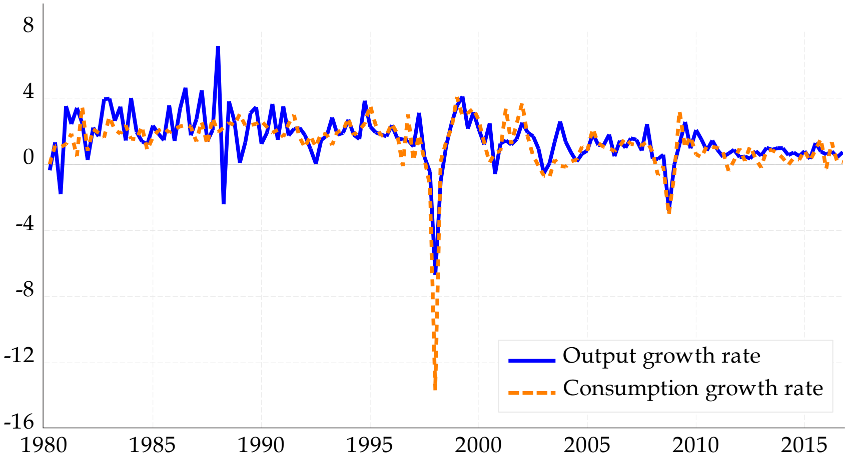


Figure 1
Real GDP and Consumption (1980–2016)

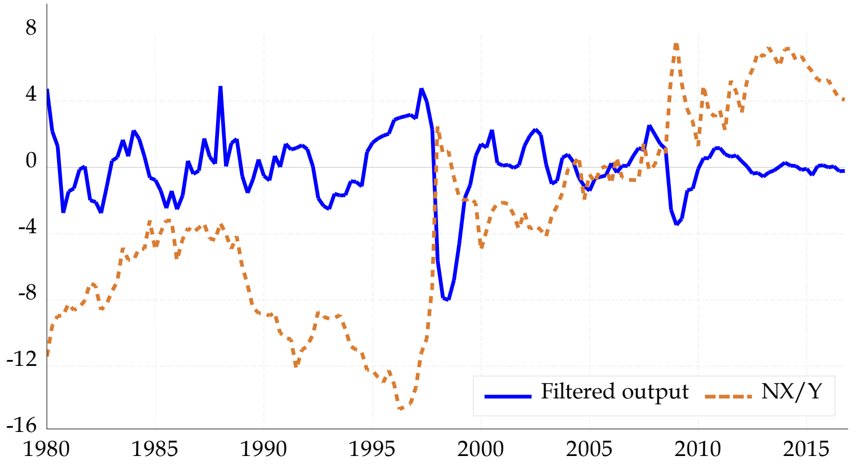


FIGURE 2
HP-FILTERED REAL GDP AND NET EXPORTS OVER GDP

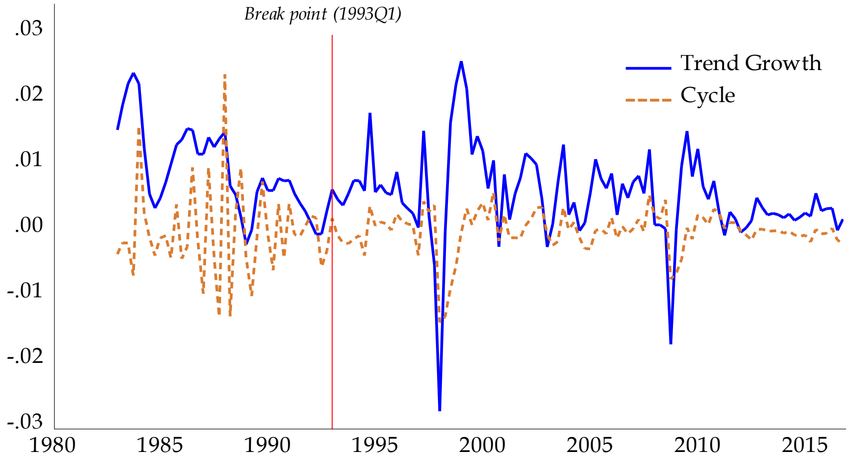
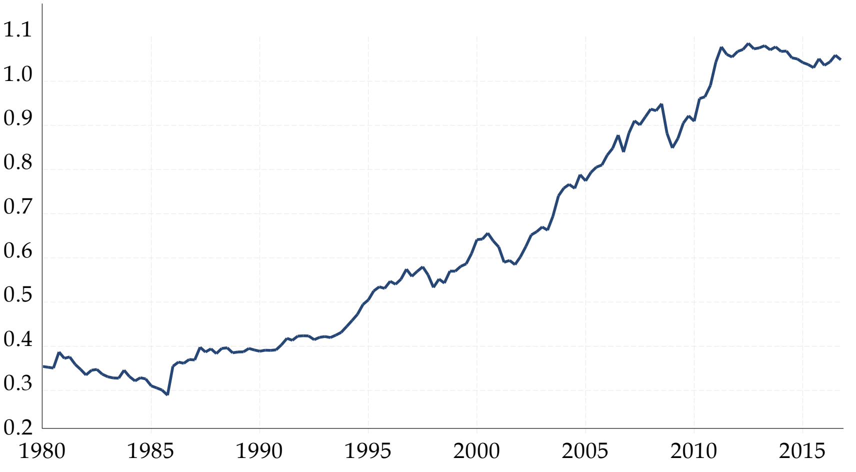


FIGURE 3
SMOOTHED TREND GROWTH AND CYCLE

A. Sum of Exports and Imports/ GDP Ratio



B. Reported Cases of Foreign Investment

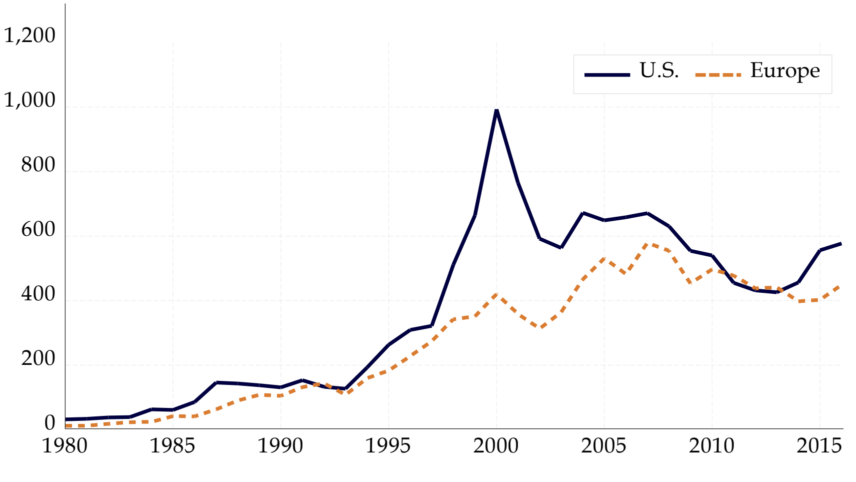


Figure 4
Openness of Korea

Appendix 1: Confidence Intervals for Bai (1997) Estimator

We start with the regression model as follows:

$$y_t = \beta_1' x_t 1(t \leq m) + \beta_2' x_t 1(t > m) + e_t.$$

Bai (1997) proposes *two cases of asymptotic distribution* of the break date. In the first case, x_t and e_t are second-order stationary for the whole sample. Define $L = \frac{(\delta' Q \delta)^2}{\delta' \Omega \delta}$, where $\delta = \beta_2 - \beta_1$, $Q = \mathrm{E}(x_t x_t')$, and $\Omega = \mathrm{E}(x_t x_t' e_t^2)$. If $\delta \to 0$, then $L(\hat{m} - m) \xrightarrow{d} z$, where the distribution of z is

$$G(z) = 1 = \sqrt{\frac{z}{2\pi}} \exp\left(-\frac{z}{8}\right) - \frac{1}{2}(z+5)\Phi\left(-\frac{\sqrt{z}}{2}\right) + \frac{3}{2}\exp(z)\Phi\left(-\frac{3\sqrt{z}}{2}\right)$$

for $z \geq 0$ and $G(z) = 1 - G(-z)$. Define $\hat{L} = \frac{(\hat{\delta}' \hat{Q} \hat{\delta})^2}{\hat{\delta}' \hat{\Omega} \hat{\delta}}$, where $\hat{\delta} = \hat{\beta}_2 - \hat{\beta}_1$, $\hat{Q} = (1/T)\sum_{t=1}^{T} x_t x_t'$, and $\hat{\Omega}$ is the Newey–West (1987) covariance estimator. Then $(\hat{L} - L)(\hat{m} - m) \xrightarrow{p} 0$. A $100(1-\alpha)\%$ confidence interval for $\hat{m}$ is given by $[\hat{m} - [c/\hat{L}] - 1, \hat{m} + [c/\hat{L}] + 1]$, where c is the $(1-\alpha/2)$th quantile of $G(z)$ and $[c/\hat{L}]$ is the integer part of $c/\hat{L}$.

In the second case, x_t and e_t are stationary within each subsample. Define $\xi = \frac{\delta' Q_2 \delta}{\delta' Q_1 \delta}$, $\phi = \frac{\delta' \Omega_2 \delta}{\delta' \Omega_1 \delta}$, and $L = \frac{(\delta' \Omega_1 \delta)^2}{\delta' \Omega_1 \delta}$ where $Q_1 = \mathrm{E}(x_t x_t')$ and $\Omega_1 = \mathrm{E}(x_t x_t' e_t^2)$ for $t \leq m$ and $Q_2 = \mathrm{E}(x_t x_t')$ and $\Omega_2 = \mathrm{E}(x_t x_t' e_t^2)$ for $t > m$. If $\delta \to 0$, then $L(\hat{m} - m) \xrightarrow{d} z$. The distribution of z for $z \geq 0$ is

$$G(z) = 1 + \beta\sqrt{\frac{z}{2\pi}} \exp\left(-\frac{\beta^2 z}{8}\right) - \frac{1}{2}(\beta^2 z + 2d - 4)\Phi\left(-\frac{\beta\sqrt{z}}{2}\right)$$
$$+ c\exp(az)\Phi(-b\sqrt{z})$$

where $\beta = \frac{\xi}{\sqrt{\phi}}$, $a = \frac{\xi + \phi}{2}$, $b = \frac{\xi + 2\phi}{2\sqrt{\phi}}$, $c = \frac{\xi(\xi + 2\phi)}{\phi(\xi + \phi)}$, and $d = \frac{(\xi + 2\phi)^2}{\phi(\xi + \phi)}$.

For $z < 0$,

$$G(z) = -\sqrt{\frac{|z|}{2\pi}} \exp\left(-\frac{|z|}{8}\right) + \frac{1}{2}(|z| + 2d - 4)\Phi\left(-\frac{\sqrt{|z|}}{2}\right)$$
$$+ c\exp(az)\Phi\left(-b\sqrt{|z|}\right)$$

where $a = \frac{1}{2}\frac{\xi}{\phi}\left(1+\frac{\xi}{\phi}\right)$, $b = \frac{1}{2}+\frac{\xi}{\phi}$, $c = \frac{\phi(2\xi+\phi)}{\xi(\xi+\phi)}$, and $d = \frac{(2\xi+\phi)^2}{\xi(\xi+\phi)}$. Let $\hat{L}$ be an estimate of L. Then a $100(1-\alpha)\%$ confidence interval for $\hat{m}$ is given by $[\hat{m}-[c_1/\hat{L}]-1, \hat{m}+[c_2/\hat{L}]+1]$, where c_1 is the $\alpha/2$th quantile, c_2 is the $(1-\alpha/2)$th quantile, and $[c_j/\hat{L}]$ is the integer part of $c_j/\hat{L}$ for $j = 1,2$.

Appendix 2: Korean Business Cycle Moments

	Full sample 1980Q1-2016Q4	Pre-break 1980Q1-1993Q1	Post-break 1993Q2-2016Q4
Volatility of GDP			
$\sigma(\tilde{y})$	2.01	1.77	2.14
$\sigma(\Delta y)$	1.56	1.71	1.35
Relative volatility of consumption, investment, and net exports			
$\sigma(\tilde{c})/\sigma(\tilde{y})$	1.37	0.51	1.58
$\sigma(\Delta c)/\sigma(\Delta y)$	1.13	0.42	1.50
$\sigma(\tilde{i})/\sigma(\tilde{y})$	2.50	2.77	2.40
$\sigma(\Delta i)/\sigma(\Delta y)$	2.16	2.19	2.14
$\sigma(NX/Y)$	5.20	2.01	5.37
Correlation of net exports with GDP			
$\rho(NX/Y, \tilde{y})$	-0.33	-0.02	-0.32
$\rho(NX/Y, \Delta y)$	-0.34	0.19	-0.37

Note: Data are derived from the Bank of Korea. Lowercase letters denote logarithms of variables. Tildes denote HP-filtered series using smoothing parameter of 1,600. Δ denotes difference operator; that is, $\Delta y_t = y_t - y_{t-1}$.

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