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Medium-term macroeconomic volatility and economic development: a new technique

Sam Hak Kan Tang[1]

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Abstract A key question in development economics is why developing countries as a collective group experience so much growth volatility. This paper introduces a new technique to measure medium-term macroeconomic volatility that is defined by the trend-growth volatility of output. It shows that medium-term volatility, σ^2_{MT}, can be derived by subtracting the average short-term volatility, $(1/n)\sum_j^n \sigma^2_{Sj}$, from the total variance of output growth, σ^2_{LT}. Applying this new measure to the World Bank's output data reveals an inverted-U shaped relationship between medium-term volatility and economic development, indicating that economic development is likely to increase trend-growth volatility for emerging low-income countries.

Keywords Medium-term macroeconomic volatility · Business-cycle volatility · Trend-growth breaks · Structural breaks · Economic fluctuations · Economic development

JEL Classification O47 · O11 · E32

1 Introduction

Researchers in the area of macroeconomic volatility are increasingly concerned about the determinants of medium-term trend-growth volatility (Jerzmanowski and Cuberes 2011). This concern is caused by the finding that the growth path of most developing countries is highly unstable in the medium-term; that is, the main source of fluctuations

✉ Sam Hak Kan Tang
sam.tang@uwa.edu.au

1 Business School, The University of Western Australia, 35 Stirling Highway, Crawley, WA 6009, Australia

for developing countries comes from shocks to trend growth as opposed to transitory fluctuations around the trend (Easterly et al. 1993; Pritchett 2000; Aguiar and Gopinath 2004; Hausmann et al. 2005; Jerzmanowski 2006; Jones and Olken 2008; Cuberes and Jerzmanowski 2009). This literature has identified regime changes, political institutions, international trade and macroeconomic policies as potential factors that drive the fluctuations of the medium-term cycle for developing countries, but the effects of these potential factors are found to be complex and nonlinear (Jerzmanowski and Cuberes 2011).

The papers by Jones and Olken (2008) and Cuberes and Jerzmanowski (2009) are especially relevant to the present study. Jones and Olken demonstrate that almost all countries except the very rich ones are subject to growth "miracles" and "failures" at 10- and 15-year time frequency. Growth miracles are defined by growth episodes which converge to the USA's growth rate for the same time periods, whereas growth failures are growth episodes which diverge from the USA's growth rate. They find that both types of growth episodes are asymmetric in nature: Growth accelerations are associated with large expansions of international trade, whereas growth collapses are associated with reduced investment amidst increasing price instability. Clearly, their study sheds light on medium-term trend-growth volatility and why most countries are vulnerable to medium-term trend-growth volatility.

The paper by Cuberes and Jerzmanowski (2009) also focuses on the explanation of medium-term trend-growth volatility, rather than high-frequency growth volatility. They show both empirically and theoretically that non-democracies with higher barriers to entry of new firms suffer from greater sectoral concentration and experience large medium-term trend-growth cycles. As will be shown in Sect. 4, the present study is able to confirm their main result by using a new way of measuring medium-term trend-growth volatility.

Some previous studies of medium-term business-cycle volatility use conventional filters (such as band-pass, Hodrick–Prescott and Kalman filters) to decompose output per capita into trend and transitory components. The medium-term cycle is defined as a smooth nonlinear trend consisting of variation in the data at frequencies of 200 quarters and below (Comin and Gertler 2003). Other studies use structural break techniques such as Bai and Perron (1998, 2003) to identify the timing of growth breaks. Medium-term macroeconomic volatility can then be measured by the frequency of trend-growth breaks in the data. A common issue of using structural break techniques is that empirical studies often encounter limited time series data, but the testing procedure for structural breaks is reliant upon asymptotic properties.[1] Furthermore, researchers are often required to make arbitrary assumptions about the minimum length of time between structural breaks.

In this paper, I introduce a nonparametric approach to measure medium-term trend-growth volatility that is both intuitive and convenient for large cross-country empirical studies. More importantly, it generates results which are consistent with the predictions of growth theories and findings of the recent empirical literature. The technique makes use of the fact that the variance of annual growth rates of output per capita

[1] Cuberes and Jerzmanowski (2009) also use a Bayesian technique that does not rely on asymptotic properties.

for the long term is the total variance of output growth that include short-term high-frequency volatility, economic crises and medium-term trend-growth volatility. The basic idea is that if short-term high-frequency volatility can be subtracted from the total variance of output growth, then the amount of volatility left remaining can be attributed to shifts in medium-term trend growth. Using this technique, researchers can easily distinguish countries that experience large short-term volatility with little shifts in trend growth from countries that experience little short-term volatility with large shifts in trend growth.

This paper finds that low-income countries have the most volatile output growth among all other income country groups, but their volatile growth is driven mainly by short-term fluctuations rather than medium-term trend-growth volatility. In contrast, middle-income countries have a substantially higher proportion of medium-term trend-growth volatility in their total variance of output growth. For high-income countries, the proportion of medium-term trend-growth volatility in total variance of output growth decreases to a lower level than that of the middle-income countries. The key empirical finding of this paper is that medium-run trend-growth volatility is a more important source of output volatility for middle-income countries than for either the low-income or high-income countries.

The remainder of this paper is organized into four sections. Section 2 algebraically derives the proposed technique for measuring medium-term trend-growth volatility. Section 3 explores the properties of the technique using synthetic data generated by Monte-Carlo simulations of an assumed growth process. Section 4 applies the technique to the output data taken from the World Bank's World Development Indicator and presents the empirical results. Section 5 concludes.

2 Method

The variance of annual growth rates of output per capita, σ_{LT}^2, calculated over a long horizon is the total variance of output growth that include short-term high-frequency volatility, σ_{ST}^2, economic crises and medium-term trend-growth volatility, σ_{MT}^2. That is,

$$\sigma_{\mathrm{LT}}^2 = \sigma_{\mathrm{ST}}^2 + \sigma_{\mathrm{MT}}^2. \tag{1}$$

The implicit assumption in Eq. (1) is that the covariance between short-term and medium-term trend-growth volatilities is zero. This assumption is justified empirically in regression (11) in Sect. 4. The variance of annual growth rates of output per capita, σ_{LT}^2, is given by:

$$\sigma_{\mathrm{LT}}^2 = \frac{1}{N}\sum_{i}^{N}\left(X_i - \bar{X}_{\mathrm{LT}}\right)^2 = \frac{1}{N}\sum_{i}^{N} X_i^2 - \bar{X}_{\mathrm{LT}}^2, \tag{2}$$

where X_i is the annual growth rate of output per capita for year $i = 1\ldots N$ and $\bar{X}_{\mathrm{LT}}$ is the long-term mean growth rate of output per capita for the entire period of N years.

The length of short-term cycles can vary between countries and across time, but typically the standard representation of short-term cycles is between 2 and 32 quarters

(Comin and Gertler 2003). If the duration of a typical short-term cycle is less than 32 quarters, then the variances of annual growth rates of output per capita calculated over non-overlapping windows of less than 32 quarters (8 years) reflect the volatility of output growth due to short-term high-frequency fluctuations. Take, for example, a time horizon of 30 years between 1980 and 2009. It has ten non-overlapping 3-year windows from which ten short-term variances can be obtained. By averaging these short-term variances, one can measure average short-term volatility.[2] In general, σ^2_{ST} can be expressed as:

$$\sigma^2_{\mathrm{ST}} = \frac{1}{n}\left[\frac{1}{b}\left(\sum_{1}^{b}\left(X_i - \bar{X}_{S1}\right)^2 + \sum_{b+1}^{2b}\left(X_i - \bar{X}_{S2}\right)^2 + \cdots + \sum_{N-b+1}^{N}\left(X_i - \bar{X}_{Sn}\right)^2\right)\right], \tag{3}$$

where $\bar{X}_{S1}$, $\bar{X}_{S2}$, …, $\bar{X}_{Sn}$ are the average growth rates of output per capita for the short-term windows $1, 2, \ldots, n$. Each short-term window has b number of years, which is fixed for the entire period of N years. By collecting and rearranging terms, Eq. (3) becomes:

$$\sigma^2_{\mathrm{ST}} = \frac{1}{n}\left[\frac{1}{b}\sum_{i}^{N} X_i^2 - \sum_{j}^{n} \bar{X}^2_{Sj}\right], \tag{4}$$

where the subscript $i = 1, 2, \ldots N$ denotes the number of years, and $j = 1, 2, \ldots, n$ denotes the number of short-term windows.[3]

To find the medium-term trend-growth volatility, the short-term volatility of Eq. (4) is subtracted from the total variance of output growth of Eq. (2):

$$\sigma^2_{\mathrm{MT}} = \sigma^2_{\mathrm{LT}} - \sigma^2_{\mathrm{ST}} = \left(\frac{1}{N}\sum_{i}^{N} X_i^2 - \bar{X}^2_{\mathrm{LT}}\right) - \left(\frac{1}{n}\left[\frac{1}{b}\sum_{i}^{N} X_i^2 - \sum_{j}^{n} \bar{X}^2_{Sj}\right]\right), \tag{5}$$

which can be simplified to:

$$\sigma^2_{\mathrm{MT}} = \left(\frac{1}{N} - \frac{1}{nb}\right)\left(\sum_{i}^{N} X_i^2\right) + \left(\frac{1}{n}\sum_{j}^{n} \bar{X}^2_{Sj}\right) - \bar{X}^2_{\mathrm{LT}}. \tag{6}$$

[2] In practice, using 3-, 5- or even 7-year non-overlapping windows in the calculation of short-term volatility does not make a large difference to the results and does not certainly alter the conclusions of the paper. Results in Table 3 show that the differences in volatility between 3- and 5-year windows and between 5- and 7-year windows are no more than 0.5%.

[3] The derivation of Eq. (4) from (3) is shown in "Appendix A".

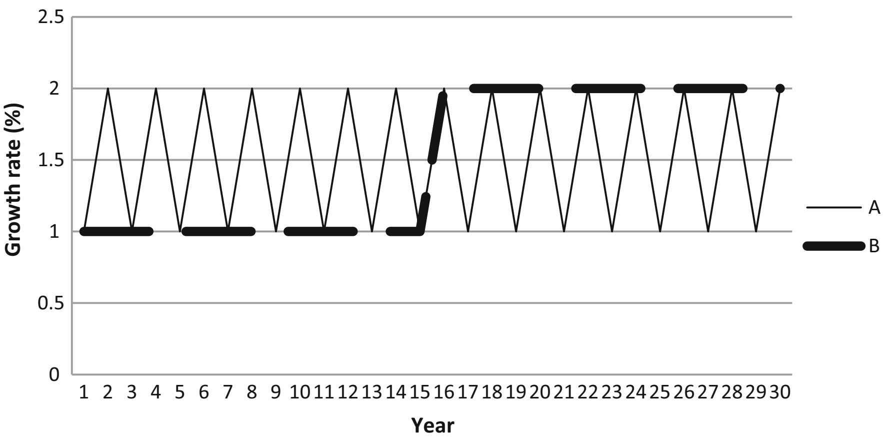

Fig. 1 Two hypothetical countries' growth patterns

Since $N = nb$, the first term on the right-hand side of Eq. (6) becomes zero and the medium-term trend-growth volatility is:

$$\sigma_{\mathrm{MT}}^{2} = \left(\frac{1}{n}\sum_{j}^{n}\bar{X}_{Sj}^{2}\right) - \bar{X}_{\mathrm{LT}}^{2}, \tag{7}$$

which can alternatively be expressed as:

$$\sigma_{\mathrm{MT}}^{2} = \frac{1}{n}\sum_{j}^{n}\left(\bar{X}_{Sj} - \bar{X}_{\mathrm{LT}}\right)^{2}. \tag{8}$$

Clearly, Eq. (8) states that medium-term trend-growth volatility is the variance of short-term average growth rates of output per capita. It measures the extent to which short-term average growth rates differ from the long-term trend growth rate. If output growth volatility is entirely caused by short-term high-frequency fluctuations without any changes in trend growth, average growth rates of output per capita for all the short-term windows, $\bar{X}_{Sj}$, would be the same as the long-term trend growth, $\bar{X}_{\mathrm{LT}}$, and the medium-term trend-growth volatility, σ_{MT}^{2}, is zero. On the other hand, if a structural break occurs which changes the growth rate of at least one short-term window, then $\bar{X}_{Sj} \neq \bar{X}_{\mathrm{LT}}$, and $\sigma_{\mathrm{MT}}^{2} > 0$.

The following example illustrates the technique using two extreme patterns of growth volatility of output per capita. Suppose two hypothetical countries, A and B, both have the same variance of annual growth rates of output per capita at 0.25% squared for the entire 30-year period of analysis. Even though they have the same variance of output growth, their volatility patterns are very different as shown in Fig. 1. Country A has oscillations of short-term growth rates between 1 and 2%, but no shift in trend growth. In contrast, Country B has no oscillations of growth rates in the short term, but a shift of trend growth from 1% in year 1–15 to 2% in year

Table 1 A comparison of two hypothetical countries' volatility patterns

	Annual growth rate of GDP per capita from year 1 to 30 (%)																													
A	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2
B	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2

	Growth volatility measured by variance (% squared)		
	Long term	Short term	Medium term
A	0.25	0.25	0.00
B	0.25	0.017	0.233

Long-term volatility is the variance of annual growth rates of output per capita for the entire 30 years. Short-term volatility is the average variance of the non-overlapping 2-year windows. Medium-term volatility is the residual after subtracting the short-term volatility from the long-term volatility

16–30. What is the medium-term macroeconomic volatility for these two countries? Table 1 summarizes the calculation results of the long-term, short-term and medium-term trend-growth volatilities for these two countries. For Country A, subtracting the average volatility of non-overlapping 2-year windows (0.25% squared) from the long-term volatility (0.25% squared) gives zero medium-term volatility. For Country B, a one-off shift in the trend growth rate results in an average short-term volatility of 0.017% squared, which leads to a medium-term trend-growth volatility of 0.233% squared (0.25–0.017).[4] Hence, the proportion of medium-term trend-growth volatility in total volatility of output growth is 0% for Country A and 93% for Country B.

Some developed OECD countries such as Germany and the USA resemble Country A in the hypothetical example above. These countries, as will be shown in Sect. 4, have the major source of their macroeconomic volatility coming from short-term business-cycle volatility, with medium-term trend-growth volatility accounting for only around 10% of their total volatility of output growth for the past 50 years. In contrast, developing countries such as Botswana, Myanmar and Tanzania resemble Country B in the hypothetical example above. These countries experience a far greater extent of medium-term trend-growth volatility which accounts for more than 50% of their total volatility of output growth.

3 Monte-Carlo simulation

This section explores the properties of the new technique using synthetic data generated by Monte-Carlo simulations of an assumed underlying growth process. I assume a two-factor Cobb–Douglas production function and standard neoclassical assumptions of constant returns to scale and diminishing marginal products of capital and labor. The familiar growth accounting equation can then be derived as follows,

[4] If the shift in trend takes place either toward the beginning or the end of the period rather than in the middle of the period, total variations of output growth for the entire period will be lower with no change in the average short-term volatility, giving a lower level of medium-term trend-growth volatility.

Table 2 Results of Monte-Carlo simulations

	Underlying growth mechanism assumed	No. of rep.	No. of breaks	SD (%) [shares]		
				Total	Short	Medium
A	$\hat{Y} = \frac{1}{3}\hat{K} + \frac{2}{3}\hat{L}$	250	None	0.644	0.571	0.073
				[100%]	[89%]	[11%]
B	$\hat{Y} = \frac{1}{3}\hat{K} + \frac{2}{3}\hat{L} + \text{upbreak}$	250	One	1.696	0.571	1.125
				[100%]	[33%]	[67%]
C	$\hat{Y} = \widehat{\text{TFP}} + \frac{1}{3}\hat{K} + \frac{2}{3}\hat{L}$	250	None	1.295	1.122	0.173
				[100%]	[87%]	[13%]
D	$\hat{Y} = \widehat{\text{TFP}} + \frac{1}{3}\hat{K} + \frac{2}{3}\hat{L} + \text{upbreak}$	250	One	1.970	1.118	0.852
				[100%]	[56%]	[44%]
E	$\hat{Y} = \widehat{\text{TFP}} + \frac{1}{3}\hat{K} + \frac{2}{3}\hat{L} + \text{doublednbks}$	250	Two	2.909	1.415	1.494
				[100%]	[49%]	[51%]
F	$\hat{Y} = \widehat{\text{TFP}} + \frac{1}{3}\hat{K} + \frac{2}{3}\hat{L} + \text{upbk} + \text{dndk}$	250	Two	1.942	1.370	0.572
				[100%]	[70%]	[30%]

See Sect. 3 for a discussion of Monte-Carlo simulations. All breaks are 3% in magnitude

$$\hat{Y} = \widehat{\text{TFP}} + \frac{1}{3}\hat{K} + \frac{2}{3}\hat{L} \tag{9}$$

where $\hat{Y}$, $\widehat{\text{TFP}}$, $\hat{K}$ and $\hat{L}$ are growth rates of output, total factor productivity, capital and labor. The capital's share of income is assumed to be one-third, and hence, labor's is two-thirds.[5] I further assume that the growth rates of total factor productivity, capital and labor are generated as $N(0, 1)$. Simulations of six different versions of Eq. (9) are conducted that include omitting TFP growth from the equation and adding different combinations of trend-growth breaks. Each of the six versions (models) is simulated 250 iterations with 30 observations in each iteration. I can then calculate the average long-term, short-term and medium-term volatilities from the simulation results using the method described in Sect. 2. These simulation results are reported in Table 2.

Row A of Table 2 presents the results of applying the technique to the synthetic data of Eq. (9) when TFP growth is assumed to be absent. First, averaging the standard deviations of output growth of 30 observations across the 250 iterations gives the average total long-term volatility of 0.64%. Second, assuming that short-term windows are 3 years in duration, I calculate the average short-term growth volatility for 10 non-overlapping short-term windows in each iteration. Then, by averaging the 250 average short-term volatilities, the overall average short-term volatility is 0.57%. Finally, medium-term volatility is calculated by subtracting the overall average short-

[5] A study by Guerriero (2012) finds that the labor share of national income varies substantially depending on which one of the six definitions of labor income is used for calculation. However, the labor share of income is generally higher in high-income countries compared to low-income and middle-income countries. Based on a dataset of 141 countries, Guerriero's calculations show that the labor share varies between 0.61 and 0.79 for developed countries, but between 0.42 and 0.70 for developing countries. The conventional assumption of using 2/3 or 0.66 for the labor share thus falls within these empirical calculations.

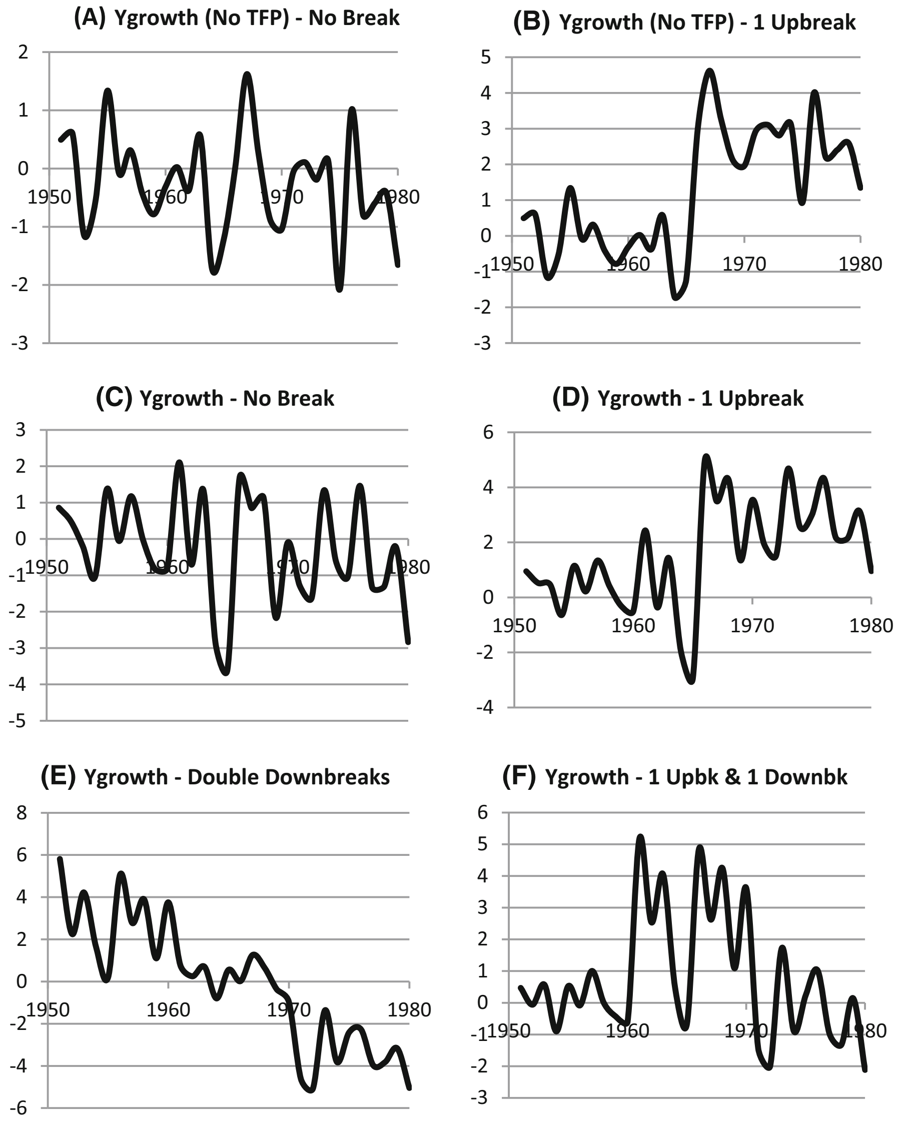

Fig. 2 Illustrations of Monte-Carlo exercises

term volatility from long-term volatility (0.64–0.57%), which is equal to 0.073%. The results of applying the new technique show that output growth volatility in model A is mainly driven by short-term volatility which accounts for approximately 90% of the total long-term volatility, whereas medium-term trend-growth volatility only accounts for roughly 10%.

Figure 2A plots one of the 250 iterations of the simulated model A. It can be seen visually that output growth fluctuates periodically around the x-axis. This is a pattern of growth fluctuations for an economy that does not experience any trend-growth break, which can be inferred from the results of the calculation using the new technique.

Row B of Table 2 introduces an upward trend-growth break of 3% (or three standard deviations) to model A between 16–30 observations.[6] The calculation in Row B indicates now that the share of medium-term volatility in long-term volatility increases from 11 to 67% and the share of short-term volatility reduces from 89 to 33%. The changes in the calculated shares reflect the occurrence of a large trend-growth break in a relatively stable series as depicted visually in Fig. 2B.

Rows C and D of Table 2 repeat the simulation exercises of Rows A and B with an additional variable TFP growth included in the growth accounting equation. It can be seen from Fig. 2C that the growth series is more volatile after adding an additional variable in the equation, but still oscillates around the x-axis. Also the shares of short-term and medium-term volatilities in long-term volatility are similar to those of the Row A at 87 and 13% respectively. The results of both Row A and C suggest that the share of medium-term volatility is around 10% when the underlying growth series has no trend-growth breaks. In Row D, an upward trend-growth break introduced in the growth series increases the share of medium-term volatility from 13 to 44% and reduces the share of short-term volatility from 87 to 56% between Row C and D. The results of Row B and D suggest that when short-term growth becomes more volatile, any shift in trend growth would be harder to detect. Figure 2D illustrates the simulated growth pattern of model D.

Rows E and F of Table 2 experiment with adding two trend-growth breaks in the growth accounting equation; Row E includes two downward trend-growth breaks whereas Row F includes one upward and one downward trend-growth breaks. The calculation results of Row E indicate that when the second trend-growth break is added onto the first one in the same direction, the share of medium-term volatility increases (as shown by the increase from 44% in Row D to 51% in Row E). Row F, however, shows that when the second trend-growth break is added onto the first one in the opposite direction, the share of medium-term volatility decreases (as shown by the decrease from 44% in Row D to 30% in Row F). Figure 2E, F illustrates the two different patterns of growth fluctuations in Rows E and F.

Using the results of Monte-Carlo simulation exercises, I can devise the following *rough* guide for future researchers adopting this technique. When the share of medium-term volatility in total long-term volatility is:

a. Less than 15%, the growth series is unlikely to contain any trend-growth break.
b. 30% or above, the growth series is likely to contain at least one substantial (two standard deviations or more) trend-growth break.
c. 15% or above but less than 30%, it is inconclusive that the growth series contains any trend-growth break.

[6] Shocks of other magnitudes have also been tried, but their results are not reported in Table 2. I have incorporated some of these unreported results in the summary of this section.

Table 3 Short-term, medium-term and total volatility by income country group

1960–2008	Non-overlapping panel window					
	3-year	5-year	7-year	10-year	All years	Medium
Low income (33)	4.6	4.8	5.2	5.6	7.2	2.6
Lower-middle income (47)	3.6	3.8	4.3	4.3	5.3	1.7
Upper-middle income (46)	3.7	4.2	4.7	4.8	6.1	2.4
High-income non-OECD (31)	3.7	3.9	4.2	4.6	5.7	2.0
High-income OECD (31)	2.0	2.2	2.3	2.5	3.0	1.0
All countries	3.5	3.8	4.2	4.4	5.5	2.0

Income groups are defined according to the World Bank classifications. The total number of countries in each income group is in the parenthesis. OPEC countries are excluded. Each figure in the table represents the average of all the standard deviations of output growth for the non-overlapping panel windows of indicated length over 1960–2008 in percentage (%)

4 Empirical results

This section reports and discusses the results obtained from applying the technique to output data from the World Bank's World Development Indicators. The data series employed is constant GDP per capita in local currency units (NY.GDP.PCAP.KN) between 1960 and 2008. There are 214 economies in the data series in total, but only those 190 economies with at least 10 years of data are included in the calculation. I first calculate the annual growth rates of output per capita by taking the logarithm of the GDP per capita series and subtracting the values in between consecutive years. Then, I calculate the standard deviations of the annual growth rates in GDP per capita for the entire period of 1960–2008, and also for every non-overlapping 3-, 5-, 7- and 10-year windows. The results of these calculations are presented in Table 3.[7]

In Table 3, the average standard deviations for the entire sample period and for different non-overlapping short-term windows are presented by the World Bank's income classification groups of low-income, lower-middle-income, higher-middle-income, high-income non-OECD and high-income OECD. Two main results can be easily observed from Table 3. First, low-income countries experienced the most volatile output growth in the past five decades, as indicated by their average standard deviation of output growth for the entire sample period (7.2%). In contrast, high-income OECD countries experience the most stable output growth with an average standard deviation of 3%. Middle-income countries and high-income non-OECD countries have average standard deviations of output growth between 5–6% for the entire sample period. It is worth noting that this result of an inverse relationship between the level and (total) volatility of output growth is consistent with the findings of a large number of cross-country studies accumulated since the seminal study of Ramey and Ramey (1995).

The second main result from Table 3 is that growth volatility increases as the length of non-overlapping time windows increases. For low-income countries, the average

[7] For the ease of discussion of the empirical results, standard deviations are used rather than variances because standard deviations have the same unit of measurement as the data observations (%).

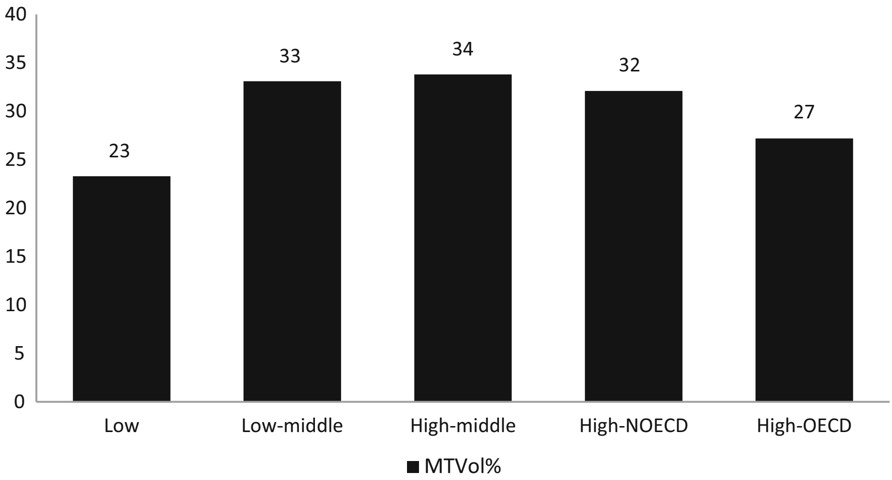

Fig. 3 Proportion of medium-term trend-growth volatility by income country group

standard deviation of output growth increases from 4.6% for the non-overlapping 3-year windows, to 4.8% for the non-overlapping 5-year windows, to 5.2% for the non-overlapping 7-year windows, to 5.6% for the non-overlapping 10-year windows and to 7.2% for the entire sample period. As explained in Sect. 2, growth volatility increases as the length of non-overlapping time windows increases because in the longer run, growth volatility is likely to include not only short-term volatility, but also economic crises and medium-term trend-growth volatility. The last column of Table 3 shows the level of medium-term trend-growth volatility calculated by subtracting the average standard deviation of non-overlapping 3-year time windows from the standard deviation of the entire sample period. For low-income countries, the level of medium-term trend-growth volatility is 2.6% compared to 1.7% for lower-middle-income countries, 2.4% for upper-middle-income countries, 2% for high-income non-OECD countries and 1% for high-income OECD countries. As stated earlier in Sect. 2, the level of medium-term volatility measures the extent to which short-term average growth rates differ from the long-term trend growth rate. Then, the interpretation of the level of the medium-term volatility of, say, 2.6% for the low-income countries is that the trend growth rate of short-term windows on average deviates from the long-term trend growth rate by 2.6%. Results in Table 3 thus show that low-income countries experience the most volatile output growth volatility both in terms of total volatility of output growth and medium-term trend-growth volatility.

Although Table 3 shows the levels of short-term volatility and the medium-term trend-growth volatility, it does not tell us how important the two components of volatilities are in total volatility of output growth. I therefore calculate the proportion of medium-term trend-growth volatility in total volatility of output growth for each individual country in the sample and summarize the results by the World Bank's income classification groups in Fig. 3. Figure 3 shows that low-income countries have the lowest median proportion of medium-term trend-growth volatility in total volatility of

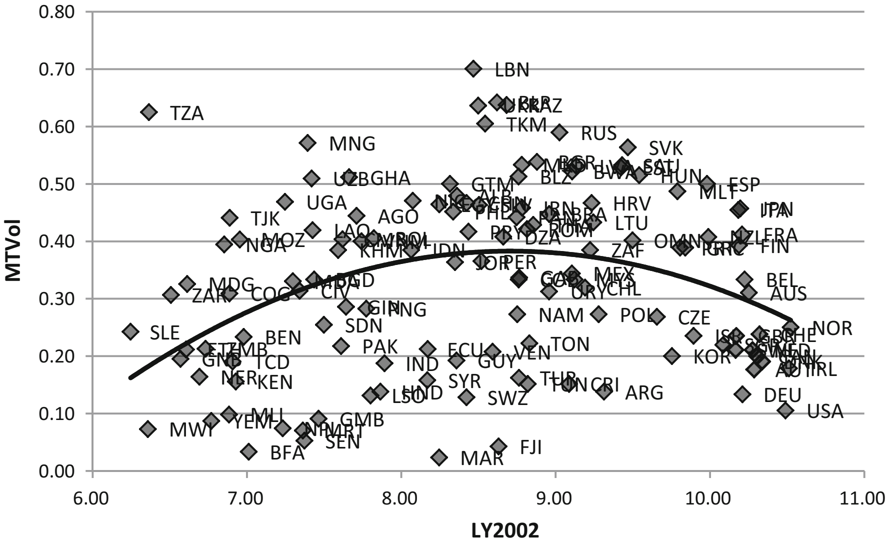

Fig. 4 Proportion of medium-term trend-growth volatility by country. Note: LY2002 is a country's income level (in log) and MTVol is the country's proportion of medium-term trend-growth volatility in total volatility of output growth

output growth at 23%. The median proportion of medium-term trend-growth volatility jumps substantially higher to 33% in lower-middle-income countries and to 34% in higher-middle-income countries. It then falls to 32% in high-income non-OECD countries and to 27% in high-income OECD countries. This result is important because it shows that low-income countries as a collective group have the lowest share of medium-term trend-growth volatility in total volatility of output growth compared to all other income groups.

Figure 4 presents a scatter plot that reveals an inverted-U shaped relationship between individual countries' income level (in log) and the proportion of medium-term trend-growth volatility in total volatility of output growth. The scatter plot shows that, on average, the proportion of medium-term trend-growth volatility increases from low-income countries to middle-income countries and peaks at around 8.5 (logged) income level, following which the proportion of medium-term trend-growth volatility decreases as income level increases further. This plot provides clear evidence that medium-term trend-growth volatility is more important for middle-income countries as a source of total volatility in output growth than other income country groups.

Table 4 reports the individual countries' total long-term volatility and its components of the shares of short-term and medium-term volatilities. Medium-term volatility is calculated by subtracting the average standard deviation for the non-overlapping 3-year windows from the standard deviation for all available data from 1960 to 2008. Myanmar, Lebanon and Azerbaijan are the countries with the highest share of medium-term volatility (70%). Additionally, Myanmar has the highest total long-term volatility (and also short-term volatility), making it the most volatile country in the world for the period 1960–2008. Following Myanmar, Liberia and Bosnia and Herzegovina are the

Table 4 Shares of short-term and medium-term trend-growth volatilities by country

Country	All (%)	Short	Medium	Country	All (%)	Short	Medium
Albania	9.6	0.52	0.48	Lebanon	15.7	0.29	0.70
Algeria	7.6	0.59	0.41	Lesotho	6.1	0.87	0.13
Angola	9.9	0.56	0.44	Liberia	18.3	0.49	0.50
Antigua and Barbuda	4.4	0.59	0.41	Liechtenstein	5.4	0.57	0.41
Argentina	5.8	0.88	0.14	Lithuania	9.7	0.57	0.43
Armenia	15.4	0.51	0.49	Luxembourg	3.2	0.88	0.13
Aruba	5.7	0.74	0.28	Macao SAR, China	6.6	0.62	0.38
Australia	2.9	0.69	0.31	Macedonia, FYR	4.5	0.47	0.53
Austria	1.7	0.82	0.18	Madagascar	4.3	0.67	0.33
Azerbaijan	16.3	0.40	0.60	Malawi	5.5	0.91	0.07
Bahamas	9.7	0.61	0.39	Malaysia	3.3	0.67	0.33
Bahrain	4.8	0.69	0.31	Maldives	4.9	0.65	0.33
Bangladesh	4.2	0.67	0.33	Mali	5.1	0.90	0.10
Barbados	4.5	0.62	0.36	Malta	3.9	0.51	0.49
Belarus	8.1	0.36	0.64	Marshall Islands	6.1	0.66	0.34
Belgium	1.8	0.67	0.33	Mauritania	5.7	0.93	0.07
Belize	3.9	0.49	0.51	Mauritius	3.5	0.71	0.29
Benin	3.0	0.77	0.23	Mexico	3.2	0.66	0.34
Bermuda	3.3	0.70	0.33	Micronesia, Fed. Sts.	3.1	0.90	0.10
Bhutan	3.0	0.67	0.37	Moldova	11.2	0.67	0.33
Bolivia	3.7	0.59	0.41	Mongolia	4.9	0.41	0.57
Bosnia and Herzegovina	16.7	0.46	0.54	Montenegro	5.5	0.67	0.33
Botswana	4.6	0.48	0.52	Morocco	4.3	1.00	0.02
Brazil	3.8	0.55	0.45	Mozambique	6.7	0.61	0.40
Brunei	6.7	0.69	0.31	Myanmar	48.8	0.30	0.70
Bulgaria	5.2	0.46	0.54	Namibia	3.3	0.70	0.27
Burkina Faso	3.0	0.97	0.03	Nepal	2.7	0.93	0.07
Burundi	5.7	0.88	0.14	Netherlands	1.9	0.79	0.21
Cambodia	2.6	0.62	0.38	New Caledonia	8.4	0.73	0.26
Cameroon	5.7	0.60	0.40	New Zealand	2.7	0.59	0.41
Canada	2.0	0.80	0.20	Nicaragua	6.8	0.53	0.47
Cape Verde	2.9	0.83	0.17	Niger	6.1	0.84	0.16
C.A.R.	3.9	0.87	0.13	Nigeria	7.1	0.59	0.39
Chad	8.4	0.81	0.19	Norway	1.6	0.69	0.25
Chile	4.7	0.66	0.32	Oman	12.2	0.60	0.40
China	7.5	0.53	0.47	Pakistan	2.3	0.78	0.22
Colombia	2.1	0.71	0.33	Palau	6.1	0.93	0.07
Comoros	3.1	0.94	0.10	Panama	4.3	0.56	0.44
Congo, Dem. Rep.	6.2	0.69	0.31	Papua New Guinea	4.6	0.72	0.28
Congo, Rep.	5.5	0.67	0.31	Paraguay	3.6	0.58	0.42

Table 4 continued

Country	All (%)	Short	Medium	Country	All (%)	Short	Medium
Costa Rica	3.3	0.85	0.15	Peru	5.2	0.63	0.37
Cote d'Ivoire	5.1	0.69	0.31	Philippines	3.1	0.55	0.45
Croatia	7.5	0.53	0.47	Poland	3.3	0.73	0.27
Cyprus	4.0	0.48	0.53	Portugal	3.6	0.61	0.39
Czech Republic	4.1	0.73	0.27	Puerto Rico	2.9	0.69	0.31
Denmark	2.1	0.81	0.19	Romania	5.7	0.58	0.42
Djibouti	3.6	0.50	0.50	Russian Federation	7.8	0.42	0.59
Dominica	5.8	0.74	0.26	Rwanda	11.8	0.64	0.37
Dominican Rep.	5.2	0.81	0.19	Samoa	3.4	0.82	0.21
Ecuador	3.3	0.82	0.21	Saudi Arabia	7.7	0.47	0.53
Egypt, Arab Rep.	2.8	0.54	0.46	Senegal	3.8	0.92	0.05
El Salvador	4.1	0.54	0.46	Serbia	14.1	0.74	0.26
Equatorial Guinea	15.5	0.61	0.39	Seychelles	5.9	0.88	0.14
Eritrea	8.3	0.70	0.30	Sierra Leone	6.6	0.76	0.24
Estonia	7.0	0.49	0.53	Singapore	4.1	0.80	0.22
Ethiopia	7.1	0.80	0.21	Slovak Republic	5.5	0.44	0.56
Fiji	4.7	0.96	0.04	Slovenia	3.9	0.31	0.69
Finland	2.8	0.61	0.39	Solomon Islands	6.8	0.57	0.43
France	1.7	0.59	0.41	Somalia	8.3	0.80	0.20
French Polynesia	4.9	0.86	0.14	South Africa	2.6	0.62	0.38
Gabon	9.8	0.66	0.34	Spain	2.6	0.50	0.50
Gambia	3.3	0.91	0.09	Sri Lanka	2.0	0.60	0.40
Georgia	12.9	0.45	0.55	St. Kitts and Nevis	4.0	0.45	0.55
Germany	1.5	0.87	0.13	St. Lucia	6.9	0.78	0.22
Ghana	4.3	0.49	0.51	St. Vincent and the Grenadines	6.2	0.79	0.21
Greece	3.6	0.61	0.39	Sudan	5.5	0.76	0.25
Greenland	4.7	0.70	0.30	Suriname	5.3	0.83	0.19
Grenada	4.7	0.89	0.11	Swaziland	3.9	0.87	0.13
Guatemala	2.4	0.50	0.50	Sweden	1.9	0.79	0.21
Guinea	1.4	0.79	0.29	Switzerland	2.1	0.76	0.24
Guinea-Bissau	8.2	0.82	0.20	Syrian Arab Republic	7.6	0.84	0.16
Guyana	5.2	0.81	0.19	Tajikistan	12.7	0.56	0.44
Haiti	4.9	0.69	0.31	Tanzania	2.4	0.38	0.63
Honduras	2.9	0.86	0.14	Thailand	3.5	0.57	0.43
Hong Kong, SAR	4.3	0.81	0.21	Togo	6.0	0.72	0.28
Hungary	3.3	0.52	0.52	Tonga	2.7	0.78	0.22
Iceland	3.6	0.81	0.22	Trinidad and Tobago	4.9	0.63	0.35
India	3.2	0.78	0.19	Tunisia	3.3	0.88	0.15
Indonesia	3.9	0.62	0.38	Turkey	3.7	0.84	0.16
Iran, Islamic Rep.	7.2	0.56	0.46	Turkmenistan	11.9	0.39	0.61

Table 4 continued

Country	All (%)	Short	Medium	Country	All (%)	Short	Medium
Ireland	2.8	0.82	0.18	Uganda	3.2	0.53	0.47
Isle of Man	3.8	0.79	0.21	Ukraine	9.9	0.36	0.64
Israel	3.4	0.74	0.24	United Arab Emirates	8.3	0.76	0.24
Italy	2.2	0.59	0.45	UK	1.7	0.76	0.24
Jamaica	4.6	0.65	0.33	USA	1.9	0.89	0.11
Japan	3.5	0.54	0.46	Uruguay	4.8	0.69	0.31
Jordan	6.6	0.64	0.36	Uzbekistan	5.3	0.49	0.51
Kazakhstan	8.0	0.36	0.64	Vanuatu	5.5	0.67	0.33
Kenya	4.5	0.87	0.16	Venezuela, RB	5.3	0.79	0.21
Kiribati	14.2	0.63	0.38	Vietnam	2.0	0.60	0.40
Korea, Rep.	4.0	0.80	0.20	Virgin Islands (U.S.)	5.1	0.86	0.14
Kuwait	9.6	0.81	0.19	West Bank and Gaza	9.0	1.01	−0.01
Kyrgyz Republic	8.7	0.60	0.41	Yemen, Rep.	2.3	0.91	0.09
Lao PDR	3.1	0.58	0.42	Zambia	4.7	0.77	0.21
Latvia	8.1	0.47	0.53	Zimbabwe	5.8	0.79	0.21

second and third most volatile countries in the world. Serbia and Equatorial Guinea are the second and third most volatile countries in the short term. Also, it is worth noting that the median share of the calculated medium-term volatility in total volatility is 31% across 190 countries. Thus, medium-term volatility accounts for approximately one-third of the total volatility and the remaining two-thirds is short-term high-frequency volatility.

Does the medium-term trend-growth volatility calculated using the new technique comparable to other measures of medium-term volatility such as the structural break approach? In Table 5, I present the correlation matrix for the long-, short-, medium-term volatilities and the number of structural breaks estimated by Jones and Olken (2008).[8] Long-term volatility is positively correlated with either the short-term volatility (with a correlation coefficient of 0.8426 and a p value of 0.0000) or medium-term trend-growth volatility (0.9322, p value = 0.0000). There is also a positive correlation between the short-term and medium-term volatilities (0.5908, p value = 0.0000). However, the number of structural breaks is correlated only with the medium-term trend-growth volatility (0.2063, p value = 0.0250) but not with the long-term volatility (− 0.0372, p value = 0.6895) or the short-term volatility (− 0.1794, p value = 0.0519). The interpretation is that by construction all three types of long-, short-, and medium-term volatilities are related, but the correlation coefficient is lower between the short- and medium-term volatilities than between either the short- and long-term volatilities or the long- and medium-term volatilities. This is because an increase in the short-term volatility invariably increases the long-term volatility, but may (or may not)

[8] Jones and Olken (2008) using the Bai and Perron (2003) methodology find a total of 73 structural breaks in 48 of the 125 countries that have at least 20 years of Penn World Table data.

Table 5 Correlation matrix for long-, short-, medium-term volatilities and structural breaks

	Total long-term volatility	Short-term high-frequency vol.	Medium-term trend-growth vol.	Number of structural breaks
Total long-term volatility	1.00			
Short-term high-frequency vol.	0.8426*	1.00		
	(0.0000)			
Medium-term trend-growth vol.	0.9322*	0.5908*	1.00	
	(0.0000)	(0.0000)		
Number of structural breaks	−0.0372	−0.1794	0.2063*	1.00
	(0.6895)	(0.0519)	(0.0250)	

Figures in the parentheses are p values. Asterisks indicate statistical significance at the five-percent level

cause an increase in the medium-term trend-growth volatility. Again, it is worthwhile to emphasize that the correlation matrix indicates that there is a significant positive correlation between the number of structural breaks and medium-term trend-growth volatility calculated using the new technique.

To further test the validity of this paper's measure of medium-term trend-growth volatility, I regress the number of estimated structural breaks on the medium-term trend-growth volatility. To be a good measure of medium-term trend-growth volatility, I expect the medium-term trend-growth volatility calculated using the new technique to be positively correlated with the number of structural breaks estimated by Jones and Olken. The result of a simple OLS regression is:

$$\begin{aligned} \text{Breaks} &= 0.38 * \text{Constant} + 18.748 * \text{Medium\_Stdev}, \\ &\quad (\text{SE} = 0.109) \quad (\text{SE} = 7.466) \quad (n = 118) \end{aligned} \tag{10}$$

where Breaks is the number of structural breaks estimated by Jones and Olken, Constant is the intercept, and Medium_Stdev is the medium-term volatility calculated in this paper. The estimate of 18.748 for the medium-term volatility has a robust standard error of 7.466, which is positive and very statistically significant (t statistic $= 2.51$ and p value $= 0.013$).

Another interesting question is whether the calculated short-term volatility is related to the number of structural breaks estimated by Jones and Olken. An implicit assumption made in the derivation of the technique in Eq. (1) is that short-term volatility and the structural break measure of medium-term volatility are not significantly related so that the covariance between the two variables can be assumed zero. I now can test this assumption and the results are as follows,

$$\begin{aligned} \text{Breaks} &= 0.932 * \text{Constant} - 10.160 * \text{Short\_Stdev}, \\ &\quad (\text{SE} = 0.219) \quad (\text{SE} = 6.140) \quad (n = 118) \end{aligned} \tag{11}$$

where Short_Stdev denotes the calculated short-term volatility. The estimate of -10.160 for short-term volatility has a robust standard error of 6.140, which is not statistically significant (t statistic $= -1.65$ and p value $= 0.101$). Thus, as expected, the calculated short-term volatility and the estimated number of structural breaks are not significantly related.

Another validity exercise is to compare the empirical results obtained from using the calculated medium-term volatility in cross-country studies to results already established by previous studies in the literature. For instance, Cuberes and Jerzmanowski (2009) study the relationship between democracy and medium-term trend-growth volatility and find that trend volatility is lower in more democratic countries. Here, I attempt to replicate their cross-country results. Running an OLS regression using the calculated medium-term volatility as a dependent variable rather than using their number of growth reversals gives:

$$\begin{aligned} \text{Medium\_Stdev} = {} & 0.010 * \text{Constant} - 0.782 * \text{Polity2} + 0.672 * \text{GDPPC60}L \\ & (\text{SE} = 0.011) \quad (\text{SE} = 0.277) \quad (\text{SE} = 1.580) \\ & (n = 110, \mathrm{r}^2 = 0.12) \end{aligned} \tag{12}$$

where Polity2 is the measure of democracy adopted by Cuberes and Jerzmanowski from Polity IV. Polity 2 is an index ranging from -10 to $+10$, with -10 indicating absolute autocracy and $+10$ total democracy. For their cross section regressions, Cuberes and Jerzmanowski use an average measure of Polity 2 over the sample period for each country in the dataset, and this is what I follow in Eq. (12). GDPPC60L is the logarithm of the initial income level, which is added as a control for initial country condition. The estimate for democracy is -0.782, which is negative and highly statistically significant (t statistic $= -2.83$, p value $= 0.006$), indicating that medium-term volatility is lower in more democratic countries.[9] Thus, the empirical result generated from using the calculated medium-term volatility corroborates the findings of a previous study well known in the literature.[10] In sum, medium-term trend-growth volatility calculated using the new technique is highly correlated with the number of structural breaks estimated using a parametric approach and produces empirical results which are consistent with major findings of the existing literature.

5 Conclusion

The literature on development economics and economic volatility has increasingly focused on medium-term trend-growth volatility in the past decade. The increasing awareness of the importance of medium-term trend-growth volatility is due to the find-

[9] In Table 6 of Cuberes and Jerzmanowski (2009), they also add the number of breaks and one other institutional variable in the regression. I find similar results when I add the number of breaks in the regression or excluding countries of OPEC from the sample.

[10] I also find evidence that short-term volatility is significantly lower in more democratic states in a regression similar to Eq. (12) with short-term volatility rather than medium-term volatility on the left-hand side.

ing that developing countries experience large trend volatility in the medium term. As Pritchett explains: “A single time trend does not adequately characterize the evolution of GDP per capita in most developing countries. Instability in growth rates over time for a single country is great, relative to both the average level of growth and the variance across countries (Pritchett 2000).” It is thus imperative to find the determinants of medium-term trend-growth volatility.

This paper proposes an intuitive measure of medium-term trend-growth volatility. It shows that medium-term trend-growth volatility for a country can be measured by subtracting the average short-term variance of annual growth rates of output per capita from the long-term variance of annual growth rates of output per capita. Not only does this measure easy to understand and implement, but also highly correlated with the number of structural breaks estimated by using structural break econometric technique and produce empirical results which are consistent with findings of previous cross-country studies in the literature. However, the new technique neither detects the number nor the timing of structural breaks, but only gives a measure of medium-term trend-growth volatility. In spite of its limitation, the technique can be a handy tool for researchers aiming to study the determinants of medium-term trend-growth volatility of developing countries.

The finding in this paper of an inverted-U shaped relationship between medium-term trend-growth volatility and country income level provides further empirical evidence that economic development is likely to increase trend-growth volatility for emerging low-income countries. The causes of this increase in trend-growth volatility for emerging low-income countries have yet to be fully understood. This paper will help future research in the area by providing a convenient and accurate way of measuring medium-term trend-growth volatility.

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Appendix A

Equation (4) can be derived from Eq. (3) as follows,

$$\sigma_{\mathrm{ST}}^2 = \frac{1}{n}\left[\frac{1}{b}\left(\sum_{1}^{b}\left(X_i - \bar{X}_{S1}\right)^2 + \sum_{b+1}^{2b}\left(X_i - \bar{X}_{S2}\right)^2 + \cdots + \sum_{N-b+1}^{N}\left(X_i - \bar{X}_{Sn}\right)^2\right)\right]$$

$$\sigma_{\mathrm{ST}}^2 = \frac{1}{n}\left[\frac{1}{b}\left(\left(\sum_{1}^{b} X_i^2 - b\bar{X}_{S1}^2\right) + \left(\sum_{b+1}^{2b} X_i^2 - b\bar{X}_{S2}^2\right) + \cdots \right.\right.$$
$$\left.\left. + \left(\sum_{N-b+1}^{N} X_i^2 - b\bar{X}_{Sn}^2\right)\right)\right]$$

$$\sigma_{\mathrm{ST}}^{2}=\frac{1}{n}\left[\frac{1}{b}\left(\left(\sum_{1}^{b}X_i^2+\sum_{b+1}^{2b}X_i^2+\cdots+\sum_{N-b+1}^{N}X_i^2\right)\right.\right.$$
$$\left.\left.-\left(b\bar{X}_{S1}^{2}+b\bar{X}_{S2}^{2}+\cdots+b\bar{X}_{Sn}^{2}\right)\right)\right]$$
$$\sigma_{\mathrm{ST}}^{2}=\frac{1}{n}\left[\frac{1}{b}\left(\left(\sum_{i}^{N}X_i^2\right)-b\left(\bar{X}_{S1}^{2}+\bar{X}_{S2}^{2}+\cdots+\bar{X}_{Sn}^{2}\right)\right)\right]$$

where $i=1,2,3,\ldots,N$. (N is the number of years.)

$$\sigma_{\mathrm{ST}}^{2}=\frac{1}{n}\left[\frac{1}{b}\sum_{i}^{N}X_i^2-\sum_{j}^{n}\bar{X}_{Sj}^{2}\right]$$

where $j=1,2,3,\ldots,n$. (n is the number of short-term windows.)

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