Business-cycle Volatility and Long-run Growth: How Strong is the Relationship?*

Debdulal Mallick
Department of Economics, and Alfred Deakin Research Institute
Deakin University
70 Elgar Road
Burwood, VIC 3125, Australia
Email: dmallic@deakin.edu.au

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Abstract

This paper revisits the empirical relationship between business-cycle volatility and long-run growth. The key contribution lies in controlling for fluctuations in the trend growth that also accounts for enormous heterogeneity among countries in their long-run growth trajectories. The results show that, after controlling for these fluctuations, there is no correlation between business cycle volatility and growth. Otherwise, there would be a significantly negative correlation, especially for developing countries, as documented in the literature. The results have implications for stabilization policies, and also for cross-country growth regressions in that ignoring heterogeneity among countries may lead to wrong conclusions.

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1. Introduction

This paper revisits the empirical relationship between business-cycle (BC) volatility[1] and long-run growth but the key contribution lies in controlling for fluctuations in the trend growth. Addressing these fluctuations also accounts for enormous heterogeneity among countries in their long-run growth trajectories. The main finding is that the significant volatility-growth correlation (or arguably the causal effect of BC volatility on long-run growth) documented in the literature—either negative or positive—disappears after controlling for such fluctuations.

Both the theoretical and empirical literature on the relationship between BC volatility and long-run growth lack consensus. In the Schumpeterian (1939) tradition, where the mechanism is "creative destruction," the effect of business cycles on long-run growth is positive. For example, Caballero and Hammour (1994) view recessions are a time of "cleansing," when outdated or unprofitable techniques and products are pruned out of the productive system. During recessions firms also accumulate "organizational capital" (Hall, 1991) and/or reallocate labor (Davis and Haltiwanger, 1990; 1992) that induce growth in the long run.

In contrast, a negative relationship between BC volatility and long-run growth is predicted by endogenous growth theory based on the idea of learning-by-doing or demand spill-overs (Arrow, 1962; Stadler, 1990; Martin and Rogers, 1997). For example, business cycles create fluctuations in employment, and the unemployed lose their skills in recessions. Therefore, in the presence of negative learning-by-doing, temporary shocks have negative impact on long-run growth.[2] However, in the models based on the opportunity cost arguments, the prediction of the effect of business cycles on growth can be both positive and negative (Aghion and Saint-Paul, 1998). For example, if the cost of productivity improvements positively depends on current production, and this cost drops by more than its present discounted benefit in a recession, then business cycles have a positive effect on growth. Saint-Paul (1997) provides evidence at the

[1] This is volatility of growth rate as opposed to volatility of level of GDP.

[2] Blackburn (1999) and Blackburn and Pelloni (2004) point out that the negative relationship based on learning-by-doing may not hold in a stochastic growth model.

aggregate level in favor of this argument. On the other hand, if the cost of productivity-enhancing activities does not depend on current production, the conclusion of the model reverses and recession have a negative long-run effect.

Given the lack of consensus on the theoretical predictions, the burden is on the empirical side to establish the actual relationship. But empirical evidence also lacks consensus. For example, Kormendi and Meguire (1985), Grier and Tullock (1989) and Stastny and Zagler (2007) find a positive correlation between business cycles and long-run growth. In contrast, Ramey and Ramey (1995), Martin and Rogers (2000), Kneller and Young (2001), Fatás (2002), Döpke (2004) and Rafferty (2005) find a negative correlation. The observed relationship also varies across country groups. For example, Martin and Rogers (2000) find a negative relationship for the industrialized countries but insignificant relationship for the non-industrialized countries. They attribute learning-by-doing as a mechanism that may not be at work for the latter group of countries.[3] Imbs (2007) finds volatility and growth to be positively related at the sectoral level but negatively related at the aggregate level. Furthermore, it has not been established satisfactorily whether the observed relationship is a correlation or a causal effect of BC volatility on long-run growth. It is important to point out that the theoretical models implicitly argue for an effect of BC volatility on future growth, while the empirical studies have tested a contemporaneous correlation.

Notwithstanding a large body of empirical research on the volatility-growth relationship, the literature has categorically ignored fluctuations in the trend growth. The following examples will illuminate the danger of ignoring such fluctuations in estimation. Consider two countries—*A* and *B*—with identical average growth performances over 20 years (for simplicity consider arithmetic average). Suppose that the annual growth rate in country *A* alternated every year between 2% and -2% (i.e., 2, -2, 2, -2, ---- 2, and -2), while that in country *B* was 2% in the first 10 years and -2% in the last 10 years. Both countries have the same average growth rate (zero) and volatility (measured by the standard deviation which is 2.052) but patterns of the trend growth in these two countries are clearly different. The trend growth rate in country *B* is seven times as volatile as in country *A* (the standard deviation of the trend growth calculated using the

[3] Young (1993) also argues that growth will be driven by learning-by-doing only at relatively high levels of development.

Hodrick-Prescott (H-P) filter is 0.270 and 1.908 in country *A* and *B*, respectively). On the other hand, BC volatility (measured by the standard deviation of the cyclical component calculated using the same filter) in country *A* is 3.5 times as large as in country *B* (2.001 and 0.567, respectively). Suppose, there is another country *C* that experienced a -2% growth rate in the first 12 years, zero in next 2 years and 4% in the last 6 years. Although average growth in country *C* is also zero and its BC volatility (0.573) is similar to that in country *B*, volatility of its trend growth (2.62) is greater than that in both *A* and *B*. In Section 3, we provide similar examples observed in the data.

The above examples illustrate that many dissimilar growth trajectories that differ in terms of fluctuations in the trend growth can lead to the same average growth rate. By ignoring these fluctuations, the literature also fails to address the enormous heterogeneity among countries. In this paper, we address these fluctuations by the standard deviation of the trend (long-run) growth rate calculated by the low-pass filter (we refer it to long-run (LR) volatility). The reason for controlling LR volatility in estimation can also be understood from the following volatility decomposition. Given that there are enormous transitory (cyclical) variations around the trend growth for many countries and that the trend growth *per se* is also volatile, per capita real GDP growth rate ($g_{y,t}$) can be written as the sum of two orthogonal terms, its business-cycle ($g_{y,t}^{BC}$) and long-run components ($g_{y,t}^{LR}$): $g_{y,t} = g_{y,t}^{BC} + g_{y,t}^{LR}$.[4] Its variance is then decomposed as $\text{Var}(g_{y,t}) = \text{Var}(g_{y,t}^{BC}) + \text{Var}(g_{y,t}^{LR})$.

We use this spectral relation to explore the volatility-growth relationship at the cross-country level. Our main source of data is the PWT 8.0. We choose the 1960-2007 period because of unavailability of data for control variables for periods earlier than 1960 and to ensure that our results are not influenced by the recent global financial crises that started in 2008. We also estimate for the 1960-1980, 1970-2007 and 1980-2007 sub-periods, and disaggregating by the intensity of BC volatility and country income groups. To verify the results from an alternative dataset and different time periods, we perform a separate analysis for the 1878-2010 period using

[4] Romer (2012, p. 136) stresses that statistical tests do not determine whether growth rate is stationary or nonstationary; rather they suggest that "there are highly transitory movements in growth that are large relative to any long-lasting movements that may be present." The question of stationarity is also economically unimportant.

the historical time series compiled by Angus Maddison for a relatively small number of countries. As an additional robustness check, we replicate Ramey and Ramey (1995, AER) using their data.

The BC and LR volatility are calculated as the standard deviation of the cyclical and long-run components of (annual) per capita real GDP growth rate, respectively. We extract these two components employing the Baxter-King (B-K) (1999) filter at the business-cycle and low frequencies, respectively. We choose a window of 3 years, and critical periodicities (inversely related to frequencies) of 2 and 8 years for the business cycle, and 8 years and above for the long-run. We estimate both cross-section and panel data. The cross-section data is constructed by taking average and calculating standard deviation of the relevant variables over the sample period. To construct the panel data, non-overlapping average over 7 years has been taken for the annual growth rate and other series. We show that averaging over 7 years performs better in terms of reweighting the variances of the raw series across low frequencies than averaging over 5 years as commonly done in the cross-country growth literature. BC and LR volatility have been calculated as the standard deviation of the respective filtered growth rates over the same interval but the filter has been modified as one-sided using only lag values so that an artificial reverse causality from growth to volatility is not generated.

We test both the contemporaneous correlation between BC volatility and growth following the empirical literature, and the neglected theoretical prediction of the effect of BC volatility in the previous period on current growth. We find that there is no correlation between BC volatility and growth. The result is robust in both cross-sectional and panel estimations, and in both the PWT and Angus Madison datasets. But if LR volatility is incorrectly excluded from the regression, the correlation becomes significantly negative, especially for developing countries in the post-1970 period. There is also no effect of BC volatility in the previous period on current growth. The direction of bias in the coefficient on BC volatility depends on the correlation between growth rate and LR volatility excluded in the regression. Our measure of LR volatility can also be interpreted as persistence in volatility. We find that persistence in volatility has a negative association with growth for developing countries in the post-1970 period.

Our results have important implications for stabilization policies in light of the recent global financial crises that caused a prolonged recession and depressed many developed economies enough to lower the trend growth. However, such contractions are more frequent in developing than developed countries. Berg, Ostry and Zettelmeyer (2012) show that inequality of the income distribution, lack of democratic institutions and macroeconomic instability are some factors that cause shorter growth spells (prolonged and more frequent recessions). Mallick (2014) shows that terms-of-trade volatility and financial underdevelopment cause persistent growth volatility. But these characteristics may also be symptoms as well as propagation mechanisms of volatility persistence. Understanding volatility persistence is crucial for designing stabilization policies but is an under-researched area, even in the context of developed countries.

The rest of the paper proceeds as follows. Section 2 discusses the data including construction of both BC and LR volatility. Section 3 motivates the paper by presenting examples of heterogeneity observed across countries in terms of their growth trajectories. This section also presents some key descriptive statistics. The estimation strategy is explained in Section 4. The results are discussed in Section 5. Section 6 compares the relative importance of volatility and its persistence in explaining growth. Section 7 compares the paper's contribution in the cross-country macroeconomic literature regarding volatility persistence. Finally, Section 8 concludes.

2. Data

In this section we explain the data used in our empirical analysis including construction of BC and LR volatility.

The main source of data is the PWT 8.0. Average per capita growth rate and volatility have been calculated from the RGDP^{NA} series (the real GDP at constant national prices), which is recommended to compare growth rates across time and countries (Feenstra, Inklaar and Timmer, 2013, Table 5 in p. 30). Per capita real GDP (*Y*) is calculated by dividing RGDP^{NA} by population (POP). Annual growth rate is calculated as the log difference: $dy_t = \ln(Y_t / Y_{t\text{-}1})$.

The BC and LR volatility have been calculated as the standard deviation of the cyclical and long-run components of dy_t, respectively, extracted employing the B-K filter.[5] A window of

[5] Levy and Dezhbakhsh (2003) and Mallick (2014) calculate BC and LR volatility using the spectral method by integrating the spectrum over the relevant frequency ranges. However, this method requires relatively long time series, so that it cannot be employed at our panel data analysis. Fatás (2000a, 2000b), Levy and Dezhbakhsh (2003), Aguiar and Gopinath (2007) and Nakamura, Sergeyev and Steinsson (2012) employ the Cochrane's (1988) variance ratio to calculate LR volatility but this method cannot be used to calculate BC volatility. Another alternative can be unobserved component (UC) model. For example, Stock and Watson (2007) and Ascari and Sbordone (2014)

3 years, and critical periodicities of 2 and 8 years for cyclical components (band-pass filter), and 8 years and above for long-run components or equivalently low frequency components (low-pass filter) have been chosen.[6] The main purpose of a filter is to extract the cyclical components of a series, and the long-run components are then recovered as the residual. But we extract the long-run components using the low-pass filter assuming that per capita real GDP growth is stationary.

Average growth rate (Δy) is the average of dy_t. For the cross-section data, we take average of dy_t, and calculate the standard deviation of the filtered series over the entire sample period. The panel data has been constructed by non-overlapping averaging over 7 years. Volatility calculated as the standard deviation of the filtered growth series may be problematic for our purpose because the B-K filter is based on a (symmetric) moving average of the lead and lag values. As a result, volatility for a particular interval also incorporates information about growth of the preceding interval, which artificially generates a reverse causality from growth to volatility. To avoid this problem, we transform the growth series by one-sided filter using only the lag values, and calculate the standard deviation of this modified filtered series.

For initial level of GDP, we use the CGDP^e series (expenditure-side real GDP at current PPPs in million 2005 US$ that compares relative living standards across countries at a single point in time), as recommended by Feenstra, Inklaar and Timmer (2013). Terms of trade (ToT) is

estimate the time varying volatility of the trend and cyclical components of inflation for the USA. This method is not suitable at the cross-country level because iteration does not converge for many countries, especially the developing ones.

[6] Comin and Gertler (2006), Comin (2009) and Comin et al. (2014) employ a non-standard definition of long-run in terms of the periodicity of 200 quarters and above. They refer to the periodicities between 2 and 200 quarters as the medium-term business cycle of which periodicities between 2 and 32 quarters as the high-frequency component of the medium-term (the standard business cycles), and frequencies between 32 and 200 quarters as the medium-frequency component of the medium-term. The authors also show that high and medium term fluctuations of GDP are connected. Our definition of long-run periodicities of 8 years (32 quarters) and above includes their medium-frequency components, and we emphasize the importance of correlation between growth volatility at business cycle and long-run periodicities. Chirinko and Mallick (2014) demonstrate in a different context that a critical periodicity of 8 years sufficiently captures the long-run information and gain from further increasing this cut-off is negligible.

calculated as the ratio of export to import price (PL_X / PL_M). Investment and government expenditure shares of GDP are the CSH_I and CSH_G series, respectively.

Openness is the sum of exports and imports as a share of GDP at the current price and the data is obtained from the PWT 7.1 (this data is not available in the PWT 8.0). Educational attainment data is from the Barro-Lee (2013) dataset. Political violence is captured by the total summed magnitudes of all societal and interstate major episodes of political violence (MEPV) in a country compiled by Center for Systemic Peace.[7] Private credit data has been collected from Financial Development and Structure Dataset complied by Beck et al. (2000) and revised by Čihák et al. (2012).

3. Heterogeneous growth trajectories: Some examples

We have earlier illustrated hypothetical examples on possible heterogeneity among countries in their growth trajectories. In this section, we provide several examples of such heterogeneity observed in the data in terms of growth rate, BC volatility and LR volatility for 1960-2007 period. Detail information for all sample countries is provided in Appendix A.1. We also discuss some descriptive statistics at the end of this section.

Namibia vs. Nepal: Both countries had the same average growth rate (about 0.013) and BC volatility (0.026), but in Namibia (0.019) LR volatility was about twice as large as in Nepal (0.010).

Columbia vs. Australia: Both countries had almost the same average growth (0.020 vs. 0.021) and BC volatility (0.015 vs. 0.014), but in Columbia LR volatility was much larger than in Australia (0.013 and 0.008, respectively).

[7] MEPV is an annual, cross-national, time-series data on interstate, societal, and communal warfare magnitude scores (independence, interstate, ethnic, and civil violence and warfare) for all countries. We use the ACTOTAL series in the dataset. ACTOTAL is calculated as the sum of the magnitude score of episode(s) of: i) international violence, ii) international warfare, iii) civil violence, iv) civil warfare, v) ethnic violence, and vi) ethnic warfare involving that state in that year. Each type of violence/warfare is scaled from 1 (lowest) to 10 (highest) for each MEPV; magnitude scores for multiple MEPV are summed with 0 denoting no episodes.

Argentina vs. Burkina Faso: These two countries also differ only by their LR volatility (0.022 vs. 0.014); otherwise, they are similar in terms of average growth (about 0.011) and BC volatility (about 0.044).

Romania vs. Malaysia: Both countries had the same average growth (0.041). But BC volatility was larger in Malaysia (0.033) than in Romania (0.026), while Romania (0.044) had more than twice as large LR volatility as Malaysia (0.020).

Japan vs. Cyprus: Both countries had the same average growth (0.043). However, compared to Cyprus, Japan experienced milder BC volatility (0.033 vs. 0.056) but greater LR volatility (0.036 vs. 0.020).

Mauritania vs. Fiji: Both countries experienced the same average growth (0.018) but Mauritania had much greater BC volatility (0.064 vs. 0.043) as well as LR volatility (0.039 vs. 0.017) than Fiji.

Israel vs. Egypt: The two neighbors experienced similar average growth (0.034 vs. 0.037) but Israel had greater BC volatility (0.053 vs. 0.032) as well as LR volatility (0.036 vs. 0.015) than Egypt.

There are also examples where similar fluctuations are related to divergent average growth. For example, growth rate was much higher in Hong Kong (0.048) than in Bangladesh (0.011) although both countries had the same BC volatility (0.035) and LR volatility (0.019). Niger and Cyprus can be another likely pair. Both countries had very similar BC volatility (0.054 vs. 0.056) and LR volatility (0.025 vs. 0.020), but Niger economy declined at an average rate of 0.012, while Cyprus grew rapidly at the rate of 0.043. The heterogeneity can also be present among developed countries. For example, for the 1970-2007 period, average growth rate and BC volatility in Japan and Austria were the same at 0.024 and 0.014, respectively, but LR volatility was more than twice in Japan (0.014) than in Austria (0.06).

The above examples illustrate an enormous heterogeneity among countries in their growth trajectories. More specifically, very dissimilar growth trajectories can lead to the same average growth. On the other hand, apparently similar growth trajectories can also lead to different average growth. Figures 1(a)-(j) display growth trajectories of the countries mentioned above in terms of their long-run growth rate calculated by the low-pass filter.

Insert Table 1 and Figures 1-2 here

Average growth rate, BC volatility and LR volatility for the 1960-2007 period in a sample of 107 countries[8] are summarized in Table 1. Countries are classified as high, middle and low income following the World Bank classification. BC volatility decreases with income level—it is 0.046 in low income countries compared to 0.036 and 0.024 in middle (upper and lower middle income combined) and high income countries, respectively. LR volatility is same in both low and middle income countries (around 0.023) and slightly smaller in high income countries (0.020). Figures 2(a)-(b) display that both BC and LR volatility decrease with initial income level. Although BC volatility is larger than LR volatility for all income groups, the ratio of BC volatility to LR volatility is the largest for low income countries followed by middle and high income countries (column (4)). The correlation between BC and LR volatility along with the 95% confidence intervals are reported in column (5). The correlation is 0.61 for all sample countries; it is the largest for high income countries at 0.84 followed by middle and low income countries (0.60 and 0.45, respectively). Figure 3 confirms the positive relationship between BC and LR volatility.

4. Estimation strategies

Our estimation strategy is simple in which long-run growth is regressed on BC volatility and a set of conditioning variables among which LR volatility is the most important one. The cross-section specifications are given by:

$$\Delta y_i = \alpha + \gamma_{1C} BCvol_i + \gamma_2 LRvol_i + \beta y_{i,0} + \mathbf{X}_i' \boldsymbol{\delta} + v_i \, , \qquad \text{---(1a)}$$

$$\Delta y_i = \alpha + \gamma_{1U} BCvol_i + \beta y_{i,0} + \mathbf{X}_i' \boldsymbol{\delta} + u_i \, . \qquad \text{---(1b)}$$

Here Δy_i is the average growth rate of real per capita GDP (explained in Section 2), $y_{i,0}$ is the log of real per capita GDP in the initial period and $\mathbf{X}$ is a set of conditioning variables. Our attention is on γ_{1C}, the (corrected or credible) coefficient on BC volatility ($BCvol_i$) in equation

[8] These 107 countries are based on the availability of RGDP^{NA} data without any discontinuity. Among these countries, we consider possible six outliers (based on BC and LR volatility in Appendix A.1)—Equatorial Guinea, Iran, Rwanda, Gabon, Guinea-Bissau and Syria—but do not exclude them from the sample. The descriptive statistics and regression results do not qualitatively change if these countries are excluded from the sample.

(1a). We also estimate γ_{1U} (the uncorrected coefficient) in equation (1b) without controlling for LR volatility ($LRvol_i$) to compare and contrast with other results in the literature. We show the direction of bias in γ_{1U} at the end of this section.

Choice of controls ($\mathbf{X}$) in cross-country growth regressions is a difficult task given that a large number of variables have been found to be significant in different studies. Some studies control the variables that are robustly significant in extreme bound analysis (or Bayesian model averaging). We take a different approach in order to avert the omitted variable bias that involves controlling only those determinants of growth that also affect BC volatility. Omission of controls will not cause any bias as long as they are uncorrelated with BC volatility.

The following variables are included in $\mathbf{X}$: (i) investment share in GDP, (ii) (initial) human capital measured by the year of schooling for aged over 15 years, (iii) population growth rate, (iv) trade openness measured by the sum of exports and imports as a percentage of GDP, (v) growth rate of government share in GDP, (vi) terms of trade (ToT) volatility measured as the standard deviation of the ratio of the export to import prices (as a proxy for external shocks), (vii) political violence (explained in Section 2), and ix) financial development proxied by the credit disbursed to the private sector by banks and other financial institutions relative to GDP. Initial (log) per capita income is also included to account for conditional convergence and the transitional dynamics so as to avert a positive bias on the coefficient on BC volatility (Martin and Rogers, 2000, p. 365). The controls (i)-(iii) are common in growth-volatility regressions (for example, Ramey and Ramey, 1995) but can also be justified by economic reasoning. Investment is crucial for economic growth but it is also the most volatile component of GDP over business cycles. Higher population growth can cause economic (and political) instability in a country unless accompanied by economic growth faster enough to reduce unemployment.[9] Higher human capital, although plays an important role in economic growth, also cause economic and political instability if left unutilized—the Arab Spring is a recent example (Kuhn, 2012).

The role of openness in economic growth is established both theoretically and empirically but openness also affects volatility. Using an industry-level panel dataset of manufacturing

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[9] Higher population growth has also been found to be related to higher consumption volatility (Bekaert, Harvey and Lundblad, 2006).

production and trade, Giovanni and Levchenko (2009) document a positive and economically significant relationship between trade openness and overall volatility. Mallick (2014) also observes similar effects using aggregate data at the cross-country level. Kose, Prasad and Terrones (2006) find out that openness stimulates both growth and volatility.

Growth of the share in government expenditure is intended to account for government expenditure shocks documented in the Real Business Cycle literature.

Easterly et al. (1993) document that shocks, measured by the change in the ToT, influence growth directly and also indirectly through policy variables. A negative robust impact of the change in the ToT on growth volatility is documented by Mallick (2014) and Agénor et al. (2000). Mendoza (1995) quantifies ToT shocks as accounting for 40%-60% of the observed variability of GDP at the cross-country level. Koren and Tenreyro (2007) find strong negative correlations between growth and volatility of country level macro shocks.

Rodrick (1999) show that domestic social conflicts are a key to understanding lack of persistence in growth performance and growth collapse since the mid-1970s. Social conflicts interact with external shocks and the domestic institutions of conflict-management. Acemoglu et al. (2003) argue that bad macroeconomic policies that increase volatility and lower growth are the results of weak institutions, which is also related to social and political instability.[10] Ploeg and Poelhekke (2009) show that ethnic tensions cause higher volatility and lower growth.[11] Financial development is one of the main channels through which volatility affects growth (Aghion and Banerjee, 2005).

The above list of variables is certainly not a complete one. There may be other variables that trigger both growth and BC volatility. It is conceivable that many omitted variables are related to the level of economic development, and therefore controlling for initial income level in the regression, to a large extent, captures these omitted variables. We additionally include region dummies (Latin America, Sub-Saharan Africa, Asia Pacific, and Middle East and North Africa)

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[10] We think that political violence, to a large extent, captures the institutional development. Nonetheless, we also additionally control for *Polity2* to verify robustness, especially for developing countries.

[11] In investigating the effect of uncertainty on growth, Baker and Bloom (2013) used natural disasters, terrorist attacks and unexpected political shocks as instruments of uncertainty measured by the first and second moments of the stock prices. However, the authors recognize the endogeneity of these shocks in the long run.

in the regression as some regions are more volatile than others for reasons not discussed above; these dummies also capture omitted variables in growth regressions (Berg, Ostry and Zettelmeyer, 2012). Finally, we include dummies for legal origins and landlocked to account for country fixed effects as well as omitted variables. For example, La Porta et al. (1997; 2008) document that financial development of a country is greatly influenced by its legal origin. Financial development data is not available for many developing countries before 1980. Therefore, in the specification that exclude financial development, legal origin dummies act as proxies. Growth performance of landlocked countries is dismal and these countries also experience greater volatility as a result of lack of access to the market (Malik and Temple, 2009).

We construct three cross-sectional datasets for the 1960-2007, 1970-2007 and 1980-2007 periods, respectively, to verify stability of the results across time periods and sample countries (fewer countries are retained in the 1960-2007 period because of unavailability of data for some control variables).

The cross-sectional estimation captures the "between" country variations. Panel data allows a richer investigation by also capturing the "within" country variations. The estimating equations are written as:

$$\Delta y_{i,\tau} = \alpha + \gamma_{1C} BCvol_{i,\tau} + \gamma_2 LRvol_{i,\tau} + \beta_1 y_{i,\tau_0} + \mathbf{X}'_{i,\tau-1}\boldsymbol{\delta} + \mu_i + \eta_\tau + v_{i.\tau}, \qquad \text{---(2a)}$$

$$\Delta y_{i,\tau} = \alpha + \gamma_{1U} BCvol_{i,\tau} + \beta_1 y_{i,\tau_0} + \mathbf{X}'_{i,\tau-1}\boldsymbol{\delta} + \mu_i + \eta_\tau + u_{i,\tau}. \qquad \text{---(2b)}$$

Here, μ_i is the country fixed effects captured by dummies for legal origins and landlocked, η_τ is the aggregate time effects captured by time dummies and y_{i,τ_0} is the log of real per capita GDP in the initial year of each interval. All control variables are lagged by one period ($\mathbf{X}_{i,\tau-1}$).

Equation (2a), like equation (1a), will estimate a correlation between BC volatility and growth. To estimate a casual effect, we need to correct the endogeneity due mainly to reverse causality from growth to BC volatility. The reverse causality can be both negative and positive. For example, in Aghion and Banerjee (2005), higher growth leads to volatility. Investment and borrowing are higher in a boom, leading to higher interest rates. This in turn creates a pecuniary externality by increasing the debt burden of all entrepreneurs, constraining the growth of entrepreneurial wealth and investment capacity. At some point, investment capacity falls below total savings, the economy recedes, and interest rates decrease. The process then reverts to a boom.[12] Lack of growth may also cause political instability that in turn leads to economic instability. Endogeneity in LR volatility will also bias the coefficient on BC volatility. Instrumental variable estimation is the solution but it is almost impossible to find exclusion restrictions for identification in the cross-country growth regressions in the sense that some exogenous variables affect long-run growth only through BC volatility (unless someone is lucky enough to find a natural experiment).[13] Lagged values are potential candidates for instruments of contemporaneous values in the panel data. But, as implicit in the literature discussed in introduction, lagged BC volatility affects growth through cleansing/reallocation effect or learning-by-doing, so they cannot be valid instruments.[14]

One way to solve the reverse causality problem is to directly include lagged volatility in the regression instead of contemporaneous values. This procedure also tests the theoretical

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[12] However, the authors also argue that this can happen only at certain level of financial development. Credit constraint is very high in a highly financially underdeveloped country, so that entrepreneurs rely entirely on their retained earnings for investment. Conversely, in financially developed countries, firms face no credit constraints and thus can invest up to the expected net present value of their projects. Therefore, financially developed or underdeveloped countries will not experience volatility; the remaining countries at the intermediate level of financial development are vulnerable to volatility.

[13] Several studies have tried to establish causality from BC volatility to growth using the instrumental variable regressions. For example, Hnatkovska and Loayza (2005) used the following variables as the instruments of volatility: the standard deviation of the inflation rate, a measure of real exchange rate misalignment, the standard deviation of ToT shocks, and the frequency of systematic banking crises. Martin and Rogers (2000) used the standard deviation of the growth rate of the preceding decade, the initial inflation rate of the decade, the initial level of GDP per capita and the number of revolutions and coups as instruments for the developing countries. Mobarak (2005) used diversification as the instrument of volatility. However, exogeneity of these instruments in the long run can be disputed. Bazzi and Clemens (2013) provide an excellent discussion on the problem of instrument variable estimation in cross-country growth regressions.

[14] A matrix of instruments following the Arellano and Bond (1991) or Blundell and Bond (1998) dynamic panel estimation using lagged level and differences could also be constructed in a static panel. In addition to the direct effect of lagged volatility on growth, these instruments also suffer from weak instrument problem because the requirement for instrumental strength that the variance of the residual must be larger than the variance of the fixed effect is almost always violated in the cross-country data (see, Bazzi and Clemens, 2013; Newey and Windmeijer, 2009).

predictions of the effect of BC volatility in the previous period on current growth. Provided that the omitted variable problem is satisfactorily addressed and that BC (and LR) volatility are calculated using the growth series transformed by one-sided filter using only lag values to avoid generated reverse causality (discussed in Section 2), the coefficient on BC volatility in the previous period (interval) will represent a causal effect on current growth. Our identification approach in this particular context will be more reliable than employing invalid and weak instruments.[15] The following specifications are estimated to obtain a causal effect:

$$\Delta y_{i,\tau} = \alpha + \gamma_{1C} BCvol_{i,\tau-1} + \gamma_2 LRvol_{i,\tau-1} + \beta_1 y_{i,\tau_0} + \mathbf{X}'_{i,\tau-1}\boldsymbol{\delta} + \mu_i + \eta_\tau + v_{i.\tau}, \qquad \text{---(3a)}$$

$$\Delta y_{i,\tau} = \alpha + \gamma_{1U} BCvol_{i,\tau-1} + \beta_1 y_{i,\tau_0} + \mathbf{X}'_{i,\tau-1}\boldsymbol{\delta} + \mu_i + \eta_\tau + u_{i,\tau}. \qquad \text{---(3b)}$$

Since $Cov(v_{i.\tau}, BCvol_{i,\tau-1}) = Cov(v_{i.\tau}, LRvol_{i,\tau-1}) = Cov(v_{i.\tau}, \mathbf{X}_{i,\tau-1}) = 0$, pooled OLS regression will obtain consistent estimates. The standard errors are clustered at the country level.

Finally, we estimate correlation (both contemporaneous and lagged) at longer horizon using the historical data constructed by Angus Maddison. We choose the 1875-2010 period in order to retain a relatively large number of countries in the sample. We first calculate the annual growth rate by log-differencing per capita real GDP and then construct a 7-year panel data similar to that constructed in the PWT data. We control only for the (log) initial per capita GDP, time dummies and dummies for the pre-1914, 1914-1945, 1946-1985; and post-1985 periods,[16] as other controls are not available for such a long period.

To know the direction of bias in the coefficient on BC volatility when LR volatility is incorrectly excluded from the regression, simplify equations (1a)-(1b) excluding the controls:

$$\Delta y_i = \alpha + \gamma_{1C} BCvol_i + \gamma_2 LRvol_i + v_i, \qquad \text{---(4a)}$$

[15] The correlation between volatility and growth is arguably no less important than the causal effect. In another context, Acemoglu, Hassan and Robinson (2011) estimate correlation between the severity of the persecution, displacement, and mass murder of Jews due to the Holocaust and long-run economic and political outcomes in Russia because of the lack of exogenous instruments.

[16] Romer (2012, p. 192) suggested that macroeconomic history of the USA since the late 1800s consists of four broad periods: i) before the Great Depression, ii) the Great Depression and World War II, iii) at the end of the World War II to about mid-1980s, and iv) after mid-1980s. This classification can be readily generalized to other sample countries except for the first period due to the World War I. Therefore, we modify the first period accordingly.

$$\Delta y_i = \alpha + \gamma_{1U} BCvol_i \qquad\qquad + u_i \ . \qquad\qquad \text{---(4b)}$$

The estimated coefficient on BC volatility in equations (4a) and (4b) can be expressed, respectively, as:

$$\hat{\gamma}_{1C} = \frac{\text{corr}(\Delta y, BCvol) - \text{corr}(\Delta y, LRvol) * \text{corr}(BCvol, LRvol)}{1 - \left[\text{corr}(BCvol, LRvol)\right]^2} * \frac{\text{Var}(\Delta y)}{\text{Var}(BCvol)}, \qquad \text{---(5a)}$$

and $\hat{\gamma}_{1U} = \text{corr}(\Delta y, BCvol) * \dfrac{\text{Var}(\Delta y)}{\text{Var}(BCvol)}$. ---(5b)

In the data, corr(*BCvol*, *LRvol*) >0. Therefore, the direction of bias in $\hat{\gamma}_{1U}$ depends on the sign of corr(*Δy*, *LRvol*) or, equivalently, the sign of γ_2 in equation (4a). If corr(*Δy*, *LRvol*) < 0, $\hat{\gamma}_{1U}$ will be biased downward (i.e., if $\hat{\gamma}_{1C}$ is positive, $\hat{\gamma}_{1U}$ will move towards 0 (or even can become negative); if $\hat{\gamma}_{1C}$ is negative, $\hat{\gamma}_{1U}$ will increase in absolute value with the negative sign). Similarly, if corr(*Δy*, *LRvol*) > 0, $\hat{\gamma}_{1U}$ will be biased upward (i.e., if $\hat{\gamma}_{1C}$ is positive, $\hat{\gamma}_{1U}$ will be larger; if $\hat{\gamma}_{1C}$ is negative, $\hat{\gamma}_{1U}$ will move towards 0). Even if corr(*Δy*, *LRvol*) = 0, $\hat{\gamma}_{1U}$ will still be biased upward because of corr(*BCvol*, *LRvol*) >0 (in the denominator).

5. Results

We report $\hat{\gamma}_{1C}$ and $\hat{\gamma}_{1U}$ estimated from cross-sectional and panel data for different time periods and countries. The former represents a credible correlation of BC volatility (or a causal effect of lagged BC volatility), while the latter represents a biased correlation. We also report $\hat{\gamma}_2$, the coefficient on LR volatility, to judge its merit relative to $\hat{\gamma}_{1C}$ in explaining growth, and to show the direction of bias in $\hat{\gamma}_{1U}$. This allows both treatment of the issues we intend to address and a direct comparison with other results in the literature.

5.1 Correlation in cross-sectional data

The OLS results are summarized in Table 2 for the full (1960-2007), 1960-1980, 1970-2007 and 1980-2007 periods.[17] The odd-numbered columns report $\hat{\gamma}_{1C}$ (and also $\hat{\gamma}_2$) estimated from equation (1a). In all periods, $\hat{\gamma}_{1C}$ is close to zero and insignificant (and also no pattern in its sign) suggesting a lack of correlation between BC volatility and growth. As mentioned earlier, private credit data are available for a good number of developing countries only after 1980. Therefore, we have estimated for 1980-2007 period both with and without controlling for private credit (and *Polity2*) (columns (5) and (7), respectively). The results are robust in both specifications.

The even-numbered columns present $\hat{\gamma}_{1U}$ estimated from equation (1b). It is large negative and statistically significant in 1970-2007 and 1980-2007 periods (columns (6) and (8), respectively). It is larger in absolute value and significant at higher level if private credit is not controlled for (column (10)). This result suggests the importance of financial development as an important channel through which BC volatility interacts with growth.[18] With a negative (and significant) $\hat{\gamma}_2$ in equation (1a), $\hat{\gamma}_{1U}$ is biased downward as shown in equations 5(a)-5(b). Comparing the results from equations (1a) and (1b) for the 1970-2007 period, the coefficient of BC volatility changes from -0.002 to -0.121. The quantitative implications of this difference is huge. One standard deviation increase in BC volatility is associated with only 0.003 percentage point decrease in long-run growth, which is statistically insignificant and also economically trivial. But if the correlation of LR volatility is removed from the regression, the same increase in BC volatility would incorrectly be associated with 0.219 percentage point decrease in long-run growth.

Insert Table 2 here

[17] The full sample period reduces to 1964-2004 because the first observation is lost after calculating growth rate from level, and then the next three observations are lost because of employing a one-sided filter with a 3-year window.

[18] If investment is excluded, the coefficient on BC volatility hardly changes suggesting that investment is not an important channel, which is also consistent with Ramey and Ramey (1995).

One might suspect that the results from equation (1a) are driven by multicollinearity between BC and LR volatility. For example, in the 1980-2007 period, $\hat{\gamma}_{1C}$ is 0.053 (positive though very close to 0 and insignificant), but $\hat{\gamma}_{1U}$ is -0.157 (significant at 10% level) after removing the correlation of LR volatility. We rule out such a possibility by calculating the variance inflation factor (VIF) (alternatively, tolerance = 1/VIF). The VIFs (tolerances) of BC and LR volatility are 2.85 (0.351) and 2.80 (0.357), respectively, which are far less (higher) than any conventionally considered critical level. Even if only BC and LR volatility are included in the regression excluding other controls, the VIF (tolerance) is even lower (higher) at 2.31 (0.432).

To further address heterogeneity among countries for reasons other than fluctuations in the trend growth, we perform disaggregated analysis in several ways. First, we divide the sample countries into three groups in terms of their intensity of BC volatility: i) least volatile (0-33 percentile), ii) moderately volatile (33-66 percentile), and iii) most volatile (67-100 percentile). There are 30 countries in each group in the full period, and 36, 35 and 36 countries, respectively, in both 1970-2007 and 1980-2007 periods. We construct dummies for each volatility group and interact them with BC volatility. The results are summarized in Table 3. There is no correlation between BC volatility and growth for any of these three groups, and it is robust across time periods and sample countries. However, if the correlation of LR volatility is incorrectly removed, $\hat{\gamma}_{1U}$ becomes significantly negative for the most volatile group of countries in both 1970-2007 and 1980-2007 periods.

We now estimate equations (1a)-1(b) disaggregating by income level. The results for developing (low and middle income combined) countries, summarized in Table 4, are similar to those for all countries in that there is no correlation between BC volatility and growth. When developing countries are further disaggregated into three similar groups by their intensity of BC volatility as the full sample countries, the results are also qualitatively similar (Table 5). There is also no significant correlation for developed (high income) countries, and the sign of $\hat{\gamma}_{1C}$ changes across periods (Table 6).

Insert Tables 3-6 here

The above results indicate an absence of relationship between BC volatility and long-run growth. However, if the correlation of LR volatility is incorrectly removed, the results are aligned to the literature to indicate a significant negative relationship especially for developing countries in the post-1970 period.

5.2 Correlation in cross-sectional data for alternative frequency bands and filtering

Previous estimations are based on the implicit assumption that both developed and developing countries are characterized by similar cyclical patterns. Although there is a large literature on business cycles in the context of developed countries, very little is known about business cycles in developing countries. Agénor McDermott and Prasad (2000) point out that there are both similarities (procyclical real wages, countercyclical variation in government expenditures) and differences (countercyclical variation in the velocity of monetary aggregates) between macroeconomic fluctuations in developing and developed countries. Rand and Tarp (2002) demonstrate that developing countries differ considerably in terms of the nature and characteristics of short-run macroeconomic fluctuations. Analyzing a sample of 15 developing countries (five countries each from sub-Saharan Africa, Latin America, and Asia and North Africa), the authors document that average lengths of expansion and contraction are 4.8 and 5.2 years, respectively. This suggests that cycles are generally shorter in developing countries. Male (2009) contrasts this conclusion but stresses that there is heterogeneity at the regional level in that cycles are shorter in Latin America and longer in Asia.

We now calculate BC and LR volatility using an alternative critical periodicity of 5 years for developing countries but retain the same critical periodicity for developed countries. The results, summarized in Appendix A.2, are qualitatively similar to their benchmark counterparts based on the B-K filter for both the full sample (Panel A) and developing countries (Panel B).

We also calculate BC and LR volatility using the Hodrick Prescott (1997) and Christiano and Fitzgerald (2003) band-pass filters. These filters extract the cyclical components, and the trend is retrieved as the residual. Although the H-P filter is optimal for an I(2) process and the C-F filter is optimal for a random walk process, we nonetheless employ them to verify the robustness of the results. We use the same window and periodicity in the C-F filter as we have used in the B-K filter. For the H-P filter, we use a smoothing parameter of 6.25 based on the recommendation by Ravn and Uhlig (2002, p. 371) that the parameter should be adjusted approximately with the fourth power of the frequency change.[19] The results using both the H-P and C-F filters (Appendices A.3 and A.4, respectively) are very similar to the benchmark results.

5.3 Correlation and causation in panel data

Before presenting the results, it is imperative to explain the reasons for constructing a 7-year panel. A common practice is to take 5-year non-overlapping average of annual growth rate to calculate its long-run value (some papers also take 10-year average for robustness check). Using the spectral density, we show in Appendix A.5 that data averaged over 5-year period does not reweight the variances of the raw series enough across low frequencies, thus data are contaminated by high frequencies. This contamination decreases substantially in the case of 7-year averaging. Further improvement is small for averaging over longer horizon, such as 8 or 10 years. Since averaging over longer horizon leaves fewer observations for estimation, we choose 7 years as an optimal compromise. Note that a window of 3 years is also chosen for annual data in the B-K filter, which is equivalent to averaging over 7 years.

We estimate equations (2a)-3(b) by pooled OLS for both full period (1960-2007) and 1978-2007 sub-period.[20] The results for all countries for these two periods are summarized in Panels A and B in Table 7, respectively. Columns (1)-(4) present the results for the (contemporaneous) correlation estimated from equations (2a)-(2b); the first two columns control for private credit (and *Polity2*), while the last two do not (so the number of observations increases; and this can also be a test for stability of the results across countries). Columns (5)-(8) present the effect of lagged BC volatility estimated from equations (3a)-(3b). The coefficient of BC volatility is insignificant and small in magnitude, thus suggesting a lack of correlation between BC volatility and growth. There is also no effect of lagged BC volatility on growth as suggested by its insignificant (and close to zero) coefficient. The results follow similar patterns for developing countries (Table 8). In both Tables 7 and 8, the correlation becomes significantly negative and larger in magnitude if LR volatility is incorrectly excluded from the regression. For developed countries, the results are also similar except that there is a positive correlation of BC

[19] STATA also recommends a smoothing parameter of 6.25 for annual data.

[20] The effective sample periods 1964-2007 and 1978-2007 cannot be divided into seven equal intervals; for the last interval, we take average over 9 years (1999-2007).

volatility in the 1978-2004 period (Table 9). The significance of the correlation does not change after controlling for LR volatility because of small (and insignificant) value of $\hat{\gamma}_2$ (0.10).

Insert Tables 7-9 here

To summarize, the results in the panel data corroborate the main conclusion in the cross-sectional data. In addition, there is no significant effect of lagged BC volatility on growth. All the results remain robust (not reported) if the two-sided symmetric filter is used to calculate BC and LR volatility.

5.4 Correlation in the historical (1878-2010) panel data

We now estimate the relationship using the historical data compiled by Angus Maddison for the 1875-2010 period.[21] This estimation allows us to verify the results from an alternative dataset and time period. A 7-year panel is constructed similar to the PWT data. There are 28 countries of which 20 are developed by the current income level (A list of countries is provided in the note for Table 10), and there are 18 observations for each country.[22] Due to unavailability of data for control variables, we control only (log) initial level of GDP, time dummies, and dummies for major economic episodes: pre-1914, 1914-1945, 1946-1985, and post-1985 periods. As a result, country fixed effects will be correlated with the omitted variables, so we estimate the fixed effect regression. We interpret both the coefficients on BC volatility and its lag as correlation.

Insert Table 10 here

[21] Data goes back to earlier period but the number of countries decreases. For example, data is available since 1820 for only 8 countries (Australia, Italy, Denmark, France, Netherlands, Sweden, UK and USA).

[22] In the dataset, consecutive values of real per capita GDP since 1875 are available for 28 countries. The actual time period retained in the analysis is 1879-2010 because the first observation is lost due to calculation of growth rate from level of GDP, and next three observations are lost due to using the one-sided filter. The time period is then divided into 18 equal 7-year intervals except the last interval (2004-2010).

Panels A and B in Table 10 summarize the results for full sample, and 20 developed countries, respectively. The results are similar in both panels. There is no contemporaneous or lagged correlation between BC volatility and growth. The correlation becomes negative and significant, and the lagged correlation becomes positive and significant after incorrectly removing correlation of LR volatility and its lag, respectively.

5.5 Replication of Ramey and Ramey (1995)

Our final robustness check is to replicate Ramey and Ramey (1995), arguably the most influential study on the volatility-growth relationship, using their data and controls. We replicate their basic cross-sectional specification, which is comparable to our specification. Using the PWT 5.6 data, Ramey and Ramey estimated the relationship for two sets of countries: a full sample of 92 countries for the 1960-1985 period, and 24 OECD countries for the 1950-1988 period. It is worth mentioning that the PWT data has been revised several times and subsequent revisions are not strictly comparable. Ponomareva and Katayama (2010) replicated Ramey and Ramey and found that conclusions based on one version of the PWT may not hold under another version; however, growth and uncertainty are negatively and significantly related for countries with the worst data quality.[23]

Ramey and Ramey calculated growth rate (and volatility) from the "Real GDP per capita, 1985 international prices: Chain Index (RGDPCH)" (their Data Appendix, p. 1150). This is not the appropriate variable to compare the growth rates over time and across countries; the appropriate variable is the growth of GDP at constant national prices (also strongly recommended by Feenstra, Inklaar and Timmer (2013) in the PWT 8.0 user guide, p. 25). GDP at constant national prices data was not available in the PWT 5.6, so Ramey and Ramey conducted the best possible exercise given the data. We therefore additionally replicate Ramey and Ramey using the growth of GDP at constant national prices from the PWT 8.0 for the same

[23] Dawson et al. (2001) also replicated Ramey and Ramey (1995) and found that the results do not hold after controlling for data quality.

countries and time period. However, this can be done only for their 24 OECD countries as data is not available for a good number of countries in their full sample.[24]

Insert Table 11 here

The results are summarized in Table 11. Panel A reports the results for 92 countries for the 1960-1985 period. In column (1), the coefficient on volatility (standard deviation of the growth rate) in the specification without any control reported by Ramey and Ramey is reproduced—it is -0.15 with a *t*-statistic of -2.3 (it becomes -2.6 after correcting heteroskedasticity). However, as we discuss in detail in Section 6, the standard deviation of the growth rate differ from our measure of BC volatility (the standard deviation of the business cycles components of growth rate). In the same specification, the coefficient on BC volatility is very close at -0.16 with a *t*-statistic of -2.59 (column (2)). When their controls— initial income, average population growth, average investment share of GDP and initial human capital—are included in the regression, the coefficient on BC volatility decreases to -0.109 with a *t*-statistic of -1.636 (which slightly falls short of 10% level significance) (column (3)). But after controlling for LR volatility, the coefficient on BC volatility is almost zero (0.006) with a very low *t*-statistic of 0.066 (column (4)).

The results for the 24 OECD countries are summarized in Panel B. The coefficient on BC volatility in the specification with all controls is large negative (-0.41) and significant (*t*-value of -2.46), and does not meaningfully change after controlling for LR volatility (columns (3) and (4)) (the coefficient on LR volatility is positive but insignificant). However, when we replicate these results (with same countries, time period and controls) using the growth of GDP at constant national prices data from the PWT 8.0 (Panel C), the coefficient on BC volatility is small and

[24] In the PWT 8.0, data are not available for the following 9 countries in the Ramey and Ramey sample: Afghanistan, Algeria, Guyana, Haiti, Myanmar (Burma), Nicaragua, Papua New Guinea, Yugoslavia (country disintegrated), and Zaire. For Iraq, Sudan and Swaziland, GDP data starts from 1970, and for Liberia from 1964. Therefore, a total of 13 countries are missing from the sample.

statistically insignificant both without and with controlling for LR volatility, and the sign differs in the two specifications. These results are perfectly in line with our previous results, and suggests a lack of relationship between BC volatility and growth.

6. Volatility vs. its persistence

LR volatility is also interpreted as persistence in volatility (Levy and Dezhbakhsh, 2003; Ascari and Sbordone, 2014). In the following, we compare the relative importance of BC volatility and persistence in volatility in explaining long-run growth.

We have found that there is no correlation between BC volatility and growth, and no effect of lagged BC volatility on growth. But the correlation becomes significant and stronger if LR volatility is incorrectly excluded from regression. Moreover, the results show a negative and significant correlation between LR volatility and growth, especially for developing countries and in the post-1970 period. On the other hand, the correlation is positive in the 1960-1980 period but not robust across country income groups. It is positive for developed countries in the post-1970 period but not robust to estimation methods. The correlation is weakly negative in the Angus Madison panel data (Table 10). The effect of lagged LR volatility is positive for developed countries (Table 9, Panel B and Table 10). These findings signify the importance of LR volatility in explaining growth. They also imply that if LR volatility is omitted from the regression, its effect, to a large extent, will be reflected in the coefficient of BC volatility.

Several studies (for example, Ramey and Ramey, 1995) use standard deviation of (unfiltered or raw) growth rate as a proxy for BC volatility. This measure is based on the assumption of a constant trend, while BC volatility calculated as the standard deviation of the cyclical components of growth assumes a time varying trend. As shown in introduction, total variance of growth rate is sum of the variances of its cyclical and long-run components. Therefore, volatility measured as the standard deviation of growth rate will capture the combined effects of both BC and LR volatility. In other words, both the standard deviation of the cyclical components of growth (in misspecified regression that excludes LR volatility) and that of the (unfiltered or raw) growth will capture the effect of LR volatility.

Insert Table 12 here

To verify the above argument, we estimate correlation (and effect) of total volatility defined as the standard deviation of (unfiltered or raw) growth rate. The results for some selected specifications based on the significance of $\hat{\gamma}_2$ (coefficient on LR volatility) and/or $\hat{\gamma}_{1U}$ (uncorrected coefficient on BC volatility) are presented in Table 12. Consider the cross-sectional results for 1970-2007 period presented in columns (1)-(3) in Panel A. The first two columns reproduce the results from columns (5) and (6) in Table 2, respectively. In column (3) we add the result for total volatility (based on the same specification). The coefficient on total volatility is negative and significant. Quantifying the result, one standard deviation increase in total volatility is associated with 0.263 percentage point decrease in growth. On the other hand, $\hat{\gamma}_{1C}$ (corrected coefficient on BC volatility) was insignificant but $\hat{\gamma}_2$ was negative and significant. The latter result can be quantified as 0.297 percentage point decrease in growth for one standard deviation increase in LR volatility. But $\hat{\gamma}_{1U}$ became negative and significant after omitting LR volatility in the regression—it implied that one standard deviation increase in BC volatility was incorrectly associated with 0.219 percentage point decrease in growth. These results support our argument that the contribution of LR volatility is misconstrued as the contribution of total volatility or that of BC volatility because of misspecification.

To summarize, it is not BC volatility but persistence in volatility that is associated with growth, and the association differs across time periods and country groups.

7. Relating the contribution in the literature

Our paper is situated in a large body of literature on the volatility-growth relationship but can be distinguished by its contribution in accounting for the persistence in growth volatility. The issue of persistent fluctuations has been raised in the cross-country macroeconomic literature in several contexts. In the following, we compare and contrast our contributions in this literature.

Fatás (2000a, 2000b) document a strong positive correlation between long-run growth rates and persistence of output (not growth) fluctuations in a cross section of countries. The results suggest that volatility of the permanent component of output is larger for countries with high growth rates. In contrast, we deal with a different question regarding growth volatility and document that the relationship between growth and persistence in growth volatility differ across time periods and country groups.

Some studies have distinguished volatility between its unexpected (uncertain) and expected components. It is imperative to distinguish between uncertainty in, and volatility of, growth. Uncertainty accounts for only the unpredicted component of growth, while volatility accounts for both predicted and unpredicted components (Wolf, 2005).[25] Uncertainty is usually calculated as the residual of a forecasting equation where GDP growth is regressed on its own lags and linear (and quadratic) trends (see, Ramey and Ramey, 1995; Fatás, 2002; Rafferty, 2005). Although introducing the trends removes low frequency movements from the data and therefore is comparable to the band-pass filtered growth, BC volatility in our paper is a measure of *ex post* realized volatility as opposed to uncertainty. Ramey and Ramey (1995) and Rafferty (2005) included in the regression both unexpected and expected volatility, where the latter was calculated as the standard deviation of the fitted value of growth rate. Our measure of LR volatility is different from the expected volatility in the same way as low-pass filtering differs from fitting. The aim of low-pass filtering is to retain slow-moving values, whereas fitting concentrates on achieving as close a match of data values as possible. Furthermore, filtering, unlike fitting, does not involve use of an explicit function form. These differences are also manifest in the differences in results discussed below.

Ramey and Ramey (1995) found that both the coefficients on unexpected and expected volatility were insignificant (negative and a low *t*-statistic) in a sample of 92 countries. On the other hand, in a sub-sample of OECD countries, the coefficient on unexpected volatility was negative and highly significant, and the coefficient on expected volatility was positive and significant. Kormendi and Meguire (1984) earlier found that standard deviation of monetary shocks has a significant negative effect and standard deviation of growth rate has a significant positive effect on growth. Ramey and Ramey (1995) conjectured that the standard deviation of monetary shocks may be correlated with unexpected volatility. Thus, the positive effect of the standard deviation of output in Kormendi and Meguire may be capturing the effect of predictable movements in growth, similar to their expected volatility. On the other hand, we find a lack of correlation between BC volatility and growth, and a negative and significant correlation between LR volatility and growth, especially for developing countries in the post-1970 period. Similarly, using the Angus Maddison historical data for 18 developed countries for the 1880-1990 period, Rafferty (2005) found that unexpected volatility reduces, and expected volatility increases, long-

[25] Bloom (2014) discusses different measures of uncertainty employed in the literature.

run growth. Using the same data, we instead find no association (and effect) of BC volatility, and a weak negative association of LR volatility with growth.

Hnatkovska and Loayza (2005) distinguish between "regular" and "crisis" volatility and show that only "crisis" volatility is statistically significant for explaining growth when both types of volatility are included in the regression. The authors define "crisis" volatility as the portion of the standard deviation of GDP growth that corresponds to downward deviations below a certain threshold. They set the threshold equal to one standard deviation of the world distribution of overall volatility measures. Regular volatility, on the other hand, is defined as the portion of the standard deviation of GDP growth corresponding to deviations that fall within the threshold. Their distinction of the two types of volatility can be compared to our disaggregation of countries in terms of their intensity of BC volatility. But our contribution lies in accounting for LR volatility for which Hnatkovska and Loayza have no counterpart.

Aguiar and Gopinath (2007) point out that shocks to trend growth can be the primary source of fluctuations in the emerging market economies as opposed to transitory fluctuations around the trend. The authors document that these economies on average have a business cycle twice as volatile as that of their developed counterparts. They measured business cycle by volatility of the H-P band-passed filtered log output, and volatility of the first difference of unfiltered log output, which corresponds to our measure total volatility in Section 6. They also document that the first-order autocorrelation of unfiltered output growth is twice as large, suggesting greater persistence in business cycles in emerging economies (their Table 1, p. 74). Although our study differs from theirs in regard to the research question, we document in Table 1 that both BC and LR volatility decrease with income level, but so does their ratio. This implies that LR volatility relative to BC volatility is also larger in developed than in developing countries.

Our paper is also situated in a burgeoning literature on growth spells first pioneered by Pritchett (2000).[26] Pritchett pointed out heterogeneity among countries in terms of instability in growth rates over time. Country experiences differ enormously by steady growth, rapid growth followed by stagnation, rapid growth followed by decline or even catastrophic falls, continuous

[26] Some recent papers have attempted to explore the determinants of the growth spells (for example, Berg, Ostry and Zettelmeyer, 2012; Bluhm, Crombrugghe and Szirmai, 2014).

stagnation, or steady decline. He cautioned that econometric growth literature using the panel nature of data may be uninformative to account for the heterogeneity. Our motivation and approach to account for heterogeneity address this concern.

8. Concluding remarks

This paper finds that at the cross-country level there is no relationship between BC volatility and long-run growth. The main departure from the extant empirical literature is in accounting for fluctuations in the trend growth that we refer to as LR volatility. However, a significant negative relationship can be found, especially for developing countries, if LR volatility is incorrectly excluded from regression, which is consistent with the findings in the literature. Our measure of LR volatility—standard deviation of the low-pass filtered growth rate—also represents persistence in volatility. We find that persistence in volatility is negatively associated with growth, especially for developing countries in the post-1970 period. We also test the theoretical prediction of the effect of BC volatility in previous period on current growth but do not find any such effect. There might be an asymmetry in the effect of BC volatility in that volatility in expansionary and contractionary phases may have differential impacts on growth, which can be an interesting topic to explore further.

Our results have important implications for stabilization policies in light of the recent global financial crises. The large decline in output and very slow recovery after the 2008 recession compared to the previous recessions suggest a reduction in the trend growth rate in many developed countries. But such contractions are more frequent in developing countries. Causes and remedies of such fluctuations are largely unknown and require further investigation. Our finding of lack of (or weak) correlation between BC volatility and growth does not necessarily imply irrelevance of stabilizing business cycles since cyclical fluctuations may affect heterogeneous agents differently that is not evident at the aggregate data.[27] Our results have also

[27] Lucas (1987) documented that the welfare effects of eliminating business cycle are very small, well below 1% of national income. Krusell and Smith (1999) investigate these effects in a model with substantial consumer heterogeneity that arises from uninsurable and idiosyncratic uncertainty in preferences and employment status. The results suggested a welfare loss larger than Lucas (1987), but still very small. However, this model is based on the assumption that individual shocks are unaffected by the removal of the cycles. If this assumption is relaxed, the

important implications for cross-country growth regressions in that ignoring heterogeneity among countries may lead to wrong conclusions.

average gain from eliminating cycles is as much as 1% in consumption equivalents, which is large for both the poor and rich (Krusell et al., 2009).

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Tables

Table 1: Descriptive statistics (1960-2007)

Income group	Growth rate	BC volatility	LR volatility	Ratio of BC volatility to LR volatility	Correlation between BC and LR volatility	Number of countries
	(1)	(2)	(3)	(4)	(5)	(6)
All	0.021 (0.017)	0.035 (0.019)	0.023 (0.012)	1.659 (0.703)	0.612 [0.477 0.718]	107
High income	0.033 (0.013)	0.024 (0.016)	0.020 (0.017)	1.378 (0.499)	0.842 [0.702 0.920]	33
Middle and low income	0.015 (0.016)	0.040 (0.019)	0.024 (0.010)	1.783 (0.747)	0.509 [0.317 0.661]	74
Middle (upper + lower) income	0.021 (0.015)	0.036 (0.016)	0.024 (0.010)	1.591 (0.620)	0.603 [0.388 0.756]	49
Upper-middle income	0.025 (0.016)	0.037 (0.017)	0.026 (0.010)	1.484 (0.409)	0.699 [0.427 0.855]	26
Lower-middle income	0.017 (0.012)	0.035 (0.016)	0.022 (0.009)	1.711 (0.788)	0.465 [0.065 0.736]	23
Low income	0.004 (0.011)	0.046 (0.021)	0.023 (0.010)	2.161 (0.838)	0.452 [0.069 0.719]	25

Figures in parentheses are standard deviations. Figures in brackets are 95% confidence interval.
Note: The ratio of BC volatility to LR volatility has been calculated for each country and the average of this cross-section is reported in column (4).

Table-2: OLS estimation using cross-sectional data (all countries)

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	1960-2007		1960-1980		1970-2007		1980-2007$^{\chi}$		1980-2007	
BC volatility	0.023	0.065	-0.013	0.110	-0.002	-0.121*	0.053	-0.157*	0.013	-0.171***
	(0.309)	(0.925)	(-0.088)	(0.786)	(-0.025)	(-1.709)	(1.045)	(-1.724)	(0.248)	(-2.848)
LR volatility	0.153		0.429*		-0.292**		-0.458***		-0.450***	
	(1.076)		(1.724)		(-2.195)		(-5.776)		(-5.172)	
p-value of the joint significance	0.412		0.178		0.006		0.000		0.000	
Adjusted R-square	0.616	0.615	0.440	0.419	0.542	0.512	0.598	0.499	0.579	0.495
Observations	90	90	89	89	107	107	103	103	107	107

Robust *t*-statistics are in parentheses; *** p<0.01, ** p<0.05, * p<0.1.
All regressions include a constant, initial per capita GDP (log), investment-GDP ratio, initial human capital, population growth, openness, political violence, share of government expenditure, ToT volatility, and dummies for regions, legal origins and landlocked countries.
χ = Private credit/GDP and Polity2 are also controlled.

Table-3: OLS estimation using cross-sectional data (all countries): Disaggregating by the intensity of BC volatility

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	1960-2007		1960-1980		1970-2007		1980-2007$^{\chi}$		1980-2007	
BC volatility * Dummy-1	0.100	0.097	0.226	0.440	-0.233	-0.359	-0.078	-0.424	-0.061	-0.285
	(0.397)	(0.389)	(0.409)	(0.814)	(-0.967)	(-1.242)	(-0.252)	(-1.007)	(-0.203)	(-0.863)
BC volatility * Dummy-2	0.007	0.036	-0.189	-0.025	0.053	-0.048	-0.045	-0.325	-0.035	-0.245
	(0.041)	(0.209)	(-0.547)	(-0.073)	(0.362)	(-0.303)	(-0.274)	(-1.368)	(-0.225)	(-1.385)
BC volatility * Dummy-3	0.030	0.066	-0.001	0.134	-0.022	-0.137*	0.035	-0.186*	0.007	-0.180***
	(0.329)	(0.782)	(-0.006)	(0.698)	(-0.315)	(-1.707)	(0.644)	(-1.729)	(0.123)	(-2.792)
LR volatility	0.166		0.416*		-0.278**		-0.451***		-0.449***	
	(1.162)		(1.700)		(-2.245)		(-5.737)		(-5.154)	
p-value of the joint significance	0.6874		0.041		0.0065		0.000		0.0000	
Adjusted R-square	0.607	0.606	0.468	0.448	0.548	0.520	0.590	0.494	0.569	0.485
Observations	90	90	89	89	107	107	103	103	107	107

Robust *t*-statistics are in parentheses; *** p<0.01, ** p<0.05, * p<0.1.
All regressions include a constant, initial per capita GDP (log), investment-GDP ratio, initial human capital, population growth, openness, political violence, share of government expenditure, ToT volatility, and dummies for regions, legal origins and landlocked countries.
χ = Private credit/GDP and Polity2 are also controlled.
Dummy-1: 1 = if BC volatility < 33% percentile in the sample; 0 = otherwise.
Dummy-2: 1 = if BC volatility >= 33% percentile but < 67% percentile in the sample; 0 = otherwise.
Dummy-3: 1 = if BC volatility >= 67% percentile in the sample; 0 = otherwise.

Table-4: OLS estimation using cross-sectional data (Developing (Low and medium income) countries)

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	1960-2007		1960-1980		1970-2007		1980-2007χ		1980-2007	
BC volatility	0.054	0.086	0.023	0.114	0.024	-0.146	0.093	-0.206*	0.011	-0.218***
	(0.604)	(0.982)	(0.137)	(0.713)	(0.324)	(-1.650)	(1.421)	(-1.925)	(0.178)	(-3.204)
LR volatility	0.129		0.330		-0.403***		-0.546***		-0.500***	
	(0.726)		(1.103)		(-3.499)		(-5.873)		(-4.750)	
p-value of the joint significance	0.555		0.460		0.000		0.000		0.000	
Adjusted R-square	0.449	0.456	0.225	0.222	0.455	0.382	0.597	0.464	0.564	0.453
Observations	64	64	63	63	75	75	73	73	75	75

Robust *t*-statistics are in parentheses; *** p<0.01, ** p<0.05, * p<0.1.
All regressions include a constant, initial per capita GDP (log), investment-GDP ratio, initial human capital, population growth, openness, political violence, share of government expenditure, ToT volatility, and dummies for regions, legal origins and landlocked countries.
χ = Private credit/GDP and Polity2 are also controlled.

Table-5: OLS estimation using cross-sectional data: Disaggregating by the intensity of BC volatility (Developing (Low and medium income) countries)

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	1960-2007		1960-1980		1970-2007		1980-2007χ		1980-2007	
BC volatility * Dummy-1	-0.003	0.056	0.499	0.634	0.281	0.052	0.145	-0.361	0.210	-0.064
	(-0.010)	(0.230)	(0.731)	(0.959)	(1.015)	(0.169)	(0.348)	(-0.687)	(0.482)	(-0.135)
BC volatility * Dummy-2	0.064	0.103	-0.177	-0.085	0.291	0.079	0.040	-0.412	-0.011	-0.332
	(0.342)	(0.627)	(-0.413)	(-0.207)	(1.510)	(0.407)	(0.180)	(-1.376)	(-0.047)	(-1.298)
BC volatility * Dummy-3	0.040	0.081	0.051	0.131	0.080	-0.105	0.094	-0.228	0.022	-0.211**
	(0.372)	(0.845)	(0.210)	(0.591)	(0.896)	(-1.017)	(1.224)	(-1.651)	(0.273)	(-2.378)
LR volatility	0.141		0.260		-0.417***		-0.538***		-0.489***	
	(0.790)		(0.920)		(-3.495)				(-4.880)	
p-value of the joint significance	0.789		0.0827		0.001		0.000		0.000	
Adjusted R-square	0.427	0.433	0.293	0.297	0.462	0.380	0.584	0.456	0.556	0.450
Observations	64	64	63	63	75	75	73	73	75	75

Robust *t*-statistics are in parentheses; *** p<0.01, ** p<0.05, * p<0.1.
All regressions include a constant, initial per capita GDP (log), investment-GDP ratio, initial human capital, population growth, openness, political violence, share of government expenditure, ToT volatility, and dummies for regions, legal origins and landlocked countries.
χ = Private credit/GDP and Polity2 are also controlled.
Dummy-1: 1 = if BC volatility < 33% percentile in the sample; 0 = otherwise.
Dummy-2: 1 = if BC volatility >= 33% percentile but < 67% percentile in the sample; 0 = otherwise.
Dummy-3: 1 = if BC volatility >= 67% percentile in the sample; 0 = otherwise.

Table-6: OLS estimation using cross-sectional data (Developed countries)

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	1960-2007		1960-1980		1970-2007		1980-2007	
BC volatility	0.186	0.201	0.040	0.102	-0.071	0.028	-0.002	0.074
	(1.229)	(1.424)	(0.402)	(1.223)	(-1.021)	(0.455)	(-0.038)	(1.508)
LR volatility	0.144		0.324		0.525***		0.299**	
	(0.456)		(1.388)		(3.475)		(2.127)	
p-value of the joint significance	0.374		0.260		0.006		0.089	
Adjusted R-square	0.811	0.823	0.799	0.800	0.890	0.856	0.791	0.786
Observations	30	30	28	28	38	38	38	38

Robust *t*-statistics are in parentheses; *** p<0.01, ** p<0.05, * p<0.1.
All regressions include a constant, initial per capita GDP (log), investment-GDP ratio, initial human capital, openness, share of government expenditure, ToT volatility, private credit/GDP, Polity2 and dummies for regions, legal origins and landlocked countries.

Table-7: Pooled OLS estimation using 7-year panel data (all countries)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: 1960-2007							
BC volatility	0.014	-0.111	-0.055	-0.193**				
	(0.168)	(-1.577)	(-0.486)	(-2.137)				
LR volatility	-0.316**		-0.248**					
	(-2.244)		(-2.229)					
Lagged BC volatility					0.022	0.033	0.009	0.001
					(0.278)	(0.636)	(0.144)	(0.016)
Lagged LR volatility					0.027		-0.017	
					(0.184)		(-0.238)	
p-value of the joint significance	0.018		0.000		0.796		0.971	
Adjusted R-square	0.242	0.233	0.264	0.254	0.223	0.225	0.225	0.227
Observations	380	380	449	449	380	380	449	449
No. of countries	87	87	91	91	87	87	91	91
	Panel B: 1978-2007							
BC volatility	0.163	0.009	-0.061	-0.210**				
	(0.954)	(0.060)	(-0.384)	(-2.166)				
LR volatility	-0.378**		-0.259*					
	(-2.220)		(-1.733)					
Lagged BC volatility					0.058	0.078	0.143	0.057
					(0.671)	(1.000)	(1.123)	(0.923)
Lagged LR volatility					0.051		-0.163	
					(0.275)		(-1.033)	
p-value of the joint significance	0.090		0.000		0.607		0.533	
Adjusted R-square	0.224	0.213	0.201	0.192	0.216	0.219	0.147	0.145
Observations	273	273	314	314	273	273	314	314
No. of countries	100	100	106	106	100	100	106	106

Robust clustered (at the country level) *t*-statistics are in parentheses; *** p<0.01, ** p<0.05, * p<0.1.
All regressions include a constant, time dummies, lag of (initial per capita GDP (log), investment-GDP ratio, population growth, openness, political violence, share of government expenditure, ToT volatility), initial human capital for each interval, and dummies for regions, legal origins and landlocked countries.
Columns (1), (2), (5) and (6) additionally control for private credit/GDP and polity2.

Table-8: Pooled OLS estimation using 7-year panel data (Developing (low and middle income) countries)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: 1960-2007							
BC volatility	0.024	-0.146*	-0.093	-0.215**				
	(0.235)	(-1.853)	(-0.741)	(-2.645)				
LR volatility	-0.426**		-0.212					
	(-2.366)		(-1.516)					
Lagged BC volatility					0.061	0.033	0.006	-0.007
					(0.596)	(0.490)	(0.071)	(-0.139)
Lagged LR volatility					-0.074		-0.024	
					(-0.363)		(-0.280)	
p-value of the joint significance	0.005		0.000		0.829		0.925	
Adjusted R-square	0.221	0.206	0.238	0.232	0.189	0.192	0.193	0.196
Observations	262	262	324	324	262	262	324	324
No. of countries	63	63	66	66	63	63	66	66
	Panel B: 1978-2007							
BC volatility	-0.017	-0.208*	-0.210	-0.300***				
	(-0.123)	(-1.764)	(-1.601)	(-4.099)				
LR volatility	-0.469**		-0.150					
	(-2.439)		(-1.120)					
Lagged BC volatility					0.038	-0.006	0.139	0.035
					(0.368)	(-0.084)	(0.863)	(0.465)
Lagged LR volatility					-0.114		-0.190	
					(-0.531)		(-1.040)	
p-value of the joint significance	0.003		0.000		0.866		0.489	
Adjusted R-square	0.337	0.319	0.261	0.261	0.279	0.282	0.153	0.150
Observations	188	188	224	224	188	188	224	224
No. of countries	71	71	75	75	71	71	75	75

Robust clustered (at the country level) *t*-statistics are in parentheses; *** p<0.01, ** p<0.05, * p<0.1.
All regressions include a constant, time dummies, lag of (initial per capita GDP (log), investment-GDP ratio, population growth, openness, political violence, share of government expenditure, ToT volatility), initial human capital for each interval, and dummies for regions, legal origins and landlocked countries.
Columns (1), (2), (5) and (6) additionally control for private credit/GDP and polity2.

Table-9: Pooled OLS estimation using 7-year panel data (Developed countries)

	(1)	(2)	(3)	(4)
	Panel A: 1960-2007			
BC volatility	0.035	-0.029		
	(0.248)	(-0.271)		
LR volatility	-0.177			
	(-0.990)			
Lagged BC volatility			-0.084	-0.055
			(-0.614)	(-0.473)
Lagged LR volatility			0.061	
			(0.429)	
p-value of the joint significance	0.541		0.822	
Adjusted R-square	0.494	0.491	0.489	0.493
Observations	142	142	142	142
No. of countries	30	30	30	30
	Panel B: 1978-2007			
BC volatility	0.572**	0.622***		
	(2.663)	(5.115)		
LR volatility	0.100			
	(0.300)			
Lagged BC volatility			0.069	0.284***
			(0.457)	(2.932)
Lagged LR volatility			0.467*	
			(1.733)	
p-value of the joint significance	0.000		0.011	
Adjusted R-square	0.385	0.392	0.278	0.260
Observations	104	104	104	104
No. of countries	36	36	36	36

Robust clustered (at the country level) *t*-statistics are in parentheses; *** p<0.01, ** p<0.05, * p<0.1.
All regressions include a constant, time dummies, lag of (initial per capita GDP (log), investment-GDP ratio, population growth, openness, share of government expenditure, ToT volatility, and private credit/GDP), initial human capital for each interval, and dummies for regions, legal origins and landlocked countries.

Table 10: Fixed effect estimation using the 7-year panel data (Angus Maddison historical data for the 1875-2010 period)

	(1)	(2)	(3)	(4)
	Panel A: All countries			
BC volatility	0.029	-0.126**		
	(0.209)	(-2.296)		
LR volatility	-0.300			
	(-1.276)			
Lagged BC volatility			-0.080	0.166***
			(-1.192)	(4.727)
Lagged LR volatility			0.480***	
			(4.061)	
p-value of the joint significance	0.014		0.000	
Within R-square	0.276	0.265	0.318	0.290
Between R-square	0.017	0.020	0.011	0.007
Observations	504	504	476	476
No. of countries	28	28	28	28
	Panel B: Developed countries			
BC volatility	0.134	-0.134**		
	(0.981)	(-2.264)		
LR volatility	-0.507*			
	(-2.085)			
Lagged BC volatility			-0.115	0.185***
			(-1.467)	(6.406)
Lagged LR volatility			0.580***	
			(4.008)	
p-value of the joint significance	0.010		0.000	
Within R-square	0.391	0.361	0.427	0.389
Between R-square	0.424	0.427	0.324	0.328
Observations	360	360	340	340
No. of countries	20	20	20	20

Robust clustered (at the country level) *t*-statistics are in parentheses; *** p<0.01, ** p<0.05, * p<0.1. All regressions include a constant, initial log income for each 7-year interval, time dummies, and dummies for the pre-1914, 1914-1945, 1946-1985; and post-1985 periods.

Countries in Panel A are: Argentina, Australia, Austria, Belgium, Brazil, Canada, Italy, Chile, Colombia, Denmark, Finland, France, Germany, Greece, Netherlands, Japan, Norway, New Zealand, Peru, Portugal, Spain, Sri Lanka, Sweden, Switzerland, UK, Uruguay, USA and Venezuela.

Countries in Panel B are: Australia, Austria, Belgium, Canada, Italy, Denmark, Finland, France, Germany, Greece, Netherlands, Japan, Norway, New Zealand, Portugal, Spain, Sweden, Switzerland, UK and USA.

Table 11: Replication of Ramey and Ramey (1995) using PWT5.6 and PWT 8.0 data

	(1)	(2)	(3)	(4)
	Panel A: PWT 5.6 data for 92 Developing countries (1960-1985 period)			
Total volatility	-0.154**			
	(-2.610) [-2.337]			
BC volatility		-0.161**	-0.109	0.006
		(-2.594)	(-1.636)	(0.066)
LR volatility				-0.363*
				(-1.720)
Observations	92	92	92	92
Adjusted R-squared	0.047	0.042	0.209	0.233
	Panel B: PWT 5.6 data for 24 OECD countries (1950-1988 period)			
Total volatility	0.147			
	(0.924) [0.672]			
BC volatility		-0.119	-0.408**	-0.417**
		(-0.574)	(-2.463)	(-2.508)
LR volatility				0.200
				(0.767)
Observations	24	24	24	24
Adjusted R-squared	-0.024	-0.038	0.759	0.751
	Panel B: PWT 8.0 data for 24 OECD countries (1950-1988 period)			
Total volatility	0.364			
	(1.492) [1.986]*			
BC volatility		0.263	0.170	-0.193
		(0.769)	(0.834)	(-1.245)
LR volatility				0.816**
				(2.658)
Observations	24	24	24	24
Adjusted R-squared	0.113	0.002	0.639	0.747

Robust *t*-statistics in parentheses; Non-robust *t*-statistics in bracket; *** p<0.01, ** p<0.05, * p<0.1.
Notes: Columns (3)-(4) control for initial log GDP per capita, average population growth, average investment share of GDP and initial human capital.

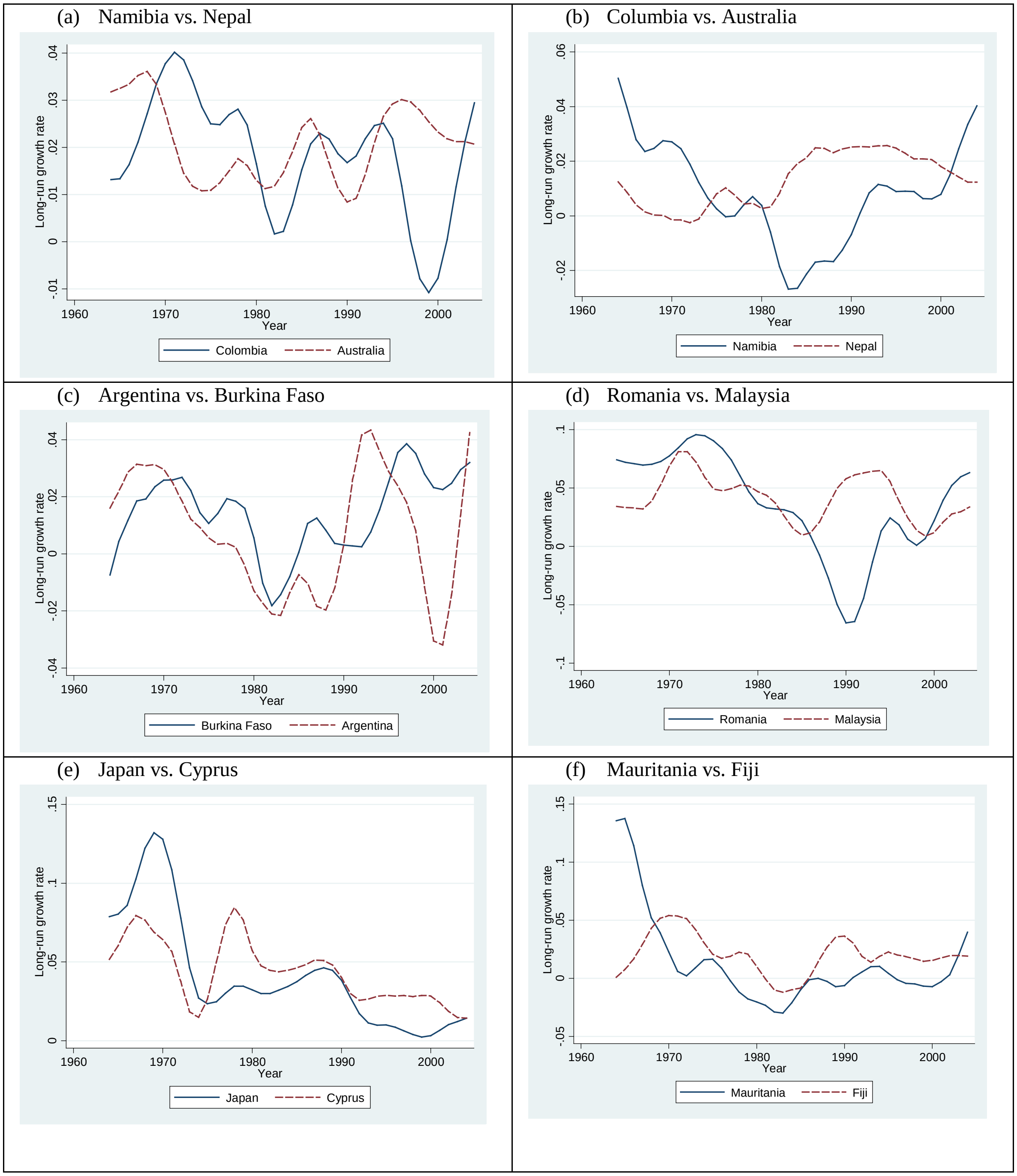
Table-12: Relative contribution of BC volatility and persistence in volatility

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A (Cross-sectional correlation)					
	PWT (1970-2007)			PWT (1980-2007)		
BC volatility	-0.002	-0.121*		0.053	-0.157*	
	(-0.025)	(-1.709)		(1.045)	(-1.724)	
LR volatility	-0.292**			-0.458***		
	(-2.195)			(-5.776)		
Total volatility			-0.132**			-0.187***
			(-2.048)			(-2.848)
	Panel B (Panel correlation)					
	PWT (1978-2007) (Developing countries)			Angus Maddison (1875-2010)		
BC volatility	-0.017	-0.208*		0.029	-0.126**	
	(-0.123)	(-1.764)		(0.209)	(-2.296)	
LR volatility	-0.469**			-0.300		
	(-2.439)			(-1.276)		
Total volatility			-0.188 (-1.897)			-0.156 (-4.275)
	Panel C (Panel lagged effect)					
	PWT (1978-2007) (Developed countries)			Angus Maddison (1875-2010)		
Lagged BC volatility	0.069	0.284***		-0.080	0.166***	
	(0.457)	(2.932)		(-1.192)	(4.727)	
Lagged LR volatility	0.467*			0.480***		
	(1.733)			(4.061)		
Lagged total volatility			0.331 (4.087)			0.160 (4.516)

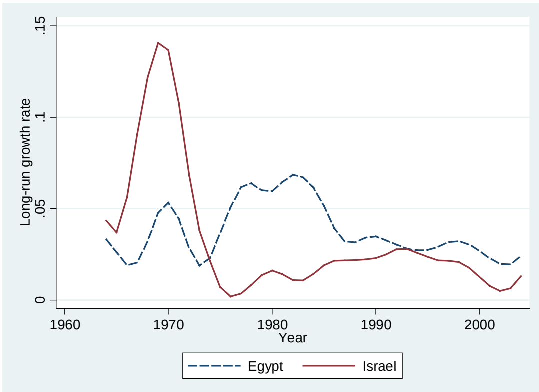
Robust clustered (at the country level) *t*-statistics are in parentheses; *** p<0.01, ** p<0.05, * p<0.1.
Panel A: Columns (1), (2), (4) and (5) have been reproduced from columns (5), (6), (7) and (8), respectively, in Table 2.
Panel B: Columns (1) and (2) have been reproduced from columns (1) and (2), respectively, in Table 8, Panel B. Columns (4) and (5) have been reproduced from columns (1) and (2), respectively, in Table 10, Panel A.
Panel C: Columns (1) and (2) have been reproduced from columns (3) and (4), respectively, in Table 9, Panel B. Columns (4) and (5) have been reproduced from columns (5) and (6), respectively, in Table 10, Panel A.

Figures

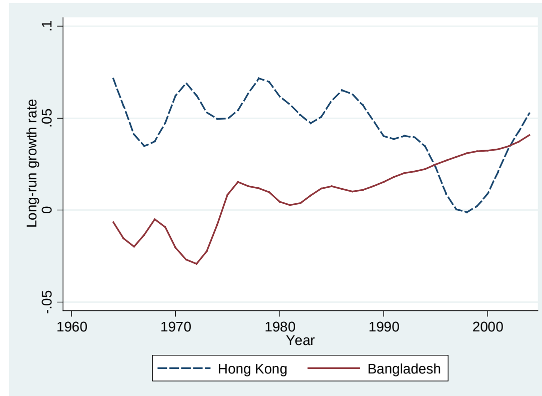
Table 1: Comparison of long-run growth trajectories



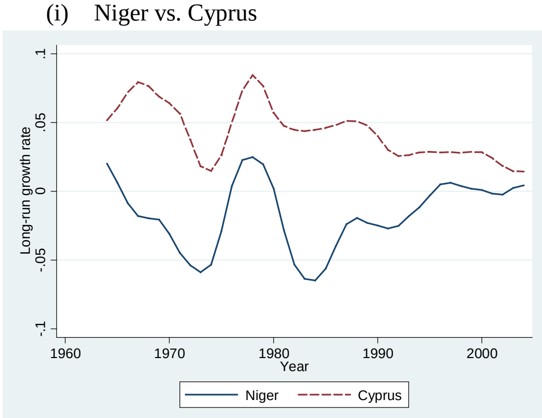
(g) Israel vs. Egypt



(h) Hong-Kong vs. Bangladesh



(i) Niger vs. Cyprus



(j) Japan vs. Austria

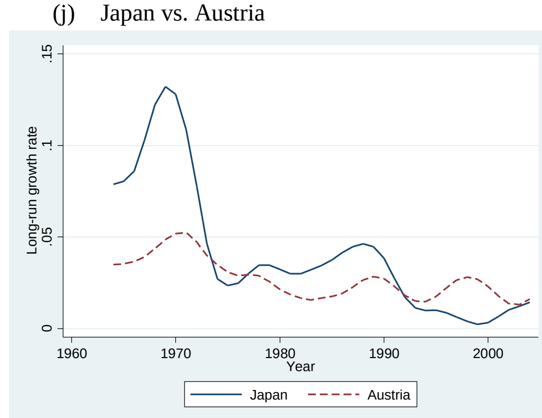


Figure 2: Relationship of initial per capita GDP (log) with BC and LR volatility

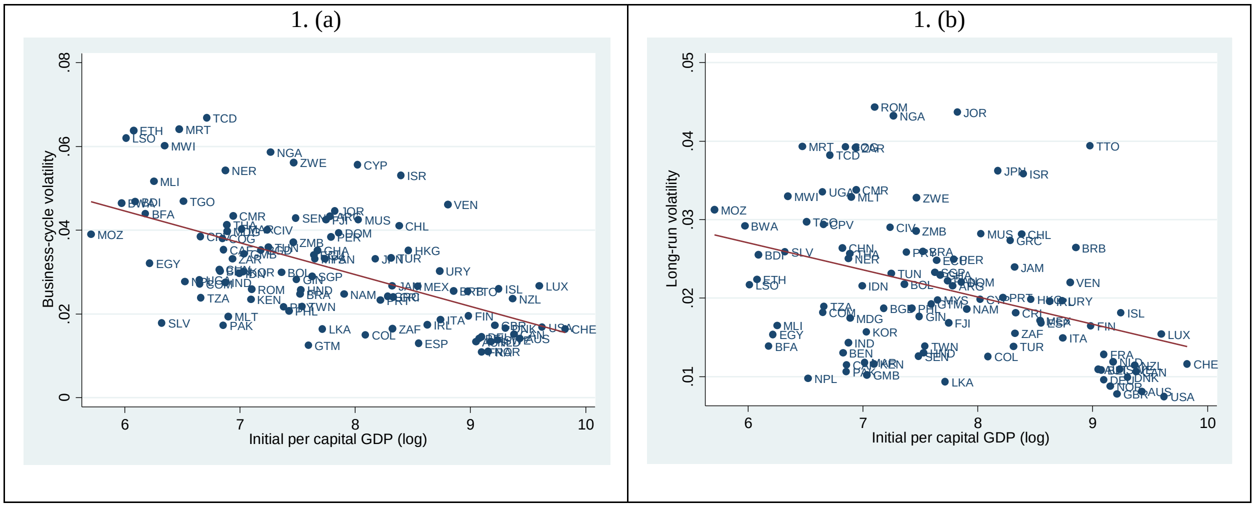
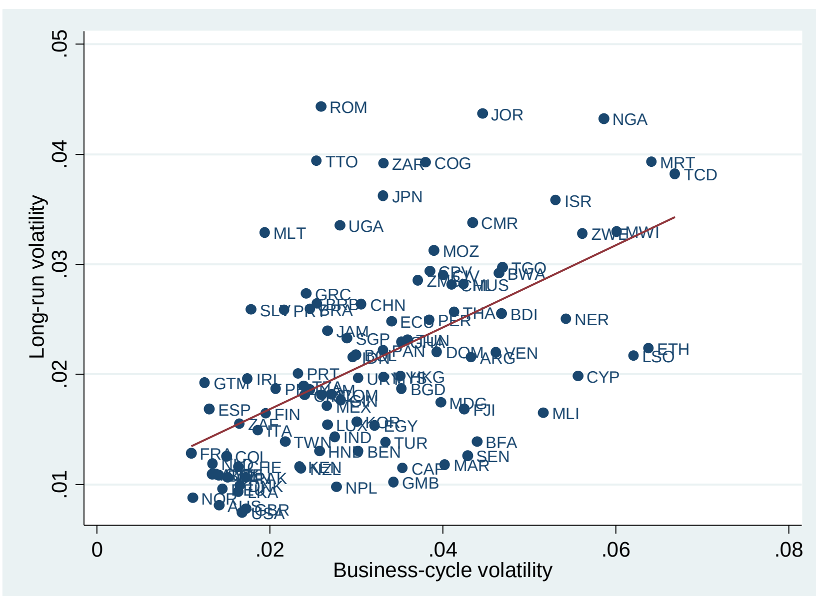


Figure 3: Relationship between BC and LR volatility



Appendix

A.1: Average growth, BC volatility and LR volatility for the 1960-2007 period

WB code	Country name	Average growth	Standard deviation	Business-cycle volatility	Long-run volatility
		High income countries			
AUS	Australia	0.0211	0.0175	0.0141	0.0081
AUT	Austria	0.0275	0.0177	0.0133	0.0109
BEL	Belgium	0.0260	0.0183	0.0141	0.0108
CYP	Cyprus	0.0430	0.0590	0.0556	0.0198
DEU	Germany	0.0237	0.0184	0.0145	0.0096
DNK	Denmark	0.0233	0.0210	0.0165	0.0099
ESP	Spain	0.0324	0.0269	0.0130	0.0168
FRA	France	0.0248	0.0176	0.0109	0.0128
GBR	United Kingdom	0.0222	0.0194	0.0172	0.0077
IRL	Ireland	0.0383	0.0272	0.0174	0.0196
ISR	Israel	0.0342	0.0646	0.0531	0.0358
ITA	Italy	0.0277	0.0249	0.0186	0.0149
JPN	Japan	0.0426	0.0506	0.0331	0.0362
KOR	Korea, Republic of	0.0597	0.0361	0.0300	0.0157
LUX	Luxembourg	0.0310	0.0313	0.0267	0.0154
MLT	Malta	0.0467	0.0435	0.0194	0.0329
NLD	Netherlands	0.0244	0.0185	0.0134	0.0119
NOR	Norway	0.0290	0.0156	0.0111	0.0087
PRT	Portugal	0.0335	0.0328	0.0233	0.0201
SGP	Singapore	0.0543	0.0388	0.0289	0.0233
TWN	Taiwan	0.0572	0.0264	0.0218	0.0138
USA	United States	0.0225	0.0194	0.0168	0.0075
HKG	Hong Kong	0.0477	0.0418	0.0351	0.0198
CAN	Canada	0.0221	0.0195	0.0151	0.0106
SWE	Sweden	0.0228	0.0191	0.0138	0.0109
FIN	Finland	0.0297	0.0281	0.0195	0.0164
GRC	Greece	0.0328	0.0401	0.0242	0.0273
ISL	Iceland	0.0287	0.0363	0.0260	0.0181
CHE	Switzerland	0.0149	0.0222	0.0164	0.0116
NZL	New Zealand	0.0144	0.0271	0.0236	0.0114

BRB	Barbados	0.0224	0.0431	0.0255	0.0264
GNQ	Equatorial Guinea	0.0654	0.1327	0.0909	0.0982
TTO	Trinidad & Tobago	0.0278	0.0517	0.0254	0.0394
		Upper middle income countries			
BWA	Botswana	0.0639	0.0573	0.0465	0.0292
CHN	China	0.0598	0.0585	0.0306	0.0264
MYS	Malaysia	0.0412	0.0389	0.0332	0.0198
TUN	Tunisia	0.0341	0.0445	0.0359	0.0231
THA	Thailand	0.0497	0.0491	0.0413	0.0257
COL	Colombia	0.0196	0.0219	0.0150	0.0125
DOM	Dominican Republic	0.0289	0.0507	0.0393	0.0220
PAN	Panama	0.0316	0.0442	0.0331	0.0222
TUR	Turkey	0.0263	0.0378	0.0334	0.0138
CRI	Costa Rica	0.0218	0.0338	0.0240	0.0181
MEX	Mexico	0.0196	0.0331	0.0266	0.0171
BRA	Brazil	0.0260	0.0385	0.0247	0.0259
MUS	Mauritius	0.0305	0.0523	0.0424	0.0282
ROM	Romania	0.0411	0.0553	0.0259	0.0443
CHL	Chile	0.0242	0.0520	0.0410	0.0281
ECU	Ecuador	0.0195	0.0420	0.0341	0.0248
URY	Uruguay	0.0132	0.0415	0.0302	0.0197
NAM	Namibia	0.0124	0.0357	0.0247	0.0186
PER	Peru	0.0103	0.0512	0.0384	0.0249
ARG	Argentina	0.0114	0.0528	0.0433	0.0216
IRN	Iran	0.0107	0.1058	0.0946	0.0419
ZAF	South Africa	0.0101	0.0251	0.0165	0.0155
JAM	Jamaica	0.0069	0.0378	0.0267	0.0239
JOR	Jordan	0.0113	0.0676	0.0446	0.0437
VEN	Venezuela	0.0071	0.0546	0.0462	0.0220
GAB	Gabon	0.0198	0.1032	0.0794	0.0576
		Lower middle income countries			
EGY	Egypt	0.0370	0.0374	0.0322	0.0154
LKA	Sri Lanka	0.0338	0.0236	0.0164	0.0093
MAR	Morocco	0.0265	0.0501	0.0403	0.0118

PAK	Pakistan	0.0260	0.0207	0.0172	0.0106
IND	India	0.0292	0.0335	0.0275	0.0143
LSO	Lesotho	0.0266	0.0661	0.0621	0.0217
FJI	Fiji	0.0185	0.0454	0.0425	0.0169
HND	Honduras	0.0106	0.0314	0.0257	0.0130
IDN	Indonesia	0.0329	0.0397	0.0296	0.0215
CPV	Cape Verde	0.0298	0.0620	0.0385	0.0294
GTM	Guatemala	0.0147	0.0245	0.0125	0.0192
PHL	Philippines	0.0133	0.0307	0.0207	0.0187
SLV	El Salvador	0.0142	0.0356	0.0178	0.0259
PRY	Paraguay	0.0159	0.0363	0.0217	0.0258
SYR	Syria	0.0211	0.0911	0.0769	0.0294
BOL	Bolivia	0.0047	0.0387	0.0299	0.0218
CMR	Cameroon	0.0054	0.0539	0.0434	0.0338
GHA	Ghana	0.0037	0.0431	0.0352	0.0229
COG	Congo, Republic of	0.0167	0.0640	0.0380	0.0393
NGA	Nigeria	0.0034	0.0777	0.0586	0.0432
CIV	Cote d`Ivoire	0.0022	0.0532	0.0401	0.0290
SEN	Senegal	-0.0016	0.0431	0.0429	0.0126
ZMB	Zambia	-0.0038	0.0490	0.0372	0.0286
		Low income countries			
NPL	Nepal	0.0129	0.0276	0.0277	0.0097
BFA	Burkina Faso	0.0115	0.0507	0.0440	0.0139
MLI	Mali	0.0123	0.0550	0.0516	0.0165
BEN	Benin	0.0109	0.0347	0.0303	0.0130
TZA	Tanzania	0.0140	0.0351	0.0239	0.0189
MOZ	Mozambique	0.0177	0.0515	0.0390	0.0313
BGD	Bangladesh	0.0112	0.0415	0.0353	0.0187
TCD	Chad	0.0066	0.0831	0.0669	0.0382
BDI	Burundi	0.0037	0.0593	0.0468	0.0255
GIN	Guinea	0.0030	0.0346	0.0282	0.0176
UGA	Uganda	0.0097	0.0458	0.0281	0.0335
KEN	Kenya	0.0054	0.0307	0.0234	0.0116
MWI	Malawi	0.0163	0.0724	0.0601	0.0330
RWA	Rwanda	0.0056	0.1162	0.1143	0.0297

ETH	Ethiopia	0.0065	0.0692	0.0638	0.0224
MRT	Mauritania	0.0183	0.0827	0.0641	0.0393
COM	Comoros	0.0076	0.0376	0.0271	0.0182
ZWE	Zimbabwe	-0.0035	0.0674	0.0562	0.0328
GMB	Gambia, The	-0.0020	0.0382	0.0343	0.0102
GNB	Guinea-Bissau	-0.0094	0.0858	0.0827	0.0242
TGO	Togo	0.0020	0.0591	0.0469	0.0297
NER	Niger	-0.0120	0.0614	0.0542	0.0250
CAF	Central African Republic	-0.0103	0.0387	0.0354	0.0115
MDG	Madagascar	-0.0081	0.0451	0.0398	0.0174
ZAR	Congo, Dem. Rep.	-0.0277	0.0607	0.0332	0.0392

Note: BC volatility and LR volatility are calculated as the standard deviation of the Baxter-King (1999) band- and low-pass filtered series with a window of 3 years and critical periodicity of 2-8 years.

A.2: OLS estimation using cross-sectional data (all countries): Alternative filter weights for developing countries)

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: All countries							
	1960-2007		1960-1980		1970-2007		1980-2007	
BC volatility	0.026	0.068	-0.075	0.088	0.024	-0.125	0.057	-0.177**
	(0.261)	(0.913)	(-0.513)	(0.645)	(0.323)	(-1.620)	(1.003)	(-2.561)
LR volatility	0.094		0.354		-0.240**		-0.359***	
	(0.650)		(1.514)		(-2.373)		(-6.456)	
p-value of the joint significance	0.548		0.303		0.007		0.000	
Adjusted R-square	0.613	0.615	0.440	0.415	0.544	0.509	0.578	0.484
Observations	90	90	89	89	107	107	107	107
	Panel B: Developing countries							
BC volatility	0.039	0.088	-0.189	0.079	0.051	-0.156	0.056	-0.237***
	(0.340)	(0.911)	(-0.905)	(0.489)	(0.541)	(-1.588)	(0.692)	(-2.994)
LR volatility	0.100		0.507		-0.307***		-0.385***	
	(0.612)		(1.535)		(-2.945)		(-4.947)	
p-value of the joint significance	0.619		0.308		0.001		0.000	
Adjusted R-square	0.447	0.455	0.258	0.214	0.446	0.379	0.549	0.442
Observations	64	64	63	63	75	75	75	75

Robust *t*-statistics are in parentheses; *** p<0.01, ** p<0.05, * p<0.1.
All regressions include a constant, initial per capita GDP (log), investment-GDP ratio, initial human capital, population growth, openness, political violence, share of government expenditure, ToT volatility, and dummies for regions, legal origins and landlocked countries.

A.3: OLS estimation using cross-sectional data (all countries): Hodrick-Prescott filter

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	1960-2007		1960-2008		1970-2007		1980-2007	
BC volatility	0.020	0.079	0.016	0.155	-0.054	-0.137*	-0.009	-0.206***
	(0.244)	(1.067)	(0.105)	(0.951)	(-0.700)	(-1.721)	(-0.131)	(-2.886)
LR volatility	0.203		0.397		-0.204		-0.452***	
	(1.285)		(1.514)		(-1.105)		(-3.914)	
p-value of the joint significance	0.287		0.273		0.089		0.000	
Adjusted R-square	0.620	0.617	0.447	0.425	0.521	0.512	0.559	0.496
Observations	90	90	89	89	107	107	107	107

Robust *t*-statistics in parentheses; *** p<0.01, ** p<0.05, * p<0.1.
All regressions include a constant, initial per capita GDP (log), investment-GDP ratio, initial human capital, population growth, openness, political violence, share of government expenditure, ToT volatility, and dummies for regions, legal origins and landlocked countries.

A.4: OLS estimation using cross-sectional data (all countries): Christiano-Fitzgerald filter

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	1960-2007		1960-1980		1970-2007		1980-2007	
BC volatility	0.031	0.073	0.021	0.123	-0.008	-0.119*	0.009	-0.171***
	(0.438)	(1.057)	(0.138)	(0.850)	(-0.114)	(-1.684)	(0.158)	(-2.873)
LR volatility	0.126		0.329*		-0.229**		-0.372***	
	(1.157)		(1.688)		(-2.017)		(-4.720)	
p-value of the joint significance	0.343		0.157		0.013		0.000	
Adjusted R-square	0.618	0.617	0.440	0.423	0.539	0.511	0.577	0.496
Observations	90	90	89	89	107	107	107	107

Robust *t*-statistics in parentheses; *** p<0.01, ** p<0.05, * p<0.1.
All regressions include a constant, initial per capita GDP (log), investment-GDP ratio, initial human capital, population growth, openness, political violence, share of government expenditure, ToT volatility, and dummies for regions, legal origins and landlocked countries.

A.5: Comparison of spectral densities

The spectral density for averaging over T years is given by: $\left(1/T\right)^2\left(1-\cos T\omega\right)/\left(1-\cos\omega\right)$, where ω is the frequency ranging between 0 and π (for derivation, see Sargent, 1987, p. 275). The spectral densities for T = 5, 7, 8 and 10 are displayed in Appendix Figure A.1. They are normalized using appropriate scalars so that the area under the curves are equal. A vertical line is drawn at 0.786 to mark the critical frequency that separates the long-run from cyclical components. Note that the periodicity (p) and frequency are inversely related by the formula: $p = 2\pi/\omega$. For a critical periodicity of 8 years, the corresponding critical frequency is 0.786. It can be seen from the graph that 5-year averaging does not reweight the variances of the raw series enough across low frequencies, thus the transformed data are more likely to be contaminated by high frequencies. The area under the spectral density to the right of the vertical line is 14% of the total area for 5-year averaging. The area substantially reduces 9.3% for 7-year averaging; it remains the same for 8-year averaging and reduces only to 8.8% for 10-year averaging.

Figure A.1: Spectral density for 5-, 7-, 8- and 10-year averaging.