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Abstract

This paper revisits the empirical relationship between volatility and long-run growth, but the key contribution lies in decomposing growth volatility into its business-cycle and trend components. This volatility decomposition also accounts for enormous heterogeneity among countries in terms of their long-run growth trajectories. We identify a negative effect of trend volatility, which we refer to as long-run volatility, on growth, but no effect of business-cycle volatility. However, if long-run volatility is omitted, there would be a spurious (negative) effect of business-cycle volatility. Our results draw attention to a crucial question about different volatility measures and their implications in macroeconomic analyses.

JEL Classification Codes: E32, F44, O11, O40.

Keywords: Growth; Business cycles; Volatility; Volatility persistence; Frequency.

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1 Introduction

The study of business-cycle (BC) volatility is the core of modern macroeconomics. In contrast, the volatility of the stochastic trend has not received enough attention, although it plays an important role in several areas of macroeconomics, such as welfare analysis and long-run growth.[1] Furthermore, both BC and trend volatility may simultaneously influence the outcome variables, and, therefore, understanding their relative importance is crucial.

In this paper, we put forward this idea to revisit the empirical relationship between BC volatility and long-run growth. Notwithstanding a large body of research, a consensus on the nature of the relationship is elusive. We argue that the empirical specification that has previously been employed to estimate the effect of BC volatility fails to account for the fluctuations in the trend growth and thereby leads to incorrect inferences about the true relationship. Hence, our contributions are two-fold: we correct the bias of the effect of BC volatility, and estimate the effect of trend volatility, on growth.

The following example illustrates the importance of different volatility components in the study of long-run growth. Over the period 1970-2014, both Switzerland and Guatemala had the same average growth rate (0.010). However, BC volatility, calculated as the standard deviation of the cyclical components of the GDP growth rate, was milder in Guatemala (0.013) than in Switzerland (0.018), whereas the volatility (standard deviation) of the trend growth rate was greater in Guatemala (0.017) than in Switzerland (0.009).[2] The long-run growth trajectories of these two countries clearly differ, and the empirical specification must consider this difference.

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[1] Recently, Hansen and Ohanian (2016) document that, in the post-Korean war quarterly US data, long-run annual US data, and post-war European data, low frequency fluctuations in aggregate time series are quantitatively large and, in some cases, even larger than the traditional business-cycle component.

[2] As a hypothetical example, consider two countries—*A* and *B*—that have identical average growth performances over a 20-year period (for the sake of simplicity, consider the arithmetic average). Suppose that the annual growth rate in country *A* alternated between 2% and -2% each year (i.e., 2, -2, 2, -2, ---- 2, and -2), whereas the annual growth rate 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 standard deviation, but the patterns of the trend growth rate in these two countries clearly differ. Specifically, the trend growth rate in country *B* is several times as volatile as that in country *A*, while BC volatility (standard deviation of the cyclical component) in country *A* is several times as large as that in country *B*. In Appendix A.1 and Appendix Figures 1a-1h, we provide examples of various patterns of volatility of cyclical and trend growth rates observed in the data.

We refer to the fluctuations in the trend growth rate[3] as *long-run (LR) volatility*. The importance of LR volatility in the volatility-growth relationship can also be understood based on the following volatility decomposition. Given that there are enormous transitory (cyclical) variations around the trend growth rate in many countries and that the trend growth rate is *per se* 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, as follows: ($g_{y,t}^{LR}$): $g_{y,t} = g_{y,t}^{BC} + g_{y,t}^{LR}$. Its variance is then decomposed as $\mathrm{Var}(g_{y,t}) = \mathrm{Var}(g_{y,t}^{BC}) + \mathrm{Var}(g_{y,t}^{LR})$. We use this spectral relation to explore the volatility-growth relationship at the cross-country level.

We calculate BC and LR volatility as the standard deviations of the cyclical and long-run components, respectively, of the (annual) per capita real GDP growth rate. To extract the cyclical and long-run components, we filter the data at the business-cycle and low frequencies, respectively, with the Baxter-King (henceforth, BK) (1999) filter.[4] We choose a window of 3 years, and critical periodicities in the range between 2 and 8 years for the business-cycle and 8 years and above for the long-run. To construct panel data, we calculate volatility as the standard deviations of the filtered growth series over 7 years. We take non-overlapping averages of the annual (unfiltered or raw) growth rate and other series over 7 years. In Appendix A.2 (and Appendix Figure 2), we use spectral density to show that averaging over 7 years performs better in terms of reweighting the variances of the raw series across low frequencies than does averaging over 5 years, which is a common practice in the cross-country growth literature. Data averaged over a 5-year period are contaminated by high frequencies. This contamination decreases substantially when a 7-year period is used for averaging. Further improvement is small when longer horizons, such as 8 or 10 years, are used. Because averaging over longer horizons leaves fewer observations for estimation, we choose a 7-year period as an optimal compromise.

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[3] We use trend, long-run, and low-frequency interchangeably throughout the paper.

[4] 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, because this method requires relatively long time series, it cannot be employed in our panel data analysis. Fatás (2000a, 2000b), Levy and Dezhbakhsh (2003), Aguiar and Gopinath (2007) and Nakamura, Sergeyev, and Steinsson (2012) employ Cochrane's (1988) variance ratio to calculate LR volatility, but this method cannot be used to calculate BC volatility. Another alternative method for extracting BC and LR volatility is the unobserved component model (UCM). For example, Stock and Watson (2007) and Ascari and Sbordone (2014) estimate the time-varying volatility of the trend and cyclical components of inflation for the USA. However, the UCM is not suitable for the cross-country level, because it requires assumptions about the specification of the components.

Our primary source of data is the PWT 9.0 for 1970–2014 (discussed in Section 3). To verify the results using an alternative dataset and different time periods, we perform a separate analysis for 1875–2010 using the historical time series compiled by Angus Maddison. As an additional robustness check, we replicate Ramey and Ramey (1995, AER), the seminal study that initiated the empirical volatility-growth literature, using their data.

Our empirical strategy, discussed in Section 4, is cross-country regression in that growth rate is regressed on BC volatility and a set of conditioning variables but departs from the existing literature by also controlling for LR volatility. Our argument is that the omission of LR volatility causes misspecification of the regression equation and, thus, leads to incorrect inferences about the relationship. The effect of LR volatility is also of interest to us. Our identification strategy to account for the endogeneity of BC and LR volatility relies on instrumental variable estimation (detailed discussion in Section 4.3).

We find that there is no effect of BC volatility on growth after correcting the misspecification. However, in the misspecified equation that omits LR volatility, the results are aligned to some existing studies; the effect becomes significantly negative, especially for developing countries. We also find that LR volatility has a negative effect on growth for all groups of countries. These results are robust to the choice of alternative critical frequency for developing countries, different assumptions about the integration properties of the growth rate, and split sample analyses for different income groups, regions, and sub-periods. All results are presented in Section 5.

Our measure of LR volatility can also be interpreted as persistence in volatility (Levy and Dezhbakhsh, 2003; Ascari and Sbordone, 2014; Müller and Watson, 2015). Therefore, our findings suggest that the persistent component of volatility, rather than the BC component, is harmful for growth. Most studies use standard deviation of the (unfiltered or raw) growth rate as a proxy for BC volatility (we refer it to *total volatility*; detailed discussion in Section 6.1). This measure is based on the assumption of a constant trend, whereas the calculation of BC volatility as the standard deviation of the cyclical components assumes a time-varying trend. Based on our volatility decomposition, we show that the contribution of volatility persistence is misconstrued as being the contribution of BC volatility. To summarize our results, volatility at low frequencies, rather than at business-cycle frequencies, adversely affects long-run growth.

Many studies have investigated the effect of uncertainty on macroeconomic variables, including long-run growth. It is imperative to distinguish between volatility measured in our paper and uncertainty. Uncertainty accounts only for the unpredicted component, whereas volatility accounts for both predicted and unpredicted components (Wolf, 2005).[5] Uncertainty is usually calculated as the standard deviation of the residual (or as the squared residual) of a forecasting equation, in which growth rate is regressed on its own lags and linear (and quadratic) trends (for example: Ramey and Ramey (1995), Fatás (2002), Rafferty (2005), Stastny and Zagler (2007), in the case of growth uncertainty; Fatás and Mihov (2013), in the case of policy uncertainty; Bloom et al. (2014), in the case of TFP uncertainty). Although introducing the trends removes low-frequency movements from the data and, therefore, the remaining component is comparable to band-pass-filtered growth, BC volatility in our paper is a measure of *ex post* realized volatility, as opposed to uncertainty. Some studies (Ramey and Ramey, 1995; Rafferty, 2005) include both unexpected and expected volatility in their regressions and calculate expected volatility as the standard deviation of the fitted value of the growth rate. Our measure of LR volatility differs from expected volatility in the same manner as low-pass filtering differs from fitting. The aim of low-pass filtering is to retain values at low frequencies, whereas fitting aims to achieve the closest possible match of data values. Furthermore, filtering, unlike fitting, does not involve use of an explicit function form. These differences are manifest in the differences between the results.[6]

The issue of LR volatility, or persistence in volatility, is largely unexplored in the growth literature. The studies closest to ours are probably by Fatás (2000a, 2000b), who documents a strong positive correlation between long-run growth rates and the persistence of output (not growth) fluctuations in a cross-section of countries. His results suggest that volatility of the permanent component of output is larger for countries with high growth rates. We address a different question regarding growth volatility and find that the relationship between growth and

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

[6] Ramey and Ramey (1995) find that the coefficients on both unexpected and expected volatility are insignificant (negative with a low *t*-statistic) in a sample of 92 countries. In contrast, for a sub-sample of OECD countries, the coefficient on unexpected volatility is negative and highly significant, and the coefficient on expected volatility is positive and significant. In our study, we do not find any effect of BC volatility on growth but find a negative and significant effect of LR volatility on growth. Similarly, Rafferty (2005) uses the Angus Maddison historical data for 18 developed countries from 1880 to 1990 and finds that long-run growth is reduced by unexpected volatility and increased by expected volatility. Using the same data, we find no association of BC or LR volatility with growth.

persistence in growth volatility is negative and robust across time periods and country groups. Our paper is also situated within a burgeoning literature on growth spells, which was pioneered by Pritchett (2000). Pritchett observes heterogeneity among countries in terms of instability of growth rates over time. Country experiences differ enormously with respect to steady growth, rapid growth followed by stagnation, rapid growth followed by decline (or even catastrophic falls), continuous stagnation, and steady decline. Our motivation and approach address this heterogeneity among countries.

A few studies have investigated the determinants of LR volatility (Berg, Ostry, and Zettelmeyer, 2012; Mallick, 2014), but there is no theory that explains the effect of LR volatility on growth. In Section 6.2, we provide some possible explanations on why LR volatility negatively affects growth. Finally, we conclude in Section 7.

2 Literature Review

In the following, we briefly review studies on the volatility-growth relationship that are most relevant to the research question in our paper. There are strands of literature that investigate the determinants of both growth and volatility and the channels through which volatility affects growth. We touch on this literature in Section 4.2, where we explain selection of the control variables in the regression.

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

In contrast, endogenous growth theory predicts a negative relationship between BC volatility and long-run growth, based on the notions of learning-by-doing and 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 during recessions. Therefore, in the presence of negative learning-by-doing, temporary shocks have a negative impact on long-run growth.[7] Furthermore, the models based on opportunity cost arguments predict that the effect of business cycles on growth can be either positive or negative (Aghion and Saint-Paul, 1998a; 1998b). For example, if the cost of productivity improvements positively depends on current production and this cost drops by more than its present discounted benefit during a recession, then business cycles have a positive effect on growth; Saint-Paul (1997) provides evidence at the aggregate level to support this argument. Conversely, if the cost of productivity-enhancing activities does not depend on current production, the conclusion of the model is reversed, and recessions have a negative long-run effect.

Given the lack of consensus regarding theoretical predictions, the burden is on empirical research to establish the actual relationship between BC volatility and long-run growth. However, the empirical literature also lacks consensus. For example, Kormendi and Meguire (1985), Grier and Tullock (1989), Stastny and Zagler (2007), and Moro (2015) find a positive correlation between business cycles and long-run growth, whereas Ramey and Ramey (1995), Martin and Rogers (2000), Kneller and Young (2001), Fatás (2002), Döpke (2004), Hnatkovska and Loayza (2005), Mobarak (2005), Rafferty (2005), and Loayza et al. (2007) find a negative correlation.[8] Moreover, the observed relationship varies across country groups. Martin and Rogers (2000) find a negative relationship in industrialized countries but an insignificant relationship in non-industrialized countries; they posit that the learning-by-doing mechanism may not operate in the latter group of countries.[9] Imbs (2007) finds that volatility and growth are positively related at the sectoral level but negatively related at the aggregate level. Notably, it has not been satisfactorily established whether the observed relationship is a correlation or a causal effect of BC volatility on long-run growth. Finally, the role of persistence in growth volatility in explaining long-run growth is unexplored in the literature.

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

[8] Empirical studies have also considered different mechanisms that influence the relationship. For example, Moro (2015) deals with the role of structural change towards services in influencing the relationship, while some studies emphasize the cyclical properties of the technological progress.

[9] Young (1993) argues that growth is driven by learning-by-doing only at relatively high levels of development.

3 Data and Descriptive Statistics

The main source of data is the PWT 9.0 (Feenstra, Inklaar, and Timmer, 2015). We choose 1970–2014 because of the availability of data for the control variables. We retain those countries in the sample that have GDP data for the entire sample period. We exclude the ex-socialist countries.

Average per capita growth rate and volatility have been calculated based on the $RGDP^{NA}$ series (real GDP at constant national prices), which is recommended for the comparison of 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, $dy_t = \ln(Y_t / Y_{t-1})$.

Average growth rate is the non-overlapping average of dy_t over 7 years. Other variables are similarly averaged over 7 years.[10] BC and LR volatility have been calculated as the standard deviations over 7 years of the cyclical and long-run components of dy_t, respectively, which are extracted employing the BK filter.[11] A window of 3 years has been selected, along with critical periodicities ($\tilde{p}$) in the range between 2 and 8 years for cyclical components (band-pass filter) and 8 years and above for long-run or equivalently low-frequency components (low-pass filter). Typically, the main purpose of a filter is to extract the cyclical components of a series; the long-run components are then recovered as the residual. However, we extract the long-run components using the low-pass filter based on the assumption that per capita real GDP growth is stationary.[12]

[10] We retain the GDP series from 1966, because one observation is lost due to calculation of the growth rate, and then three observations from each tail are lost due to filtering using a window of 3. Therefore, the effective sample period becomes 1970–2011. There are six 7-year intervals for this period: 1970–76, 1977–83, 1984–90, 1991–97, 1998–2004 and 2005–11.

[11] Baxter and King (1999, p. 587) discuss the advantage of calculating BC volatility using their band-pass filter, as opposed to other methods, such as the Hodrick–Prescott (1997) and Christiano–Fitzgerald (2003) band-pass filters. The HP filter is optimal for an I(2) process, and, also, choice of the smoothing parameter for the cross-country annual data is not settled [although some suggestions by Ravn and Uhlig (2002)]. On the other hand, the CF filter is optimal for a random walk process.

[12] Romer (2012, p. 136) stresses that statistical tests do not determine whether the growth rate is stationary or nonstationary; rather, these tests 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. We further explore this issue in Section 5.4.

For the initial level of GDP, we use the CGDP^e series (expenditure-side real GDP at current PPPs in millions of 2005 US dollars, which compares relative living standards across countries at a single point in time), as recommended by Feenstra, Inklaar, and Timmer [(2013); Table 5 in p. 30]. Terms-of-trade (ToT) is calculated as the ratio of export to import prices (PL_X / PL_M). Investment share of GDP is the CSH_I series. Human capital index (HC) is based on years of schooling and returns to education.

Trade openness is the sum of exports and imports as a share of GDP at current prices; the data for this variable are obtained from the PWT 7.1 (Heston, Summers, and Aten, 2012) (these data are not available in later PWT versions). Political violence is captured by the total summed magnitudes of all societal and interstate major episodes of political violence (MEPV) in a country, which were obtained from data compiled by the Center for Systemic Peace (2013).[13] Private credit data have been collected from the Financial Development and Structure Dataset, compiled by Beck et al. (2000) and revised by Čihák et al. (2012).

Insert Table 1 here

The average growth rate, BC volatility, and LR volatility for 106 countries during 1970–2014 are summarized in Table 1. Countries are classified as middle- and low-income, according to the World Bank classification scheme. BC volatility decreases with income level; it is 0.048 in low-income countries, compared with 0.031 and 0.019 in middle-income (upper- and lower-middle-income combined) and OECD countries, respectively. LR volatility follows a similar pattern. It is larger in low-income (0.030) than in middle-income countries (0.023) and almost half in OECD countries (0.013). The share of LR volatility is large (41%); it is also the same for OCED and developing countries. However, among the developing countries, it is slightly larger in middle-income countries than in low-income countries. The correlations between BC and LR

[13] MEPV scores are annual, cross-national, time-series data regarding the magnitude of interstate, societal, and communal warfare (independence, interstate, ethnic, and civil violence and warfare) in a country. We use the ACTOTAL series of the dataset. ACTOTAL is calculated as the sum of the magnitude scores of the following episodes: i) international violence, ii) international warfare, iii) civil violence, iv) civil warfare, v) ethnic violence, and vi) ethnic warfare involving that state in a particular year. Each MEPV is scored on a magnitude scale ranging from 1 (lowest) to 10 (highest), and magnitude scores for multiple MEPVs are summed (with 0 denoting no episodes).

volatility and the 95% confidence intervals are reported in column (5). The correlation for the entire sample is 0.78; it is the largest for low-income countries (0.76) and the smallest for OECD countries (0.51).

Examples of heterogeneity abound in the data, and we highlight several of them in Appendix A.1 (and Figures 1a-1h in the same Appendix). As an illustration, one example here is the comparison between Costa Rica and Trinidad and Tobago. These two countries had the same average growth rate (0.021) and BC volatility (0.026), but LR volatility in Trinidad and Tobago (0.043) was more than twice as large as was that in Costa Rica (0.017).

4 Estimation Strategies

In this section, we discuss the regression specification and identification strategy employed to uncover the volatility-growth relationship.

4.1 Estimating Equation

Our estimation strategy is based on regressions of long-run growth on BC volatility and a set of conditioning variables that includes LR volatility. The specifications are given by:

$$g_{y_{i,\tau}} = \alpha + \gamma_{BC}^{c} BCvol_{i,\tau} + \gamma_{LR} LRvol_{i,\tau} + \beta y_{i,\tau-1} + \mathbf{X}'_{i,\tau-1}\boldsymbol{\delta} + \mu_i + \eta_\tau + v_{i.\tau}\,, \quad \text{---(1a)}$$

$$g_{y_{i,\tau}} = \alpha + \gamma_{BC}^{b} BCvol_{i,\tau} + \beta y_{i,\tau-1} + \mathbf{X}'_{i,\tau-1}\boldsymbol{\delta} + \mu_i + \eta_\tau + u_{i,\tau}\,. \quad \text{---(1b)}$$

Here, $g_{y_{i,\tau}}$ is the average growth rate of real per capita GDP for interval τ . μ_i is the country fixed effects, and η_τ is the aggregate time effects captured by time (interval) dummies. These time dummies also account for the world factors (such as the global recession in the mid-1970's) that are important in explaining growth volatility (Kose, Otrok, and Whiteman, 2003). $y_{i,\tau-1}$ is the log of real per capita GDP in the previous interval. All control variables ($\mathbf{X}_{i,\tau-1}$) are lagged by one period, so that they are treated as predetermined. The coefficient on BC volatility ($BCvol_{i,\tau}$) in equation (1a), γ_{BC}^{c}, is the biased-corrected (or credible) effect of BC volatility on growth, and γ_{LR} is the effect of LR volatility ($LRvol_{i,\tau}$). On the other hand, γ_{BC}^{b} in the misspecified equation (1b) that does not control for LR volatility is the biased coefficient on BC volatility.

Given that the correlation between BC and LR volatility (corr(*BCvol, LRvol*)) is positive in the data,[14] the bias in γ^{b}_{BC} due to misspecification depends on the sign of $\mathrm{corr}(g_y, LRvol)$ or, equivalently, the sign of γ_{LR} in equation (1a). If $\gamma_{LR} < 0$ (>0), γ^{b}_{BC} will be biased downward (upward). Even if $\gamma_{LR} = 0$, γ^{b}_{BC} will remain biased upward because corr(*BCvol, LRvol*) >0.

4.2 Identification: Choice of Control Variables

Selection of control variables ($\mathbf{X}$) in cross-country growth regressions is a difficult task, because numerous variables have been found to be significant in various studies. Certain studies control the variables that are robustly significant in extreme bound analysis (or Bayesian model averaging), but we take a different approach to avoid the omitted variable bias. This approach involves carefully controlling only those growth determinants that also affect volatility. Omission of other controls will not cause any bias, as long as the omitted variables are uncorrelated with volatility.

The following variables are included in $\mathbf{X}$: (i) investment share in GDP; (ii) human capital; (iii) population growth rate; (iv) trade openness; (v) policy volatility (discussed below); (vi) terms-of-trade (ToT) volatility, which is measured as the standard deviation of the ratio of export to import prices (as a proxy for external shocks); (vii) political violence (explained in footnote 13); ix) institutional development (*polity2*); and x) financial development, which is proxied by the credit disbursed to the private sector by banks and other financial institutions relative to GDP. Lag (log) per capita income is also included to account for conditional convergence and the transitional dynamics to avoid a positive bias on the coefficient on BC volatility (for a discussion of this bias, see Martin and Rogers, 2000, p. 365). Acemoglu and Zilibotti (1997), Kose, Otrok, and Whiteman (2003) and Koren and Tenreyro (2005) also document that GDP growth is more volatile in developing than in developed countries. The variables (i)–(iii) (along with initial income level) are the most common controls in growth-volatility regressions (including Ramey and Ramey, 1995). Although investment is crucial to

[14] A positive correlation between BC and LR volatility can be due to R&D and diffusion of technologies that connect fluctuations at different frequencies (Comin and Gertler, 2006). This should not be confused with the orthogonality of the growth series at LR and BC frequencies mentioned in the introduction. By definition, the covariance (and therefore the correlation) between spectral estimates at different frequencies is zero (Priestley, 1981). The zero covariance of the growth series at the BC and LR frequencies for each country is also confirmed in the data.

economic growth, 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 it is accompanied by a rate of economic growth that is large enough to reduce unemployment.[15] Although higher human capital plays an important role in economic growth, it also causes economic and political instability if left unutilized (the recent Arab Spring is a prime example of this phenomenon) (Kuhn, 2012).

The role of openness in economic growth has been established both theoretically and empirically, but openness also affects volatility. Using an industry-level panel dataset of manufacturing production and trade, Giovanni and Levchenko (2009) document a positive and economically significant relationship between trade openness and overall volatility. Mallick (2014) observes similar effects using aggregate data at the cross-country level. Kose, Prasad, and Terrones (2006) find that openness stimulates both growth and volatility.

Policy volatility and terms of trade (ToT) volatility isolate the business-cycle shocks from policy-induced and exogenous shocks, respectively. Fatás and Mihov (2013) document that policy volatility, defined as the uncertainty in the government expenditure growth, negatively impacts economic growth. They used the PWT 6.3 data for 1970–2007 and regress economic growth on policy volatility and a set of controls that include growth volatility. We construct policy volatility following Fatás and Mihov (2013).[16] Easterly et al. (1993) document that shocks measured by the change in ToT influence growth both directly and indirectly through policy variables. A negative robust impact of the change in ToT on growth volatility is documented by Mallick (2014) and Agénor et al. (2000). Mendoza (1995) estimates that ToT shocks account 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 the volatility of country-level macro shocks.

Rodrick (1999) shows that domestic social conflicts are important to understand growth collapse and the lack of persistence in growth performance since the mid-1970s. Social conflicts

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[15] Higher rates of population growth have also been found to be related to higher consumption volatility (Bekaert, Harvey, and Lundblad, 2006).

[16] For each country in our sample, we run the following regression: $\Delta \ln G_t = \alpha + \beta \Delta \ln Y_t + \varepsilon_t$, where *G* real government consumption spending per capita, while *Y* is real GDP per capita. The estimated residual, $|\hat{\varepsilon}_t|$, is the measure of policy volatility. We take the time average of the residual for each interval.

interact with external shocks and domestic institutions of conflict management. Ploeg and Poelhekke (2009) show that ethnic tensions cause higher volatility and lower growth. Acemoglu et al. (2003) argue that flawed macroeconomic policies that increase volatility and decrease growth are the result of weak institutions, which are also related to social and political instability.[17] Financial development is one of the main channels through which volatility affects growth (Aghion and Banerjee, 2005; Beck, 2012).

Clearly, the list of variables presented above is not exhaustive, and there may be other factors that trigger both growth and BC volatility. It is conceivable that these omitted variables are related to the level of economic development and, thus, are captured to a large extent by controlling for initial income level in the regression. We also include region dummies (Latin America, sub-Saharan Africa, Asia Pacific, and the Middle East and North Africa) in the regression, because certain regions are more volatile than others, for reasons that are not discussed above; these dummies also capture omitted variables in growth regressions (Berg, Ostry, and Zettelmeyer, 2012). Finally, we include dummies for legal origins to account for both country fixed factors (μ_i) and omitted variables.[18]

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4.3 Identification: Reverse Causality and Measurement Errors

The other sources of endogeneity are the reverse causality from growth to volatility and measurement errors. The reverse causality may be both negative and positive. For example, poor growth performance in an economy may lead to social and political instability, which, in turn,

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

[18] Several studies endeavor to establish causality from BC volatility to growth using instrumental variable regressions. For example, Hnatkovska and Loayza (2005) use the following variables as 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) use the standard deviation of the growth rate of the preceding decade, the initial inflation rate of the current decade, the initial level of GDP per capita, and the number of revolutions and coups as instruments for developing countries. Mobarak (2005) uses diversification as the instrument of volatility. However, the exogeneity of these instruments in the long run is disputed. Bazzi and Clemens (2013) provide an excellent discussion on the problem of instrumental variable estimation in cross-country growth regressions.

causes higher volatility. On the other hand, if a fast-growing country opts for riskier technology, this may lead to higher volatility.[19]

Lagged values of BC and LR volatility can be potential instruments to address reverse causality; however, since these variables are constructed from a two-sided (overlapping) filtered series, their lagged values will also be correlated to growth, unless lagged by many periods, which potentially undermines the relevance of the instruments. To see the effect of filtering on instrumentation, let y_t is the growth rate of per capita real GDP at time t. For a particular interval τ, the average growth rate ($\overline{y}_\tau$) is the non-overlapping average of y_t over 7 years, i.e., $\overline{y}_\tau = (1/7)\sum_{j=0}^{6} y_{t+j}$, whereas BC volatility is calculated as the standard deviation of the band-pass filtered series of y_t (say, y_t^*) over the same interval, i.e., $\mathrm{sd}(y_\tau^*) = \left[(1/6)\sum_{j=0}^{6}\left(y_{t+j}^* - \overline{y}_t^*\right)^2\right]^{1/2}$, where $y_{t+j}^* = \sum_{q=-3}^{+3} a_q y_{t+j+q}$ (a_q 's are the filter weights). This formula shows that average growth rate, the dependent variable in the regression, is based on y_t data for (t + j) periods, while BC volatility, the explanatory variable, is based on y_t data for (t + j + 2q) periods (<u>q lead and q lag periods).</u>

To overcome the problem caused by the lead values, we construct a modified filtered series y_t^{**} based on a one-sided moving average using only the lagged value of y_t as $y_t^{**} = \sum_{q=-3}^{0} b_q y_{t+q}$; this requires *data for the same (t + j) period used to calculate the average growth rate* ($\overline{y}_\tau$), and also q lags (which do not cause reverse causality). We then calculate the standard deviation of y_t^{**} [$\mathrm{sd}(y_\tau^{**})$] and use <u>the first lag of $\mathrm{sd}(y_\tau^{**})$</u> as the instrument for BC volatility, which consists only of lagged growth data. A similar procedure is applied to construct the instrument for LR volatility.[20]

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[19] Aghion and Banerjee (2005) present a model wherein the reverse causality is also positive, but only countries at the intermediate level of financial development are vulnerable to volatility.

[20] Similar identification has been employed by Chirinko and Mallick (forthcoming). It is also worth mentioning that inclusion of BC (and LR) volatility measured as the standard deviation of y_t^{**} (as opposed to that of y_t^*) in the regression causes a *phase shift*.

Measurement errors in BC (and LR) volatility as a source of endogeneity is less clear, although this issue has been raised by Martin and Rogers (2000). Measurement errors in volatility are less likely to be inherited from measurement errors in GDP. Although certain countries might purposefully and systematically inflate their GDP figures, growth rate is less likely to be contaminated by such manipulation. One might argue that standard deviation may not represent the true volatility, but this proxy is common in many areas of economics and finance. To construct instruments for BC and LR volatility, we order the sample countries by respective volatility and construct an ordering score, or rank, for countries (a value of 1 is assigned to the least volatile country, and consecutive integers are assigned to countries with incremental volatility). This identification is based on the assumption that measurement errors do not vary in a manner that alters the distribution of countries by either BC or LR volatility. By construction, these instruments are highly correlated with respective BC and LR volatility but exogenous to the growth rate.

Because historical values of the **X** variables are unavailable, we are unable to control them in the Angus Maddison panel data. Therefore, the above instrumentation will not correct the endogeneity bias due to omitted variables and we interpret this relationship as correlation.

5 Results

We report only the coefficients of our interests: $\hat{\gamma}^{c}_{BC}$, $\hat{\gamma}^{b}_{BC}$ and $\hat{\gamma}_{LR}$, which are the unbiased (credible) coefficient on BC volatility, the biased coefficient on BC volatility in the misspecified equation, and the coefficient on LR volatility, respectively. $\hat{\gamma}^{c}_{BC}$ and $\hat{\gamma}_{LR}$ compare the relative contribution of BC and LR volatility to explaining growth. All estimations are based on a window of 3 years and $\tilde{p} = 8$, unless otherwise mentioned.[21]

[21] 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. Periodicities between 2 and 32 quarters represent the high-frequency component of the medium-term, and frequencies between 32 and 200 quarters constitute the medium-frequency component of the medium-term. Our definition of long-run periodicities as 8 years (32 quarters) and above incorporates their medium-frequency components.

5.1 OLS Estimation

We first begin with the results by pooled OLS estimation of equations (1a) and (1b). The results are presented in Table 2; the odd-numbered columns report $\hat{\gamma}_{BC}^{c}$ and $\hat{\gamma}_{LR}$, estimated from equation (1a), and the even-numbered columns present $\hat{\gamma}_{BC}^{b}$, estimated from the misspecified equation (1b). Columns (1) and (2) report the results for all sample countries in the regressions without any control variables, except for the lag of log per capita real income. Both $\hat{\gamma}_{BC}^{c}$ and γ_{BC}^{b} are insignificant but negatively signed. The important observation is that, in equation (1a), the magnitude of $\hat{\gamma}_{LR}$ (-0.28) is approximately three times larger than $\hat{\gamma}_{BC}^{c}$ (-0.11) and also has a larger *t*-statistic. When LR volatility is excluded from the regression in equation (1b), both the magnitude and *t*-statistic of γ_{BC}^{b} become approximately 50% larger than those of $\hat{\gamma}_{BC}^{c}$. The same pattern is observed if the control variables and country fixed factors are included in the regressions [columns (3)–(6)].

In the case of developing countries, both $\hat{\gamma}_{BC}^{c}$ and $\hat{\gamma}_{LR}$ are negative, and $\hat{\gamma}_{BC}^{c}$ is statistically significant at the 5% level; however, in the misspecified equation (1b), both the (absolute) magnitude and statistical significance of γ_{BC}^{b} are now substantially larger than $\hat{\gamma}_{BC}^{c}$ [(columns (7)–(8)]. On the other hand, in the case of OCED countries, $\hat{\gamma}_{LR}$ is negative (-0.51), statistically significant, and several times larger than $\hat{\gamma}_{BC}^{c}$. In the misspecified equation (1b), the magnitude and *t*-statistic of γ_{BC}^{b} also exhibit a substantial increase [columns (9)–(10)].

Insert Table 2 here

These results suffer from endogeneity; nonetheless, they reveal an important pattern, showing that the correlation between growth and BC volatility is magnified if LR volatility is omitted from the regression. These results also serve as a benchmark for comparison with the results obtained from estimation of the Maddison historical data.

5.2 Benchmark IV Estimation

It would be worth reiterating that our IV/GMM estimations are intended to account for endogeneity due to reverse causality and measurement errors. Upon selecting the appropriate control variables, our IV estimation will provide unbiased effects of both BC and LR volatility on growth.[22] On the other hand, the effect of BC volatility in equation (1b) will still be biased after instrumenting, because of omitting LR volatility.

The results are presented in Table 3. The first two columns report the results for all sample countries. The coefficient on BC volatility in equation (1a), $\hat{\gamma}^{c}_{BC}$, is negative, very small, and statistically insignificant, while the coefficient on LR volatility, $\hat{\gamma}_{LR}$, is approximately four times larger (-0.38) and significant at the 5% level [column (1)]. However, in the misspecified equation (1b), γ^{b}_{BC} almost doubles and becomes statistically significant at any conventional level [column (2)].

Given that $\hat{\gamma}_{LR}$ is negative, γ^{b}_{BC} is biased downward, as can be seen from the estimated value of γ^{b}_{BC} (= -0.177), which is about 82% smaller than $\hat{\gamma}^{c}_{BC}$ (= -0.097). The quantitative implication of this bias is discussed in Section 6.

Insert Table 3 here

The results, when estimated retaining only the developing countries, are similar to the full sample countries, both in terms of the signs and the statistical significances of the coefficients [columns (3) and (4)]. The results for the OECD countries are also similar [columns (5) and (6)]; although γ^{b}_{BC} is also insignificant in the misspecified equation, its magnitude (and *t*-statistic) is several times larger than $\hat{\gamma}^{c}_{BC}$ (and *t*-statistic), a pattern similar to those observed in the full sample and developing countries.

The instruments are valid and relevant in all cases, as suggested by the Kleibergen–Paap rk LM and Wald *F* statistics. The over-identifying restrictions are satisfied, as indicated by the *p*-value of the Hansen *J*-statistics.

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[22] Controlling for omitted variables in cross-country regressions is not an easy task and, therefore, one can dispute our argument. Therefore, we interpret the causal effect cautiously.

5.3 IV Estimation: Alternative Critical Periodicity

The previous results are based on the implicit assumption that all countries are characterized by similar cyclical patterns. Although there is a large body of literature on business cycles in developed countries, very little is known about business cycles in developing countries. Agénor, McDermott, and Prasad (2000) note that there are both similarities (procyclical real wages and 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 from developed countries 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. These results suggest that cycles are generally shorter in developing countries. Male (2011) emphasizes that there is heterogeneity at the regional level, in that cycles are shorter in Latin America and longer in Asia, compared with developed countries.

We now calculate BC and LR volatility by filtering the growth rate, using $\tilde{p} = 5$ for developing countries, but retain the benchmark $\tilde{p} = 8$ for developed countries. The results for full sample and developing countries, summarized in Table 4, are qualitatively similar to the benchmark results in Table 3. In the subsequent analyses, all results are based on the benchmark $\tilde{p} = 8$.

Insert Table 4 here

5.4 IV Estimation: Nonstationary Growth Rate

We have extracted the low-frequency components by employing low-pass filter under the assumption that growth rate is stationary. This assumption may be contested for countries that have experienced large swings in their growth rates. Ideally, the true integration property of the growth series cannot be determined in a finite sample, as emphasized by Romer (2012; see footnote 12 in this paper). Once the assumption of stationarity is relaxed, the low-pass filter cannot be applied. Under the assumption of non-stationarity, we follow the standard procedure to calculate the business-cycle components using the band-pass filter and extract the long-run component as the residual. We then calculate LR volatility as the standard deviation of the latter series. The results are presented in Table 5, but only for equation (1a), as the results for equation (1b) will be the same. There is almost no change in these results from the benchmark results, both in terms of the estimated coefficients and their *t*-statistics.[23]

Insert Table 5 here

5.5 IV Estimation: Alternative Sample Periods

Patterns of volatility have undergone changes over time. In general, except for some (regional) crises, the world has become less volatile since the mid-1980s. To understand any changes in the growth-volatility relationship, we estimate equations (1a) and (1b) for the post-1984 period (dropping the first two intervals, 1970–76 and 1977–83). On the other hand, the recent great recession is unprecedented in history except the great depression in the 1930s. However, as this recession was contained mostly to the developed countries (even some developed countries, such as Australia and New Zealand, escaped it), we re-estimate the results for the OECD countries, excluding the last interval (2005–2011). The results are summarized in Table 6. Columns (1)–(4) report the results for the post-1984 period for the full sample and developing countries. There are almost no changes in $\hat{\gamma}_{BC}^{c}$ and $\hat{\gamma}_{LR}$, compared to the benchmark results, while γ_{BC}^{b} is now insignificant (it is significant at the 11% level for the full sample countries). There is also no change in the results for the OCED countries [columns (5)–(6)].[24]

Insert Table 6 here

These results corroborate that the BC volatility has no effect on growth; rather it is the LR volatility that negatively impacts growth.

[23] Given that both assumptions of stationarity and nonstationarity give almost identical results, we do not test the integration properties of the growth rate for each country and then decompose volatility based on the test results. This tedious exercise is unlikely to change our main conclusions.

[24] The results for OECD countries in the post-1984 period, and those for the full sample and developing countries in the pre-2005 period, do not qualitatively change. However, we do not report them, because the Hansen *J*-statistics are not valid.

5.6 IV Estimation: Sub-sample Countries

Previously, we split sample countries based on their level of development. In the following, we perform more robustness checks for different subsets of countries based on alternative selection criteria.

In the first exercise, we exclude countries that may be more vulnerable to reverse causality. The possible candidates are the fast-growing countries that may opt for riskier technology and, therefore, experience greater volatility. We drop the top 25% and 50% of growth performers based on the average growth rate over 1970–2014; this leaves 86 and 55 countries, respectively. The results for both groups, reported in Table 7 [columns (1)–(4)], are in line with the benchmark results.

Insert Table 7 here

The next exercise tests whether the results are driven by high-volatile countries. We exclude from the sample the regions experiencing above average BC and LR volatility (note that our sub-sample analysis for the OCED countries, to a large extent, addressed this concern).[25] The most volatile regions under these criteria are the Middle East and North Africa, followed by Sub-Saharan Africa. BC volatilities in these two regions are 0.053 and 0.044, respectively, compared to the developing country average of 0.036. Similarly, their LR volatilities are 0.033 and 0.030, respectively, compared to the developing country average of 0.025. The results for the two sub-samples, after alternatively excluding the Middle East, North Africa, and Sub-Saharan Africa are presented in columns (5)–(8) in Table 7, and they do not meaningfully differ from the benchmark results.

[25] The assumption of orthogonality between BC and LR components of growth may not strictly hold for high volatile countries. It is important to mention that alternative methods of trend-cycle decomposition that relax the orthogonality assumption (such as the Beveridge-Nelson method) extract the trend at the zero frequency (alternatively, infinite periodicity), while we define LR over a broad frequency range (periodicities ranging from 8 years to infinity) that is consistent with the standard and well-accepted definition of business cycle. This exercise, therefore, can serve as a robustness check, excluding the countries for which the orthogonality assumption is most likely to violate.

5.7 Correlation in the Historical (1875–2010) Panel Data

We now estimate the relationship based on the historical data for 1875–2010, compiled by Angus Maddison (Maddison-Project, 2013).[26] This estimation allows us to verify the results using an alternative dataset and time period. There are 28 countries, of which 20 are developed, according to current income levels (a list of countries is provided in the note below Table 8), and there are 18 observations for each country. Due to the unavailability of data for control variables, we can control only initial (previous interval) log level of real GDP, time (interval) dummies. We also control for dummies for major economic episodes: pre–1914, 1914–1945, 1946–1985, and post-1985 periods.[27] As a result, country fixed effects will be correlated with the omitted variables; thus, we estimate the fixed effect regression. We interpret coefficients on both BC and LR volatility as correlation.

Insert Table 8 here

Panels A and B in Table 8 summarize the results for the full sample and 20 developed countries, respectively. The results are similar in both panels. There is no correlation between BC volatility and growth, but it becomes negative and significant in the misspecified regression that omits LR volatility. The coefficient on LR volatility is negative but insignificant. These results are consistent with the OLS results using the PWT data reported in Table 2, but should not be emphasized much because of endogeneity.

5.8 Replication of Ramey and Ramey

Our final robustness check entails a replication of Ramey and Ramey (1995) (henceforth, RR), which is, arguably, the most influential study on the volatility-growth relationship, using their data. We replicate their basic cross-sectional specification, because it is comparable to our

[26] The data go back to earlier periods for a small number of countries. For example, data since 1820 are available for only 8 countries (Australia, Italy, Denmark, France, Netherlands, Sweden, the UK, and the USA).

[27] Romer (2012, p. 192) suggests that the macroeconomic history of the USA since the late 1800s comprises four broad periods: i) before the Great Depression, ii) the Great Depression through World War II, iii) the end of World War II to about the mid-1980s, and iv) after the mid-1980s. This classification can be generalized to other sample countries, with the exception of the first period, which includes World War I, because most sample countries are in Europe. Therefore, we modify the first period accordingly. The four phases of capitalist development defined by Maddison (1991) are also similar, except that the last episode begins from 1973.

specification. Using PWT 5.6 data, RR estimated the volatility-growth relationship for two sets of countries: i) a full sample of 92 countries for 1960–1985, and ii) 24 OECD countries for 1950–1988. It is worth noting that the PWT data have been revised several times, and the subsequent revisions are not strictly comparable [for other replications of RR using alternative versions of the PWT data, see Ponomareva and Katayama (2010) and Dawson et al. (2001)].

RR calculated growth rate and volatility based on "Real GDP per capita, 1985 international prices: Chain Index (RGDPCH)" (their Data Appendix, p. 1150). This is not the appropriate variable to compare growth rates over time and across countries. Rather, the appropriate series is the growth of GDP at constant national prices [see Feenstra, Inklaar, and Timmer (2013); PWT 8.0 User Guide, p. 25]. Because GDP data at constant national prices were not available in the PWT 5.6, RR conducted the best possible exercise with the available data.

Insert Table 9 here

The results are summarized in Table 9. Panel-A reports the results for 92 countries for 1960–1985. In column (1), the coefficient on volatility (standard deviation of the growth rate), in the specification without any control reported by RR, is reproduced and is -0.15, with a *t*-statistic of -2.3 (which increases to -2.6 after correcting for heteroscedasticity). However, as we discuss in detail in Section 6.1, the standard deviation of the raw (unfiltered) growth rate differs from our measure of BC volatility. When BC volatility is calculated as the standard deviation of the band-pass-filtered series and used in the same regression, its coefficient remains very close (-0.16), with a *t*-statistic of -2.59 [column (2)]. When the controls used by RR— 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 falls slightly short of the 10% level of significance) [column (3)]. However, after controlling for LR volatility, the coefficient on BC volatility decreases to almost zero (0.006), with a very low *t*-statistic of 0.066 [column (4)], and the coefficient on LR volatility now becomes negative and significant.

The results for the 24 OECD countries are summarized in Panel-B. RR reported a positive and insignificant coefficient of volatility of 0.147 [column (1)]; however, if BC volatility is used instead, the coefficient changes to negative [columns (2)]. The coefficient on

BC volatility in the specification with all controls is large negative (-0.408) and significant but does not meaningfully change after controlling for LR volatility [columns (3) and (4)]. Our estimation for OECD countries using the appropriate GDP series and with an extended set of controls (of which RR controls are a subset) showed that the coefficient on LR volatility was negative and significant, while that on BC volatility was insignificant [columns (9) and (10) in Table 2].[28]

6 The Role of LR Volatility

The results discussed in the previous section raises a crucial question about the relevance of different measures of volatility employed to study the volatility-growth relationship. In the following, we compare the results based on our volatility decomposition with other measures of volatility in the literature. We also evaluate the quantitative implications of different measures of volatility in explaining growth and then discuss some possible explanations for the importance of LR volatility. It is important to mention that LR volatility can also be interpreted as persistence in volatility (Levy and Dezhbakhsh, 2003; Ascari and Sbordone, 2014; Müller and Watson, 2015).

6.1 Volatility or its Persistence?

Most studies (examples include Kormendi and Meguire, 1985; Ramey and Ramey, 1995; Martin and Rogers, 2000; Hnatkovska and Loayza, 2005; Mobarak, 2005; and Loayza et al., 2007) use standard deviation of the (unfiltered or raw) growth rate as a proxy for BC volatility. This measure is based on the assumption of a constant trend, whereas the calculation of BC volatility as the standard deviation of the cyclical components assumes a time-varying trend. As discussed in the introduction, total variance of growth rate is the sum of the variances of its cyclical and long-run components. Therefore, volatility measured as the standard deviation will capture the combined effects of both BC volatility and persistence in volatility. In other words, the effect of omitting persistence will be reflected either in the coefficient on BC volatility in the misspecified regression or in the coefficient on the standard deviation of the unfiltered or raw series.

[28] There are 25 OECD countries in our sample; the results do not change if the 24 RR sample countries are retained.

Insert Table 10 here

To verify the above argument, we calculate the standard deviation of the unfiltered growth rate and define it as *total volatility*. We then estimate the coefficient on *total volatility* to compare it with the previously estimated $\hat{\gamma}_{LR}$ (coefficient on LR volatility) and γ_{BC}^{b} (coefficient on BC volatility in the misspecified equation). Selected results are presented in Table 10. Consider the benchmark results for the full set of sample countries in columns (1)–(3). The coefficient on *total volatility*, reported in column (1), is negative at -0.220 and statistically significant at any conventional level; quantifying this result, one standard deviation increase in *total volatility* decreases growth by 0.25 percentage-points. Columns (2) and (3) reproduce the results for BC and LR volatility, respectively, which were estimated from the same specification and reported earlier, in columns (1) and (2), respectively, in Table 3. Note that there was no effect of BC volatility (γ_{BC}^{c}) after correcting the misspecification, but there was a significantly negative correlation of LR volatility ($\hat{\gamma}_{LR}$ is -0.381 and statistically significant at any conventional level). The latter result can be quantified as a 0.14 percentage-points decrease in growth caused by one standard deviation increase in LR volatility. However, in the misspecified regression that omits LR volatility, γ_{BC}^{b} is estimated at -0.177 and is significant, which leads to the incorrect inference that one standard deviation increase in BC volatility leads to a 0.18 percentage-points decrease in growth. Similar results for different income groups and time periods are presented in columns (4)–(12). These results support our argument that, because of misspecification, the contribution of volatility persistence is misconstrued as being the contribution of either *total volatility* or BC volatility.

If our measure of LR volatility merely captured non-standard growth spells [documented in Pritchett (2000), Berg, Ostry, and Zettelmeyer (2012), and Bluhm, Crombrugghe, and Szirmai (2014)], rather than the volatility of the stochastic trend, this would be more likely to be manifested in cross-sectional estimations (data time average over the entire sample period). Our panel data over a 7-year interval are largely unaffected by such spells.

Our results are consistent with the findings in the literature that document the welfare cost of business-cycle fluctuations. Lucas (1987) calculated that the welfare cost of business cycles is small—less than 0.1% of lifetime consumption. Subsequent literature has modified the original Lucas model in several dimensions but still failed to find a large welfare cost of business cycle fluctuations. However, one notable finding is that the cost can be very large if the shocks have a permanent component. The permanent shocks can, alternatively, be interpreted as being changes in the trend consumption growth, which point to changes in the potential of an economy (Barlevy, 2005). Alvarez and Jermann (2004) employed an innovative approach to calculate the cost of consumption fluctuations in terms of asset prices, rather than relying on any utility function. The authors estimate that the cost of business cycle fluctuations is small, ranging between 0.08 percent and 0.49 percent of consumption, while that of all consumption uncertainty is very large, which implies that consumption has a large permanent component. Dolmas (1998) also estimated that, in the case of permanent shocks, the cost of business cycles can be as large as 23 percent of lifetime consumption.

6.2 Why Does LR volatility Matter?

Although there is a large body of literature explaining the effect of BC volatility on growth (briefly discussed in Section 2), to our knowledge, there is no model explaining the effect of LR volatility on growth. Some possible explanations might include: i) the inability either to innovate new, or to adopt available, technologies, ii) a long lag between the innovation and adaptation of technologies, due to political, institutional, or cultural factors, iii) sector-specific technological innovation that is not suitable for widespread adoption in another country due to its structural composition, and iv) shocks to the trend,[29] originating either from long-term changes in market frictions, such as financial frictions (Chari, Kehoe, and McGrattan, 2007) and labor market frictions (Lagos, 2006), or from natural disasters or wars. These factors will lead to changes in the trend growth rate and the mechanisms through which volatility retards growth, such as decrease in the capital stock or negative learning-by-doing, will be pervasive and more harmful than are regular business cycles.

It is conceivable that the mechanisms through which LR volatility retards growth greatly differ across countries and, therefore, cannot be modelled in a single framework. We establish that, irrespective of the causes and mechanisms, LR volatility negatively affects growth.

[29] Aguiar and Gopinath (2007) argued that, in emerging market economies, shocks to trend growth, as opposed to transitory fluctuations around the trend, can be the primary source of fluctuations.

7. Concluding Remarks

This paper revisits the relationship between volatility and long-run growth by decomposing volatility into its business-cycle and trend components. The main finding is that it is the volatility of the trend, which we refer to as LR volatility, rather than BC volatility, that retards growth. But a significant (negative) effect of BC volatility, consistent with the literature, can be found if a misspecified equation omitting LR volatility is estimated. Our results draw attention to a fundamental, yet often neglected, question about the importance of different components of volatility in macroeconomic analyses. However, our results do not necessarily undermine the relevance of the stabilization policies, because cyclical fluctuations may affect heterogeneous agents in different ways that are not evident in the aggregate data.

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Tables

Table 1: Descriptive statistics (1970–2014): Mean, [Median], (Standard deviation) and {95% Confidence interval}.

Income group	Growth rate	BC volatility	LR volatility	Share of LR volatility	Correlation between BC and LR volatility	Number of countries
	(1)	(2)	(3)	(4)	(5)	(6)
All	0.016 [0.016] (0.015)	0.034 [0.029] (0.023)	0.023 [0.018] (0.016)	0.410 [0.344] (0.0945)	0.783 {0.696 0.847}	106
OECD	0.020 [0.018] (0.009)	0.019 [0.017] (0.006)	0.013 [0.011] (0.005)	0.408 [0.407] (0.079)	0.509 {0.143 0.753}	25
Middle-income	0.020 [0.019] (0.014)	0.031 [0.029] (0.013)	0.023 [0.020] (0.009)	0.424 [0.429] (0.081)	0.659 {0.473 0.789}	53
Low-income	0.004 [0.010] (0.014)	0.048 [0.041] (0.031)	0.030 [0.020] (0.0267)	0.369 [0.308] (0.129)	0.764 {0.496 0.899}	21
Developing (middle- and low-income)	0.015 [0.013] (0.016)	0.036 [0.032] (0.021)	0.025 [0.020] (0.016)	0.408 [0.406] (0.100)	0.744 {0.621 0.831}	74

The share of LR is the ratio of LR volatility to the sum of BC and LR volatility. It is calculated for each country, and the average of this ratio is reported in column (4).

Table 2: Pooled OLS estimation using 7-year panel data (1970–2014)—Benchmark $\tilde{p} = 8$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Panel-A: All countries		Panel-B: All countries		Panel-C: All countries		Panel-D: Low-income		Panel-E: OECD	
BC volatility	-0.106	-0.164	-0.015	-0.055	0.011	-0.023	-0.142*	-0.159**	-0.017	-0.066
	(-0.785)	(-1.245)	(-0.112)	(-0.430)	(0.087)	(-0.190)	(-1.846)	(-2.009)	(-0.126)	(-0.460)
LR volatility	-0.282		-0.217		-0.186		-0.096		-0.514**	
	(-1.320)		(-1.097)		(-0.917)		(-0.381)		(-2.373)	
Controls	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed factors	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.034	0.028	0.176	0.174	0.251	0.250	0.324	0.326	0.498	0.478
Observations	490	490	490	490	490	490	338	338	125	125
No. of countries	106	106	106	106	106	106	74	74	25	25

Robust t-statistics in parentheses; *** p<0.01, ** p<0.05, * p<0.1. All regressions include a constant.
Columns (1)–(2) control only for first lag of log per capita GDP.
Columns (3)–(4) control for first lag of [log per capita GDP, investment-GDP ratio, human capital, population growth, openness, political violence, policy volatility, ToT volatility, private credit/GDP, and *Polity2*].
Columns (5)–(8) add dummies for regions, legal origins, and time (interval) to columns (3)–(4).
Columns (9)–(10) exclude political violence and region dummies from columns (5)–(8).

Table 3: IV estimation using 7-year panel data (1970–2014)—Benchmark $\tilde{p} = 8$.

	(1)	(2)	(3)	(4)	(5)	(6)
	All		Developing		OECD	
BC volatility	-0.097	-0.177***	-0.119	-0.180**	-0.078	-0.210
	(-1.500)	(-2.777)	(-1.601)	(-2.422)	(-0.439)	(-1.200)
LR volatility	-0.381**		-0.321*		-0.574**	
	(-2.341)		(-1.699)		(-2.013)	
p-value of the joint significance	0.0058		0.0312		0.0591	
Kleibergen-Paap rk LM statistic	135.4	99.79	109.7	76.80	36.92	42.85
Kleibergen-Paap rk Wald F statistic	101.4	103.0	110.3	83.37	37.00	92.48
Hansen J-stat (*p*-value)	0.327	0.224	0.653	0.486	0.420	0.229
First-stage F-stat		40.92		39.10		36.80
Observations	490	490	338	338	125	125
No. of countries	106	106	74	74	25	25

Robust t-statistics in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Notes for **Tables 3–7**: All regressions include a constant, first lag of [log per capita GDP, investment-GDP ratio, human capital, population growth, openness, political violence, policy volatility, ToT volatility, private credit/GDP and *Polity2*], dummies for regions, legal origins, and time (interval). Political violence and region dummies are excluded for OECD countries.

Table 4: IV estimation using 7-year panel data (1970–2014)—Alternative $\tilde{p}$ ($\tilde{p}$ = 5 for developing countries; $\tilde{p}$ = 8 for developed countries).

	(1)	(2)	(3)	(4)
	All		Developing	
BC volatility	-0.064	-0.173**	-0.067	-0.158*
	(-0.843)	(-2.510)	(-0.734)	(-1.888)
LR volatility	-0.276**		-0.210*	
	(-2.346)		(-1.679)	
p-value of the joint significance	0.0075		0.0725	
Kleibergen-Paap rk LM statistic	130.6	100.7	103.5	74.72
Kleibergen-Paap rk Wald F statistic	125.7	105.5	133.1	84.03
Hansen J-stat (*p*-value)	0.260	0.211	0.573	0.599
First-stage F-stat		44.19		44.49
Observations	490	490	338	338
No. of countries	106	106	74	74

Robust t-statistics in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Please see notes below Table 3.

Table 5: IV estimation using 7-year panel data (1970–2014)—Assuming Non-stationary growth rate and benchmark $\tilde{p}$ = 8.

	(1)	(2)	(3)
	All	Developing	OECD
BC volatility	-0.091	-0.110	-0.077
	(-1.396)	(-1.459)	(-0.440)
LR volatility	-0.391**	-0.352*	-0.545*
	(-2.454)	(-1.881)	(-1.943)
p-value of the joint significance	0.0043	0.0225	0.0690
Kleibergen-Paap rk LM statistic	139.5	112.5	38.89
Kleibergen-Paap rk Wald F statistic	107.0	118.5	35.81
Hansen J-stat (*p*-value)	0.337	0.655	0.397
First-stage F-stat			
Observations	490	338	125
No. of countries	106	74	25

Robust t-statistics in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Please see notes below Table 3.

Table 6: IV estimation using 7-year panel data for different time periods: Benchmark $\tilde{p} = 8$

	(1)	(2)	(3)	(4)	(5)	(6)
	All (1984-2014)		Developing (1984–2014)		OECD (1970–2005)	
BC volatility	-0.014	-0.124	0.019	-0.087	-0.111	-0.197
	(-0.177)	(-1.641)	(0.220)	(-1.046)	(-0.486)	(-0.819)
LR volatility	-0.429**		-0.501**		-0.620*	
	(-2.170)		(-2.268)		(-1.734)	
p-value of the joint significance	0.0606		0.0663		0.1500	
Kleibergen-Paap rk LM statistic	72.44	48.85	61.96	45.57	29.25	30.40
Kleibergen-Paap rk Wald F statistic	47.13	41.64	74.06	72.68	25.98	48.14
Hansen J-stat (*p*-value)	0.133	0.101	0.230	0.155	0.847	0.672
First-stage F-stat		24.45		27.83		30.11
Observations	306	306	212	212	100	100
No. of countries	106	106	74	74	25	25
					-0.111	-0.197

Robust t-statistics in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Please see notes below Table 3.

Table 7: Sub-sample analysis: IV estimation using 7-year panel data (1970–2014): Benchmark $\tilde{p} = 8$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Excluding top 25% growth performers		Excluding top 50% growth performers		Excluding Sub-Saharan Africa		Excluding Middle-East and North Africa	
BC volatility	-0.060	-0.151**	-0.040	-0.108	0.009	-0.103	-0.055	-0.123**
	(-0.885)	(-2.240)	(-0.483)	(-1.312)	(0.089)	(-1.106)	(-0.841)	(-1.978)
LR volatility	-0.427**		-0.362*		-0.537***		-0.357**	
	(-2.505)		(-1.710)		(-2.697)		(-2.095)	
p-value of the joint significance	0.0146		0.1804		0.2484		0.1218	
Kleibergen-Paap rk LM statistic	105.4	76.74	56.23	39.82	88.75	90.50	135.5	97.37
Kleibergen-Paap rk Wald F statistic	72.95	74.00	32.07	34.25	101.7	184.7	124.0	112.1
Hansen J-stat (*p*-value)	0.276	0.201	0.130	0.0679	0.850	0.801	0.0389	0.0111
First-stage F-stat		31.10		17.67		33.02		45.76
Observations	401	401	248	248	323	323	448	448
No. of countries	86	86	55	55	69	69	96	96

Robust t-statistics in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Please see notes below Table 3.

Table 8: Fixed effect estimation using the 7-year panel data: Angus Maddison historical data for 1875–2010.

	(1)	(2)	(3)	(4)
	Panel A: All countries		**Panel B: Developed countries**	
BC volatility	-0.140	-0.162***	-0.109	-0.175***
	(-1.582)	(-3.404)	(-1.234)	(-3.188)
LR volatility	-0.087		-0.259	
	(-0.381)		(-1.319)	
p-value of the joint significance	0.001		0.000	
Within R-square	0.282	0.281	0.388	0.379
Between R-square	0.0202	0.021	0.419	0.432
Observations	504	504	360	360
No. of countries	28	28	20	20

Robust *t*-statistics are in parentheses; *** p<0.01, ** p<0.05, * p<0.1. All regressions include a constant, (log) initial GDP per capita, time dummies, and dummies for the pre-1914, 1914–1945, 1946–1985; and post-1985 periods.
Countries in Panel A: 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: Australia, Austria, Belgium, Canada, Italy, Denmark, Finland, France, Germany, Greece, Netherlands, Japan, Norway, New Zealand, Portugal, Spain, Sweden, Switzerland, UK, and USA.
Note: The actual time period retained in the analysis is 1879–2007, because the first observation is lost due to the calculation of the growth rate from the GDP level and three observations from each tail are lost due to filtering with a 3-year window. The time period is then divided into 18 equal 7-year intervals (except for the final interval).

Table 9: Replication of Ramey and Ramey (1995) using the PWT5.6 data.

	(1)	(2)	(3)	(4)
	Panel A: PWT 5.6 data for 92 Developing countries (1960–1985)			
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)			
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

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

Table 10: The relative contribution of BC volatility and persistence in volatility

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	1970–2014: All countries			1970–2014: Developing countries			1970–2014: OECD countries			1984–2014: All countries		
Total volatility	-0.220***			-0.213***			-0.307**			-0.193***		
	(-3.663)			(-3.059)			(-2.155)			(-2.642)		
BC volatility		-0.097	-0.177***		-0.119	-0.180**		-0.078	-0.210		-0.014	-0.124
		(-1.500)	(-2.777)		(-1.601)	(-2.422)		(-0.439)	(-1.200)		(-0.177)	(-1.641)
LR volatility		-0.381**			-0.321*			-0.574**			-0.429**	
		(-2.341)			(-1.699)			(-2.013)			(-2.170)	

Robust *t*-statistics are in parentheses; *** p<0.01, ** p<0.05, * p<0.1.
Columns (2) and (3) have been reproduced from columns (1) and (2), respectively, in Table 3. Columns (5) and (6) have been reproduced from columns (3) and (4), respectively, in the same table. Columns (8) and (9) have been reproduced from columns (5) and (6), respectively, in the same table. Columns (11) and (12) have been reproduced from columns (1) and (2), respectively, in Table 6.

Appendix

Appendix A.1: Examples of Heterogeneous Growth Trajectories

Costa Rica and Trinidad and Tobago: These two developing countries had the same average growth rate (approximately 0.021) and BC volatility (0.026), but LR volatility in Trinidad and Tobago (0.043) was more than twice as large as that in Costa Rica (0.017).

Ireland and Egypt: These countries had nearly the same average growth rate (0.031) and BC volatility (0.0189), but LR volatility in Ireland (0.026) was much larger than that in Egypt (0.015).

Austria and Japan: These two countries are similar in terms of average growth rate (approximately 0.020) and BC volatility (approximately 0.016) but differ with respect to LR volatility (0.007 and 0.015, respectively).

Fiji and Sweden: These two countries are similar in terms of average growth rate (approximately 0.016) and LR volatility (approximately 0.012) but differ with respect to BC volatility (0.039 and 0.018, respectively).

Nepal vs. Pakistan: These two countries are similar in terms of average growth rate (approximately 0.020) and LR volatility (approximately 0.009) but differ with respect to BC volatility (0.024 and 0.013, respectively).

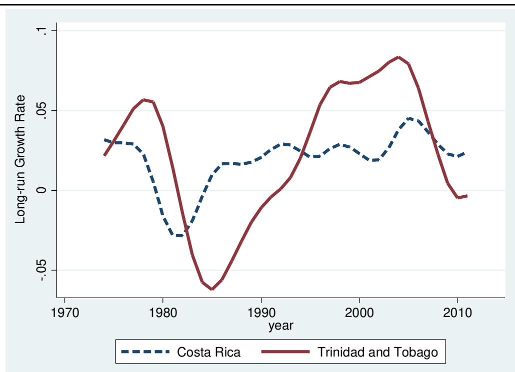
Guatemala and Switzerland: Although both countries had the same average growth rate (0.010), BC volatility was larger in Switzerland (0.018) than in Guatemala (0.013), whereas LR volatility in Guatemala (0.017) was nearly twice as large as that in Switzerland (0.009).

There are examples in which countries with very different average growth rates experienced similar fluctuations. For example, the growth rate in Vietnam (0.040) was much higher than that in Bangladesh (0.019), but both countries had the same BC volatility (0.021) and LR volatility (0.016). Similarly, China and Greece had the same BC volatility (0.025) and similar

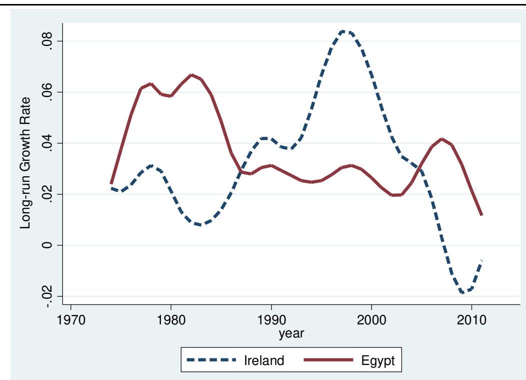
LR volatility (0.022), but China's economy grew at an average rate of 0.054, whereas the Greek economy grew at the slower rate of 0.012.

The above examples illustrate an enormous heterogeneity among countries' respective growth trajectories. More specifically, very dissimilar growth trajectories can lead to the same average growth, and apparently similar growth trajectories can lead to different average growths. This heterogeneity can also be visualized in Figures 1a–1h below, which display the long-run growth trajectories of the country pairs discussed above.

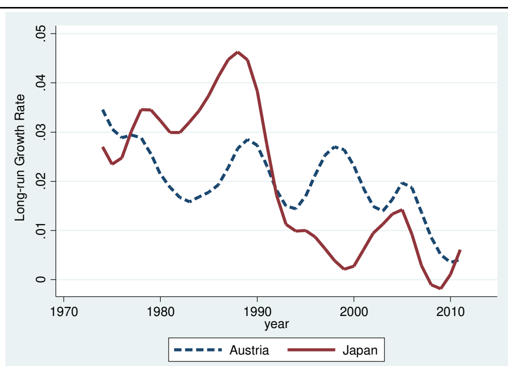
Appendix Figure 1: Comparison of long-run growth trajectories (Low-pass filtered annual growth rate).



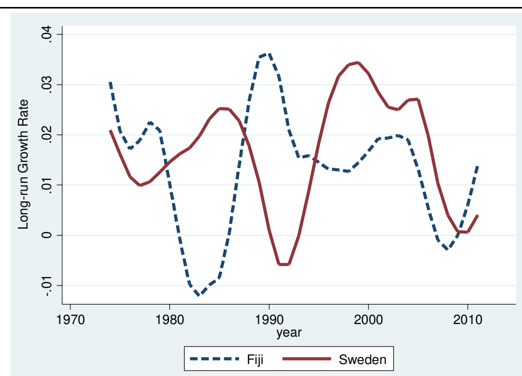
(a) Costa Rica and Trinidad and Tobago



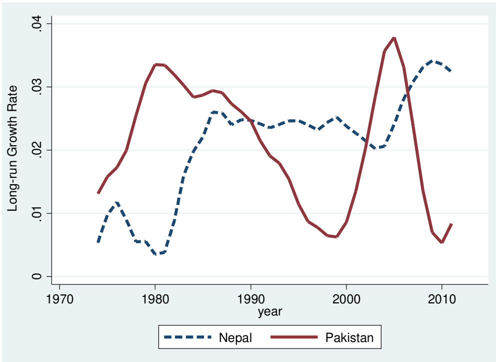
(b) Ireland and Egypt



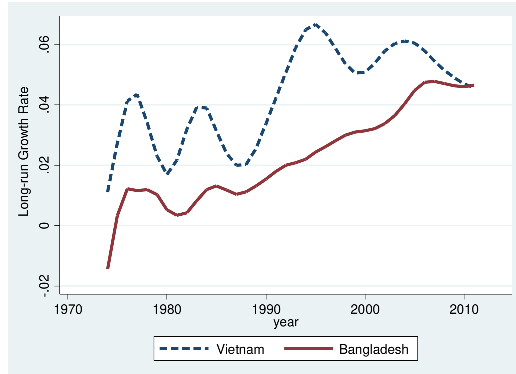
(c) Austria and Japan



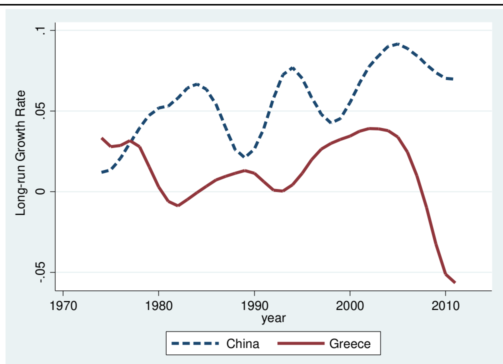
(d) Fiji and Sweden



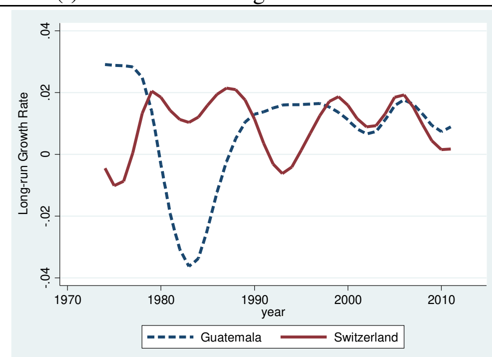
(e) Nepal and Pakistan



(f) Vietnam and Bangladesh



(g) China and Greece



(h) Guatemala and Switzerland

Appendix A.2: Comparison of Spectral Densities for 5-, 7-, 8-, and 10-year Averaging

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 Figure A.1 below. The spectral densities are normalized, using appropriate scalars, so that the area under all curves are equal. A vertical line is drawn at 0.786 to mark the critical frequency that separates the long-run from the cyclical frequencies. 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 adequately across low frequencies, thus, the transformed data are more likely to be contaminated by high frequencies. For 5-year averaging, the area to the right of the vertical line is 14% of the total area under the curve. This area substantially reduces to 9.3% for 7-year averaging, remains the same for 8-year averaging, and reduces only to 8.8% for 10-year averaging.

Appendix Figure-2: Spectral densities for 5-, 7-, 8-, and 10-year averaging.