Macroeconomic Dynamics, **18**, 2014, 651–688. Printed in the United States of America.
doi:10.1017/S1365100512000569

FINANCIAL DEVELOPMENT, SHOCKS, AND GROWTH VOLATILITY

DEBDULAL MALLICK
Deakin University

This paper uses spectral theory to develop the following two testable hypotheses in a unified framework for the predictions of business-cycle and endogenous growth models: (i) financial development affects only business-cycle volatility; and (ii) shocks affect both business-cycle volatility and long-run volatility of GDP growth. In other words, volatility caused by shocks is more persistent than that caused by financial underdevelopment. We decompose the business-cycle and long-run volatility by the spectral method and then test the hypotheses at the cross-country level. Empirical evidence provides support for both hypotheses. Higher private credit, a bank-based measure of financial development, dampens business-cycle volatility but not long-run volatility. Volatility of shocks, as measured by the volatility of changes in the terms of trade, magnifies both business-cycle and long-run volatility. The results are robust to accounting for endogeneity, a market-based measure of financial development, and an alternative method of volatility decomposition.

Keywords: Financial Development, Shocks, Growth Volatility, Business Cycle, Spectral Analysis

1. INTRODUCTION

The impact of macroeconomic structures and disturbances, such as financial development and shocks, on growth volatility has been well studied, but their impact on persistence in volatility has largely been ignored. An effective way to understand the distinction between the causes of transitory and persistent fluctuations is to unify business cycle and growth models. Although some recent models attempt this unification [for example, Aghion et al. (2010) and papers cited therein], empirical studies continue to ignore the different components of volatility, especially its persistence.

In this paper, we use results from spectral theory to formulate two testable hypotheses for the predictions of business cycle and endogenous growth models

I acknowledge helpful comments from Prasad Bhattacharya, Robert Chirinko, Arusha Cooray, Chris Doucouliagos, Devashish Mitra, Paresh Narayan, Christopher Otrok, Randy Silvers, Mehmet Ulubasoglu, the participants at the 2009 Econometric Society Australasian Meetings, two anonymous referees, and an associate editor of the journal. Partial financial support from Deakin University's Faculty of Business and Law Developing Researcher Grant is acknowledged. Address correspondence to: Debdulal Mallick, School of Accounting, Economics and Finance, Deakin University, Burwood, VIC 3125, Australia; e-mail: dmallic@deakin.edu.au.

© 2013 Cambridge University Press 1365-1005/13

https://doi.org/10.1017/S1365100512000569 Published online by Cambridge University Press

regarding the causes of different components of volatility. More specifically, we reason that financial development impacts only business-cycle volatility, whereas shocks impact both the business-cycle and long-run volatility. In other words, volatility caused by shocks is more persistent than volatility caused by financial underdevelopment.[1]

To test these hypotheses, we analyze a sample of 79 countries for the period 1980–2004. A novelty of this paper is that it extracts the business-cycle and long-run volatility of real per capita GDP growth by the spectral method. Following the literature, our proxy for financial development is credit disbursed to the private sector by banks and other financial institutions relative to GDP, and that for shocks is change in the terms of trade (TOT). The results provide support for both hypotheses. After controlling for other determinants of volatility and country-specific fixed effects, we find that private credit dampens business-cycle volatility but has no effect on long-run volatility. Volatility of the TOT, in contrast, magnifies both business-cycle and long-run volatility. The results are robust to accounting for endogeneity, alternative market-based measures of financial development such as stock market capitalization, and volatility decomposition by an alternative filtering method, and in a subsample of 68 countries for the longer period 1960–2004.

Investigation of volatility is important given its impact on growth, income inequality, and overall welfare. Beginning with the seminal work by Ramey and Ramey (1995), a strand of literature has established a negative impact of growth volatility on the growth rate. Growth volatility is also negatively related to income inequality, as evidenced by Iyigun and Owen (2004), Breen and García-Peñalosa (2005), and Laursen and Mahajan (2005). Combining these two effects and taking into account the potential linkage between growth and income distribution suggests that volatility affects poverty [Laursen and Mahajan (2005)]. The impact on poverty in terms of the vulnerability of lower-income groups to growth volatility has also been noted by Agénor (2001). Furthermore, growth volatility also causes volatility of consumption growth [Wolf (2004)]. However, this literature implicitly assumes that volatility is business-cycle fluctuations and ignores its long-run component. The impact of the latter is no less important, as implied by the findings of Hnatkovska and Loayza (2005). The authors distinguish between regular and "crisis" volatility[2] and show that only "crisis" volatility is statistically significant for explaining growth volatility when both types of volatility are considered. Our paper can be considered as an attempt to bring up the importance of volatility decomposition in growth and volatility research.[3]

The rest of the paper is organized as follows. Section 2 reviews the business cycle and endogenous growth literature as motivation for the paper, and also discusses how the spectral theory relates financial development and shocks to different components of volatility. Section 3 discusses the method for extracting different components of volatility in the frequency domain. This section also describes the data and summary statistics. Section 4 explains the estimation strategy and presents the results. Finally, Section 5 concludes.

https://doi.org/10.1017/S1365100512000569 Published online by Cambridge University Press

2. RELATED LITERATURE AND MOTIVATION

Financial development dampens growth volatility through several channels. For example, financial development lowers the costs of acquiring and verifying information [Greenwald and Stiglitz (1993)], improves risk management [Aizenman and Powell (2003)], and moderates the "external finance premium"—the wedge between the cost of external funds and the opportunity cost of internal funds [Bernanke and Gertler (1989; 1995, p. 28), Bernanke et al. (1998)]. It also impacts volatility by reducing the imbalance between savings and investment [Aghion et al. (1999)] and by enabling the diversification of idiosyncratic risks that discourage investment in more risky projects in the early stage of economic development [Acemoglu and Zilibotti (1997)]. However, these are models of business-cycle volatility, not long-run volatility. Aghion and Banerjee (2005) is a possible exception in which credit constraints can generate long-run volatility, but only for countries at the intermediate level of financial development.[4]

The empirical findings of the effect of financial development on growth volatility lack consensus. For example, Denizer et al. (2002), Easterly et al. (2002), Silva (2002), Lopez and Spiegel (2005), and Tharavanij (2007), among others, document a negative relationship between financial development and volatility at the cross-country level, although the relationship is not always linear. Raddatz (2006) documents such a negative relationship at the industry level for the United States. In contrast, Beck et al. (2006) do not find any effect of financial development on volatility. Acemoglu et al. (2003) show that financial aspects become insignificant for explaining volatility once the effect of institutions is controlled for.

The effect of shocks on business-cycle volatility is well known. The argument that shocks generate long-run volatility can be explained by endogenous growth theories. For example, in Fatás (2000), optimal research depends on the expected profitability of innovation (or imitation), which is a function of aggregate demand. Negative shocks to aggregate demand reduce the incentive to innovate and, as a result, when the economy recovers from recession, output does not revert to the trend; rather, it remains at a permanent low level. In Stadler (1986, 1990), economic downturns also impact negatively on the amount of learning-by-doing, which generates persistent fluctuations. In Kiyotaki and Moore (1997), a negative shock to profit decreases investment, which in turn reduces the price of collateral for loans. This increases borrowing constraints on investors and diminishes investment capacity, which amplifies the negative shock to profit. Consequently, a negative serial correlation in aggregate output is generated.

The empirical literature also documents a robust impact of shocks, generally proxied by the change in TOT, on growth volatility [Agénor et al. (2000); Wolf (2005)]. Mendoza (1995) quantifies TOT shocks as accounting for 40 to 60% of the observed variability of GDP at the cross-country level. Aghion et al. (2010) find that the impact of commodity price shocks on long-run investment (share of structural investment is their proxy) is more negative in countries with a lower level of financial development.

https://doi.org/10.1017/S1365100512000569 Published online by Cambridge University Press

The preceding discussion suggests that there are two distinct strands of business-cycle and growth literature; the former links financial development with business-cycle volatility, whereas the latter links shocks with both business-cycle and long-run volatility. However, empirical studies invariably estimate volatility by the standard deviation of either the GDP growth rate or its detrended component extracted by some filtering methods. Both measures capture only the cyclical fluctuations and exclude the long-run volatility.[5] In this paper, we overcome this limitation by decomposing volatility into business-cycle and long-run components to investigate the effect of financial development and shocks. We show that the predictions of the two strands of literature can be formulated in a unified framework using the results of the spectral theory.

Assuming that the output growth series is covariance-stationary, its variance can be expressed as (twice) the integral of the spectrum of the series, $g(\omega)$, across all frequencies $0 \leq \omega \leq \pi$. The total area under the spectrum would be smaller for a country with lower growth volatility than for a country with higher growth volatility. This does not necessarily mean that the spectrum of the low-volatility country will lie below at all frequency ranges. The distribution of the two spectra across different frequency ranges provides useful information about the relative volatility at different frequency ranges.[6]

If two countries are similar in their structural features and differ only in the volatility of shocks experienced, then the spectra of the output growth for the two countries will be of similar shape, but the spectrum of the country experiencing lower volatility of shocks will lie proportionately below the other at all frequency ranges. This can be explained by Wold's theorem, which suggests that a covariance-stationary series can be expressed as an infinite moving-average (MA) process. Because the spectrum of any MA series is proportional to its innovation variance, the country experiencing lower volatility of shocks will have lower innovation variance than the other, but the MA coefficients will be the same. This argument can also be understood using the concept of the normalized spectrum, $h(\omega) = g(\omega)/\sigma^2$, which indicates the fraction of the total variance, σ^2, occurring at each frequency. The normalized spectrum is invariant to the magnitude of the innovation variance because both $g(\omega)$ and σ^2 are proportional to the innovation variance. Therefore, the two normalized spectra will be the same.

In contrast, if only the structures of the two economies differ, the spectrum of the low-volatility country will lie disproportionately below at the business-cycle and higher frequencies. For example, if lower variance is due mainly to financial development, one would expect that a country with developed financial markets will have its spectrum disproportionately lower at the business-cycle frequencies than at other frequencies relative to that of a country having less developed financial markets. If better business practices, such as better inventory management, that smooth output in the very short run lower variance, it will be manifested primarily at relatively high frequencies. Measurement errors will also be reflected in those frequencies.

https://doi.org/10.1017/S1365100512000569 Published online by Cambridge University Press

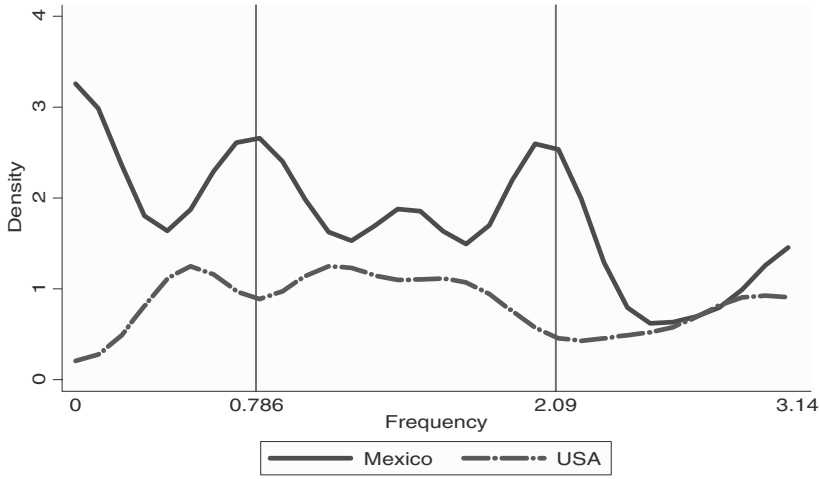


FIGURE 1. Spectrum of per capita real GDP growth for the United States and Mexico for the period 1950–2004.

Finally, if lower variance is due to the combination of changes both in shocks and in structure, which is most likely to be the case, one spectrum will lie below the other disproportionately in the relevant frequency range, depending on their relative importance.

The following examples and figures help clarify the above arguments. In Figures 1 and 2, we plot the spectrum and the normalized spectrum of the per capita real GDP growth rate, respectively, for the United States and Mexico for the period 1950–2004. Figure 1 displays that the spectrum of the United States lies below that of Mexico in all frequency ranges, implying that U.S. GDP growth is less volatile than that of Mexico. The figure also displays that the spectrum for the United States does not lie proportionately below in any particular frequency range. The normalized spectra in Figure 2 show that the two spectra are dissimilar at both long-run and business-cycle frequency ranges, suggesting that the differential volatility in GDP growth in the two countries is due to a combination of shocks and structures.

A different picture emerges when the United States and United Kingdom are compared. The spectrum and normalized spectrum for these two countries for the same period are displayed in Figures 3 and 4, respectively. It is clear from Figure 3 not only that the spectrum of U.K. GDP growth lies below that of the United States at all frequencies, but also that the two spectra are of similar shape except at high frequencies. This suggests that the two countries have similar structures, such as the level of financial development, but the variation in shocks is largely responsible for higher volatility in the United States than in the United Kingdom. This can also be verified by the respective normalized spectrum in Figure 4.

https://doi.org/10.1017/S1365100512000569 Published online by Cambridge University Press

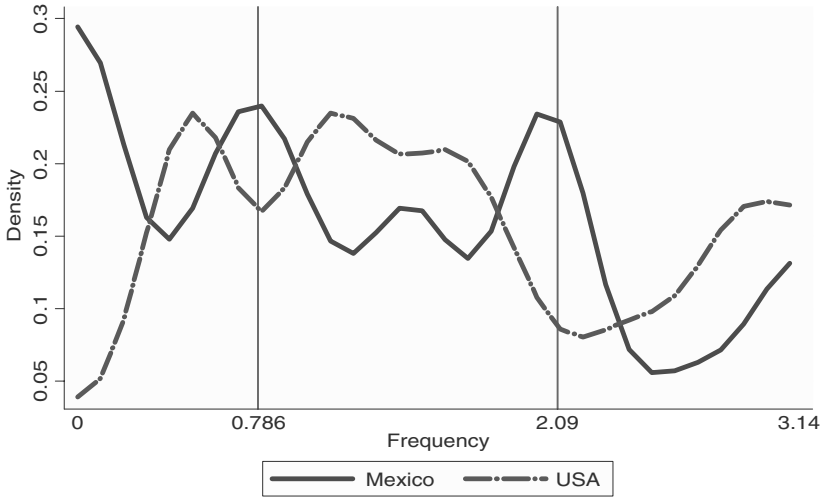


FIGURE 2. Normalized spectrum of per capita real GDP growth for the United States and Mexico for the period 1950–2004.

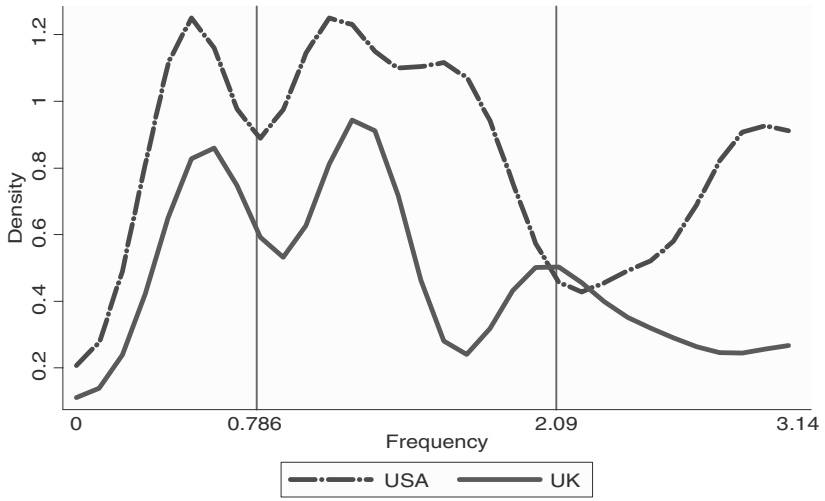


FIGURE 3. Spectrum of per capita real GDP growth for the United States and United Kingdom for the period 1950–2004.

https://doi.org/10.1017/S1365100512000569 Published online by Cambridge University Press

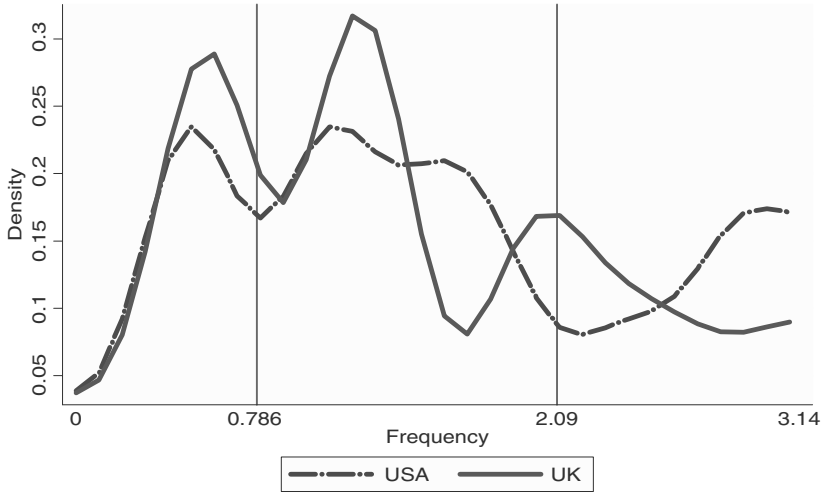


FIGURE 4. Normalized spectrum of per capita real GDP growth for the United States and United Kingdom for the period 1950–2004.

3. VOLATILITY AT THE CROSS-COUNTRY LEVEL

In this section, we discuss the spectral method that we employ to extract the variance of a stationary series in different frequency ranges. We then present the summary statistics of different variance components at the cross-country level.

3.1. Variance Decomposition by the Spectral Method

The variance of output growth can be expressed as the integral of the spectrum of this series, $g(\omega)$, across all frequencies $-\pi \leq \omega \leq \pi$. The spectrum is symmetric around zero, so only the frequency range $0 \leq \omega \leq \pi$ becomes relevant. The spectral method provides a simple yet elegant way to decompose total variance into different components. For example, the long-run component of the variance will be the integral of the spectrum over the long-run frequency range. The business-cycle and short-run components can also be extracted in a similar way by integrating the spectrum over the relevant frequency ranges.[7] The sum of the three variance components—long-run, business-cycle, and short-run—add to the total variance of the series. It is important to mention that any variance component is orthogonal to other components because the covariance between spectral estimates at different frequencies is zero.

https://doi.org/10.1017/S1365100512000569 Published online by Cambridge University Press

Suppose x_t is a covariance-stationary series. The periodogram, which is the sample analog of the spectrum, is given by

$$\hat{g}(\omega) = \frac{1}{2\pi} \sum_{j=-(T-1)}^{T-1} \hat{\gamma}^j e^{-i\omega j} = \frac{1}{2\pi} \left[\hat{\gamma}^0 + 2 \sum_{j=1}^{T-1} \hat{\gamma}^j \cos(\omega j) \right],$$

where $\hat{\gamma}^j$ is the jth-order sample autocovariance given by

$$\hat{\gamma}^j = \frac{1}{T} \sum_{t=j+1}^{T} (x_t - \bar{x})(x_{t-j} - \bar{x}), \quad \text{for } j = 0, 1, 2, \ldots, (T-1).$$

Here, $\bar{x}$ is the sample mean given by $\bar{x} = \frac{1}{T} \sum_{t=1}^{T} x_t$. By symmetry, $\hat{\gamma}^j = \hat{\gamma}^{-j}$. The integrated periodogram for the frequency range (ω_1, ω_2) is given by

$$\hat{G}(\omega_1, \omega_2) = 2 \int_{\omega_1}^{\omega_2} \hat{g}(\omega) d\omega = \frac{\omega_2 - \omega_1}{\pi} \hat{\gamma}^0 + \frac{2}{\pi} \sum_{j=1}^{T-1} \hat{\gamma}^j \frac{\sin(\omega_2 j) - \sin(\omega_1 j)}{j},$$

and represents the variance of the x_t series attributed to the frequency range $\omega_1 \leq |\omega| \leq \omega_2$. The frequency ω is inversely related to periodicity or cycle length according to $p = 2\pi/\omega$. The long-run, business-cycle, and short-run frequency ranges are given by $0 \leq \omega \leq \omega_1$, $\omega_1 \leq \omega \leq \omega_2$, and $\omega_2 \leq \omega \leq \pi$, respectively, where values of $\omega_1$and ω_2 for an annual series are chosen to be 0.786 and 2.09, respectively. These cutoff frequencies are chosen following the modern business-cycle literature in that the long run corresponds to cycles of 8 years or longer, and the business cycle corresponds to cycles of 3 to 8 years (Baxter and King, 1999).

The periodogram is an asymptotically unbiased estimate of the spectrum [Priestley (1981, p. 693)]. But this is inconsistent because the variance of $\hat{g}(\omega)$ does not tend to zero as T tends to infinity [Priestley (1981, p. 432)]. The reason is that although $\hat{g}(\omega)$ involves T sample autocovariances and the variance of each is of order $(1/T)$, the combined effect of the T terms produces a variance of order 1. One way to reduce the variance is to smooth the periodogram with the "spectral window," that is, to truncate the periodogram at some point $M < (T-1)$ and $-M > -(T-1)$. We use Bartlett's window, which assigns linearly decreasing weights to the autocovariances up to lag M and zero weights thereafter. Following Levy and Dezhbakhsh (2003, p. 1527), the number of ordinates, M, is chosen to be $2\sqrt{T}$.[8]

3.2. Data and Descriptive Statistics

The growth rate is calculated by taking the first difference of the log of real per capita GDP. Calculation of variance requires collapsing several years of growth data. Data on private credit for a long period are not available for many countries. Given that these two sets of data come from different sources, we choose the time

https://doi.org/10.1017/S1365100512000569 Published online by Cambridge University Press

period 1980–2004 for the benchmark analysis, so that GDP and private credit data are available for a relatively longer period for a good number of countries. There are 114 countries for which data are available for this period; among them, 38, 49, and 27 are low-, middle-, and high-income countries, respectively, according to the World Bank classification. Appendix A.1 provides a description of the variables, their sources, and their time periods.

Table 1 reports the descriptive statistics of different components of the variance of the GDP growth and also their relative shares (variances for all sample countries are listed in Appendices A.2–A.4). Mean total variance decreases with income level. It is 32.9, 26.6, and 9.6 for the low-, middle-, and high-income countries, respectively.[9] The mean value of the business-cycle component follows a similar pattern (13.5, 11.1, and 3.7, respectively). The mean value of the long-run component is the same in the low- and middle-income countries, at 8.4, which is twice as large as in the high-income countries. Note that the long-run component of the variance is one way of representing the degree of shock persistence. This then implies no difference in shock persistence between the low- and middle-income countries, but about 50% lower shock persistence in the high-income countries.

However, another pattern emerges if we examine the share of different variance components. For example, the mean share of the long-run component is increasing, whereas the mean share of the short-run component is decreasing with income level. The mean share of the business-cycle component is the same for low- and middle-income countries at 0.41, and is slightly lower for the high-income countries (0.39).[10] The median values of the variances follow a pattern similar to that of the mean values, although the magnitudes are considerably smaller, but the median shares are almost the same as the mean shares.

Our variance decomposition contradicts Aguiar and Gopinath (2007), who argued that shocks to trend growth are the primary source of fluctuations in the emerging markets as compared to the developed markets. We find that the ratio of long-run to business-cycle variance is highest for high-income countries (1.10), followed by middle-income (0.78) and low-income countries (0.63). It is the short-run variance that is relatively high in low- and middle-income than in high-income countries.

The descriptive statistics of other relevant variables, such as the ratio of private credit to GDP and volatility of change in the TOT, are also reported in Table 1.

4. EMPIRICAL ANALYSIS

4.1. Estimation Strategy

Our estimation strategy is in line with other kindred studies in that different volatility components of the growth rate of per capita real GDP are regressed on financial development, volatility of shocks and other variables related to growth

https://doi.org/10.1017/S1365100512000569 Published online by Cambridge University Press

https://doi.org/10.1017/S1365100512000569 Published online by Cambridge University Press

TABLE 1. Mean [median] (standard deviation) of variances of per capita real GDP growth at difference frequency range for the period 1980–2004

	Low-income (1)	Middle-income (2)	High-income (3)	All (4)
Total variance	32.92 [28.31] (24.45)	26.55[22.21] (19.81)	9.57 [5.24] (11.80)	24.65 [18.86] (21.76)
Long-run variance	8.39 [5.40] (7.23)	8.40 [5.15] (7.95)	4.10 [1.99] (5.81)	7.38 [5.07] (7.42)
Business-cycle variance	13.48 [12.01] (10.50)	11.07[8.48] (8.62)	3.65 [1.74] (4.25)	10.12 [6.98] (9.27)
Short-run variance	11.05 [9.47] (10.18)	7.08 [4.99] (5.81)	1.81 [0.86] (2.23)	7.16 [4.67] (7.83)
Long-run variance share	0.26 [0.25] (0.13)	0.32[0.31] (0.15)	0.43 [0.43] (0.12)	0.33[0.31] (0.15)
Business-cycle variance share	0.41 [0.43] (0.11)	0.41[0.40] (0.10)	0.39 [0.40] (0.07)	0.41 [0.41] (0.09)
Short-run variance share	0.33[0.31] (0.12)	0.27 [0.25] (0.14)	0.18 [0.17] (0.09)	0.27 [0.24] (0.13)
Private credit/GDP	0.43 (0.34)	0.38 (0.34)	0.47 (0.43)	0.42 (0.36)
Private credit/GDP (initial)	0.33 (0.28)	0.30 (0.24)	0.39 (0.37)	0.33 (0.29)
Sample size (N)	38	49	27	114
(Export + import)/GDP	57.73 (26.89) $N = 36$	86.07 (39.16) $N = 49$	92.75 (86.25) $N = 24$	78.18 (52.10) $N = 109$
Black market premium	183.13 (665.17) $N = 37$	58.67 (158.38) $N = 46$	1.30 (2.39) $N = 27$	86.45 (402.22) $N = 110$
Volatility of TOT change	0.087 (0.050) $N = 32$	0.056 (0.034) $N = 38$	0.020 (0.01) $N = 21$	0.059 (0.045) $N = 91$

volatility. The equations are as follows:

$$\text{GrVol_bc}_i = \text{const} + \alpha_1 \cdot \text{fin_dev}_i + \beta_1 \cdot \text{vol_shock}_i + \gamma_1' X_i + \varepsilon_i, \quad (1)$$

$$\text{GrVol_lr}_i = \text{const} + \alpha_2 \cdot \text{fin_dev}_i + \beta_2 \cdot \text{vol_shock}_i + \gamma_2' X_i + u_i, \quad (2)$$

$$\text{GrVol_total}_i = \text{const} + \alpha_3 \cdot \text{fin_dev}_i + \beta_3 \cdot \text{vol_shock}_i + \gamma_3' X_i + \phi_i, \quad (3)$$

where GrVol_bc_i, GrVol_lr_i, and GrVol_total_i are the logarithms of business-cycle, long-run, and total volatility of the growth rate of real per capita GDP in country i, respectively. Each equation is estimated separately. We first calculate the variance (and its components) using the spectral method discussed in Section 3.1, and then take its square root to calculate volatility.

We proxy financial development (fin_dev_i) by the (log) value of credit disbursed to the private sector by banks and other financial institutions relative to GDP, and take the average over the sample period. Private credit is preferred to other measures of financial development because it excludes credit extended to the public sector and funds provided from central or development banks [Aghion et al. (2010)]. As a part of robustness checks, we also use an alternative proxy—the (log) value of stock market capitalization relative to GDP. Our proxy for the volatility of shocks (vol_shock_i) is the volatility of change in the TOT defined as the ratio of export prices to import prices. The reason for this proxy is that change in the TOT, unlike domestic productivity or policy shocks, is exogenous to a country.[11] This proxy is also standard in the growth and volatility literature [examples include Mendoza (1995); Agénor et al. (2000); Aghion et al. (2010)]. We first calculate the business-cycle variance of the rate of change of TOT by the spectral method, and then take its square root to calculate volatility. This approach is similar to calculating the standard deviation of the cyclical component extracted by the Hodrick–Prescott filter, which is an alternative method of calculating the TOT shocks at the business-cycle frequencies, and is employed by, among others, Backus et al. (1994), Mendoza (1995), and Stockman and Tesar (1995).

The controls (X_i) are the standard determinants of growth volatility in the literature discussed in Section 2. They are also based on economic theory. Wolf (2005, pp. 53–54) summarizes that the main reasons for volatility are shocks, unstable macroeconomic policies, political instability, and financial crises brought about by domestic market imperfections. In an open economy with incomplete asset markets, TOT shocks may cause volatility. Therefore, the controls include openness (the sum of exports and imports as a percentage of GDP), the black market premium on foreign exchange that accounts for capitalist development, and the "Polity score" as a proxy for institutions. These variables are averaged over the sample period. The institutional variable is also intended to isolate the effect of financial development from other institutional characteristics [Aghion et al. (2010)]. Acemoglu et al. (2003) find that financial aspects become insignificant for explaining volatility once the effect of institutions is controlled for. Mobarak (2005) also finds that higher levels of democracy reduce volatility. The "Polity

https://doi.org/10.1017/S1365100512000569 Published online by Cambridge University Press

score" is taken from the Polity-IV dataset and captures the regime authority spectrum on a 21-point scale ranging from −10 (hereditary monarchy) to +10 (consolidated democracy). It examines concomitant qualities of democratic and autocratic authority in governing institutions, rather than discreet and mutually exclusive forms of governance. As shown by Koren and Tenreyro (2007), poor countries specialize in fewer and more volatile sectors. We include the (log) initial level of per capita real GDP and the initial high school enrollment rate to account for different levels of income and human capital accumulation. These two controls are also standard in the literature.

Some regions, such as East Asia and Latin America, have experienced more severe economic crises than others, and crises in some regions are also more frequent. To control for potential outliers, we include dummies for these regions. We finally include country characteristics such as latitude, dummies for tropical and landlocked countries, and legal origin to account for country-specific heterogeneity. Financial development of a country is also argued to depend on its legal origin [La Porta et al. (1997, 2008)].

In a sense, our study can be thought of as an investigation of the determinants of different volatility components. However, given the interest in the effect of financial development and shocks in the literature, and also to be consistent with our predictions from the spectral theory, our attention is focused on those two determinants.

4.2. Benchmark Results

Although the dependent variables are "generated," measurement errors are unlikely to bias our results for two reasons. First, the effect of measurement errors in the dependent variable is not a problem in the classical sense, as they are absorbed into the residual term. Second, measurement errors corrupt estimates in the high-frequency range. We retain the long-run and business-cycle components of the variance and exclude the high-frequency components.

In this section, we use (log) credit to the private sector relative to GDP as the measure of financial development. Data for the control variables included in the regressions are not available for several countries, especially for the developing countries, for the period 1980–2004; therefore, the sample size decreases to 79 countries when all controls are included (29, 32, and 18 low-, middle-, and high-income countries, respectively). Table 2 reports the results for equation (1) in which business-cycle volatility is the dependent variable. Columns (1)–(5) report the results for various combinations of the explanatory variables. In all regressions, the coefficient of private credit is negative and statistically significant at least at the 10% level. The significance level increases to 5% when possible outliers (captured by regional dummies) and country-specific fixed factors except legal origin are controlled for [column (4)]. The coefficient of private credit is −0.21, which implies that a 1% increase in private credit reduces business-cycle volatility by 0.21%. Increasing the level of (log) private credit from the 25th (−1.772) to

https://doi.org/10.1017/S1365100512000569 Published online by Cambridge University Press

https://doi.org/10.1017/S1365100512000569 Published online by Cambridge University Press

TABLE 2. Dependent variable: Business-cycle volatility (log) for the period 1980–2004

Explanatory variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Private credit (log)	−0.088*	−0.111*	−0.121**	−0.205**	−0.131**					
	(−1.68)	(−1.85)	(−2.03)	(−2.23)	(−2.03)					
Private credit (log) (low-income)						−0.176***	−0.112	−0.129*	−0.149**	−0.149*
						(−2.88)	(−1.61)	(−1.72)	(−2.03)	(−1.98)
Private credit (log) (middle-income)						−0.108*	−0.149**	−0.154**	−0.162**	−0.152*
						(−1.93)	(−2.10)	(−2.28)	(−2.13)	(−1.97)
Private credit (log) (high-income)						0.229**	0.040	0.031	−0.027	−0.004
						(2.26)	(0.31)	(0.24)	(−0.18)	(−0.02)
Volatility of TOT change (shock)		3.753***	4.992***	4.107***	4.132**		3.421**	4.658***	4.076***	4.133***
		(2.86)	(3.47)	(2.75)	(2.57)		(2.62)	(3.26)	(2.79)	(2.59)
Black market premium			−0.000	−0.000	−0.000			−0.000	−0.000	−0.000
			(−0.50)	(−0.25)	(−0.28)			(−0.46)	(−0.21)	(−0.25)
Openness			0.003***	0.002**	0.002**			0.003***	0.002***	0.002**
			(3.94)	(2.66)	(2.17)			(4.13)	(2.72)	(2.18)
R^2	0.023	0.381	0.440	0.497	0.505	0.189	0.404	0.461	0.506	0.514
N	114	79	79	79	79	114	79	79	79	79

Note: All regressions include a constant. Figures in parentheses are White (1980) heteroskedasticity-corrected t-values. ***, **, and * are 1%, 5%, and 10% significance level, respectively. Columns (2), (3), (7), and (8) control for log of per capita income in 1980, high school enrollment, in 1980 and Polity2. Columns (4) and (9) control for log of per capita income in 1980, high school enrollment in 1980, Polity2, fixed factors (landlocked and tropical dummies), and regional dummies. Columns (5) and (10) control for log of per capita income in 1980, high school enrollment in 1980, Polity2, fixed factors (landlocked, tropical, and legal origin dummies), and regional dummies. Private credit = ratio of private credit by deposit banks and other financial institutions to GDP.

the 75th (−0.528) percentile results in a 0.26 percentage–point decrease in the business-cycle volatility. The results are also robust to controlling for legal origin [column (5)]. Although the legal origin of a country explains its financial development, it is not known whether legal origin has any direct impact on volatility. In that sense, legal origin may be a bad control, carrying away the effect of financial development. We therefore test this specification for robustness check. Private credit alone can explain only 2% of the variation in business-cycle volatility.

The coefficient of volatility of TOT change enters positively and significantly, at least at the 5% level, in all regressions. It is 4.11 in the regression with all controls except legal origin, implying that if volatility of TOT decreases from the 75th (0.074—Dominican Republic) to the 25th (0.027—New Zealand) percentile, business-cycle volatility decreases by 0.19 percentage points.

To find out whether the effect of financial development differs across different stages of economic development, we replicate the preceding exercises with countries disaggregated into three income levels—low, middle, and high—and report the results in columns (6)–(10). This is done by multiplying private credit by dummies for low-, middle-, and high-income countries. We find a negative and significant coefficient of private credit for the low- and middle-income countries. The coefficient for the high-income countries is not significant and its sign changes across specifications. Volatility of TOT change enters positively and significantly in all specifications.

Table 3 reports the results of equation (2) for long-run volatility. We also estimate a kindred equation disaggregating private credit at different income levels. The coefficient of private credit is nonsignificant both at the aggregate and at the disaggregated level. The coefficient of volatility of TOT change, as predicted, is positive and significant at least at the 5% level in all regressions. With all controls except legal origin [column (4)], this coefficient is 3.615, implying that a decrease in TOT volatility from the 75th (0.074) to the 25th (0.027) percentile reduces the long-run volatility by 0.17 percentage points. The results support our hypotheses that financial development affects only the business-cycle volatility, whereas volatility of shocks affects both the business-cycle and long-run volatility.

We now estimate equation (3) for total volatility, and the kindred equation for different income levels. The results, reported in Table 4, show that private credit is weakly significant at the 10% level but not robust to different combinations of the control variables. This is because total volatility consists of both business-cycle and long-run components and, as we have shown, private credit has no explanatory power for long-run volatility. The robustness of the amplifying effect of volatility of TOT change is again corroborated.

4.3. Results Accounting for Endogeneity

Using both growth volatility and average private credit over the same period does not account for their potential endogenous determination. Because of the lack of exclusion restrictions, we address the endogeneity in two alternative ways.

https://doi.org/10.1017/S1365100512000569 Published online by Cambridge University Press

https://doi.org/10.1017/S1365100512000569 Published online by Cambridge University Press

TABLE 3. Dependent variable: Long-run volatility (log) for the period 1980–2004

Explanatory variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Private credit (log)	−0.041	−0.066	−0.076	−0.081	−0.077					
	(−0.75)	(−1.12)	(−1.28)	(−1.29)	(−1.17)					
Private credit (log)						−0.064	−0.073	−0.078	−0.082	−0.074
(low-income)						(−0.87)	(−0.88)	(−0.88)	(−0.90)	(−0.79)
Private credit (log)						−0.067	−0.074	−0.086	−0.076	−0.066
(middle-income)						(−1.08)	(−0.97)	(−1.14)	(−0.93)	(−0.76)
Private credit (log)						0.133	−0.017	−0.033	−0.095	−0.123
(high-income)						(1.56)	(−0.15)	(−0.29)	(−0.75)	(−1.03)
Volatility of TOT		4.457***	4.556**	3.615**	3.837**		4.380***	4.456**	3.632**	3.858**
change (shock)		(3.25)	(2.65)	(2.17)	(2.09)		(3.13)	(2.49)	(2.11)	(2.01)
Black market premium			0.000	0.000	0.000			0.000	0.000	0.000
			(0.69)	(0.73)	(0.61)			(0.68)	(0.69)	(0.56)
Openness			0.002***	0.001	0.001			0.002***	0.001	0.001
			(2.75)	(1.17)	(0.94)			(2.73)	(1.14)	(0.90)
R^2	0.005	0.231	0.267	0.318	0.352	0.056	0.233	0.269	0.319	0.353
N	114	79	79	79	79	114	79	79	79	79

Note: All regressions include a constant. Figures in parentheses are White (1980) heteroskedasticity-corrected t-values. ***, **, and * are 1%, 5%, and 10% significance level, respectively. Columns (2), (3), (7), and (8) control for log of per capita income in 1980, high school enrollment in 1980, and Polity2. Columns (4) and (9) control for log of per capita income in 1980, high school enrollment in 1980, Polity2, fixed factors (landlocked and tropical dummies), and regional dummies. Columns (5) and (10) control for log of per capita income in 1980, high school enrollment in 1980, Polity2, fixed factors (landlocked, tropical, and legal origin dummies), and regional dummies. Private credit = ratio of private credit by deposit banks and other financial institutions to GDP.

https://doi.org/10.1017/S1365100512000569 Published online by Cambridge University Press

TABLE 4. Dependent variable: Total volatility (log) for the period 1980–2004

Explanatory variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Private credit (log)	−0.080	−0.094*	−0.104*	−0.110*	−0.105*					
	(−1.54)	(−1.68)	(−1.85)	(−1.80)	(−1.68)					
Private credit (log)						−0.158**	−0.086	−0.097	−0.105	−0.102
(low-income)						(−2.44)	(−1.28)	(−1.32)	(−1.37)	(−1.27)
Private credit (log)						−0.103*	−0.123*	−0.131**	−0.127*	−0.119
(middle-income)						(−1.90)	(−1.81)	(−2.01)	(−1.73)	(−1.59)
Private credit (log)						0.222**	0.002	−0.011	−0.067	−0.063
(high-income)						(2.37)	(0.02)	(−0.10)	(−0.53)	(−0.52)
Volatility of TOT		3.790***	4.438***	3.513**	3.622**		3.544***	4.153***	3.448**	3.574**
change (shock)		(3.27)	(3.12)	(2.41)	(2.33)		(3.10)	(2.92)	(2.35)	(2.24)
Black market premium			0.000	0.000	0.000			0.000	0.000	0.000
			(0.22)	(0.34)	(0.25)			(0.30)	(0.39)	(0.29)
Openness			0.002***	0.002*	0.001			0.002***	0.002*	0.001
			(3.32)	(1.93)	(1.66)			(3.46)	(1.96)	(1.66)
R^2	0.020	0.423	0.467	0.515	0.525	0.179	0.435	0.478	0.517	0.526
N	114	79	79	79	79	114	79	79	79	79

Note: All regressions include a constant. Figures in parentheses are White (1980) heteroskedasticity-corrected t-values. ***, **, and * are 1%, 5%, and 10% significance level, respectively. Columns (2), (3), (7), and (8) control for log of per capita income in 1980, high school enrollment in 1980, and Polity2. Columns (4) and (9) control for log of per capita income in 1980, high school enrollment in 1980, Polity2, fixed factors (landlocked and tropical dummies), and regional dummies. Columns (5) and (10) control for log of per capita income in 1980, high school enrollment in 1980, Polity2, fixed factors (landlocked, tropical, and legal origin dummies), and regional dummies. Private credit = ratio of private credit by deposit banks and other financial institutions to GDP.

We first replace the average value of the ratio of private credit to GDP with its initial value. The results for business-cycle volatility are reported in Table 5. The coefficient of initial private credit is always negative, although not significant in all combinations of the explanatory variables. However, it is significant after accounting for possible outliers and country-specific fixed factors, except legal origin [column (4)]. When initial private credit is disaggregated at different income levels, the results are significant only for the middle-income countries [columns (6)–(10)]. The coefficient of volatility of TOT change is significantly positive in all specifications. Table 6 reports the results for long-run volatility. The results follow those without accounting for endogeneity in Table 3, showing no significant effect of initial private credit, and continued and robust significance of volatility of TOT change. Finally, in the case of total volatility, the coefficient of initial private credit is insignificant and that of volatility of TOT change is positive and significant (Table 7). We also find that trade openness magnifies business-cycle (and total) but not long-run volatility.

We now employ an alternative method of identification proposed by Lewbel (2012) that does not require exclusion restrictions but exploits heteroskedasticity for identification. Identification can be achieved without imposing any exclusion restrictions if there is a vector of exogenous variables $\mathbf{Z}$ and the errors are heteroskedastic. The $\mathbf{Z}$ vector can be a subset of exogenous regressors ($\mathbf{X}$) in the regression equation or even $\mathbf{Z} = \mathbf{X}$. In the first stage, the endogenous variable(s) is (are) regressed on the $\mathbf{Z}$ vector, and the vector of residual(s) $\hat{\boldsymbol{\varepsilon}}$ is retrieved. The estimated residuals are then used to construct the instruments $(\mathbf{Z} - \bar{\mathbf{Z}})\hat{\boldsymbol{\varepsilon}}$ for the second-stage regression, where $\bar{\mathbf{Z}}$ is the mean of $\mathbf{Z}$. Identification requires that the error terms in the first-stage regressions are heteroskedastic [Lewbel (2012)].

In the first stage, we regress the ratio of private credit to GDP on initial high school enrollment and volatility of TOT change (these variables are chosen based on the Bruesch–Pagan heteroskedasticity tests), and retrieve the residual $\hat{\boldsymbol{\varepsilon}}$. We then construct the instrument vector $(\mathbf{Z} - \bar{\mathbf{Z}})\hat{\boldsymbol{\varepsilon}}$ for the second-stage regressions. The results are presented in Table 8. Columns (1)–(3) present the results for business-cycle volatility, columns (4)–(6) present the results for long-run volatility, and columns (7)–(9) present the same for total volatility. The results strongly support the benchmark results. In all specifications, the coefficient of private credit is significant for business-cycle volatility but nonsignificant for long-run volatility. However, the magnitude of the coefficient of private credit is now much larger; for example, it is around -0.5 in the case of business-cycle volatility. Volatility of shocks magnifies both business-cycle and long-run volatility in all specifications. The effect of private credit on total volatility is found to be significant and the magnitudes of the coefficients are close to those for business-cycle volatility.

The instruments satisfy the exogeneity condition: the null of exogeneity cannot be rejected, with a p-value for the Hansen's J-statistic ranging between 0.5 and 0.9. However, we cannot estimate the model disaggregating private credit for different income levels, because we have only two instruments for three endogenous variables.

https://doi.org/10.1017/S1365100512000569 Published online by Cambridge University Press

https://doi.org/10.1017/S1365100512000569 Published online by Cambridge University Press

TABLE 5. Dependent variable: Business-cycle volatility (log) for the period 1980–2004

Explanatory variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Initial private credit	−0.123**	−0.079	−0.089	−0.109*	−0.098					
(log)	(−2.61)	(−1.37)	(−1.51)	(−1.86)	(−1.66)					
Initial private credit						−0.181***	−0.050	−0.066	−0.096	−0.100
(log) (low-income)						(−3.19)	(−0.75)	(−0.91)	(−1.26)	(−1.28)
Initial private credit						−0.128**	−0.121*	−0.129*	−0.139*	−0.120
(log) (middle-income)						(−2.42)	(−1.76)	(−1.88)	(−1.98)	(−1.64)
Initial private credit						0.180	0.064	0.062	0.001	0.074
(log) (high-income)						(1.61)	(0.43)	(0.42)	(0.01)	(0.40)
Volatility of TOT		3.514**	4.721***	3.748**	3.764**		3.132**	4.278***	3.622**	3.622**
change (shock)		(2.61)	(3.10)	(2.40)	(2.23)		(2.41)	(2.90)	(2.35)	(2.17)
Black market premium			−0.000	−0.000	−0.000			−0.000	−0.000	−0.000
			(−0.50)	(−0.25)	(−0.28)			(−0.41)	(−0.18)	(−0.22)
Openness			.003***	0.002**	0.002**			0.003***	0.002***	0.002**
			(3.71)	(2.54)	(2.00)			(4.08)	(2.68)	(2.05)
R^2	0.041	0.363	0.421	0.478	0.485	0.196	0.389	0.446	0.488	0.500
N	114	79	79	79	79	114	79	79	79	79

Note: All regressions include a constant. Figures in parentheses are White (1980) heteroskedasticity-corrected t-values. ***, **, and * are 1%, 5%, and 10% significance level, respectively. Columns (2), (3), (7), and (8) control for log of per capita income in 1980, high school enrollment in 1980, and Polity2. Columns (4) and (9) control for log of per capita income in 1980, high school enrollment in 1980, Polity2, fixed factors (landlocked and tropical dummies), and regional dummies. Columns (5) and (10) control for log of per capita income in 1980, high school enrollment in 1980, Polity2, fixed factors (landlocked, tropical, and legal origin dummies), and regional dummies. Private credit = ratio of private credit by deposit banks and other financial institutions to GDP.

https://doi.org/10.1017/S1365100512000569 Published online by Cambridge University Press

TABLE 6. Dependent variable: Long-run volatility (log) for the period 1980–2004

Explanatory variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Initial private credit (log)	−0.083	−0.055	−0.067	−0.076	−0.060					
	(−1.53)	(−0.90)	(−1.08)	(−1.16)	(−0.91)					
Initial private credit (log) (low-income)						−0.095	−0.047	−0.053	−0.069	−0.060
						(−1.43)	(−0.61)	(−0.65)	(−0.77)	(−0.66)
Initial private credit (log) (middle-income)						−0.098	−0.074	−0.090	−0.089	−0.063
						(−1.66)	(−0.92)	(−1.12)	(−1.03)	(−0.71)
Initial private credit (log) (high-income)						0.078	0.038	0.019	−0.041	−0.042
						(0.67)	(0.26)	(0.13)	(−0.24)	(−0.24)
Volatility of TOT change (shock)		4.312***	4.376**	3.409**	3.623*		4.095***	4.120**	3.359*	3.607*
		(3.15)	(2.53)	(2.04)	(1.97)		(3.00)	(2.37)	(1.99)	(1.94)
Black market premium			0.000	0.000	0.000			0.000	0.000	0.000
			(0.70)	(0.74)	(0.61)			(0.73)	(0.76)	(0.59)
Openness			0.002***	0.001	0.001			0.002***	0.001	0.001
			(2.67)	(1.16)	(0.88)			(2.77)	(1.20)	(0.88)
R^2	0.020	0.226	0.261	0.314	0.344	0.065	0.235	0.271	0.315	0.344
N	114	79	79	79	79	114	79	79	79	79

Note: All regressions include a constant. Figures in parentheses are White (1980) heteroskedasticity-corrected t-values. ***, **, and * are 1%, 5%, and 10% significance level, respectively. Columns (2), (3), (7), and (8) control for log of per capita income in 1980, high school enrollment in 1980, and Polity2. Columns (4) and (9) control for log of per capita income in 1980, high school enrollment in 1980, Polity2, fixed factors (landlocked and tropical dummies), and regional dummies. Columns (5) and (10) control for log of per capita income in 1980, high school enrollment in 1980, Polity2, fixed factors (landlocked, tropical, and legal origin dummies), and regional dummies. Private credit = ratio of private credit by deposit banks and other financial institutions to GDP.

https://doi.org/10.1017/S1365100512000569 Published online by Cambridge University Press

TABLE 7. Dependent variable: Total volatility (log) for the period 1980–2004

Explanatory variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Initial private credit	−0.121**	−0.073	−0.084	−0.093	−0.082					
(log)	(−2.47)	(−1.34)	(−1.51)	(−1.60)	(−1.38)					
Initial private credit						−0.177***	−0.054	−0.065	−0.082	−0.082
(log) (low-income)						(−3.00)	(−0.84)	(−0.92)	(−1.05)	(−1.00)
Initial private credit						−0.126**	−0.104	−0.116*	−0.116*	−0.097
(log) (middle-income)						(−2.42)	(−1.57)	(−1.76)	(−1.70)	(−1.38)
Initial private credit						0.167	0.049	0.039	−0.017	0.029
(log) (high-income)						(1.42)	(0.37)	(0.29)	(−0.11)	(0.18)
Volatility of TOT		3.585***	4.198***	3.227**	3.328**		3.277***	3.839***	3.135**	3.232**
change (shock)		(3.08)	2.87	(2.18)	(2.10)		(2.89)	(2.71)	(2.12)	(2.04)
Black market			0.000	0.000	0.000			0.000	0.000	0.000
premium			(0.22)	(0.34)	(0.25)			(0.31)	(0.42)	(0.30)
Openness			0.002***	0.001*	0.001			0.002***	0.002*	0.001
			(3.14)	(1.86)	(1.55)			(3.44)	(1.97)	(1.59)
R^2	0.043	0.411	0.454	0.503	0.512	0.193	0.429	0.472	0.508	0.517
N	114	79	79	79	79	114	79	79	79	79

Note: All regressions include a constant. Figures in parentheses are White (1980) heteroskedasticity-corrected t-values. ***, **, and * are 1%, 5%, and 10% significance level, respectively. Columns (2), (3), (7), and (8) control for log of per capita income in 1980, high school enrollment in 1980, and Polity2. Columns (4) and (9) control for log of per capita income in 1980, high school enrollment in 1980, Polity2, fixed factors (landlocked and tropical dummies), and regional dummies. Columns (5) and (10) control for log of per capita income in 1980, high school enrollment in 1980, Polity2, fixed factors (landlocked, tropical, and legal origin dummies), and regional dummies. Private credit = ratio of private credit by deposit banks and other financial institutions to GDP.

https://doi.org/10.1017/S1365100512000569 Published online by Cambridge University Press

TABLE 8. Dependent variable: Volatility (log) at different frequency range for the period 1980–2004 (IV estimation using heteroskedasticity-based identification)

	DV: Business-cycle volatility (log)			DV: Long-run volatility (log)			DV: Total volatility (log)		
Explanatory variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Private credit (log)	−0.507**	−0.511**	−0.513**	−0.430	−0.422	−0.389	−0.504**	−0.495**	−0.477**
	(−2.37)	(−2.40)	(−2.55)	(−1.52)	(−1.50)	(−1.47)	(−2.31)	(−2.27)	(−2.45)
Volatility of TOT	5.684***	5.417***	5.464***	5.114**	4.723**	4.823**	5.084***	4.796***	4.859***
change (shock)	(3.44)	(3.22)	(3.19)	(2.49)	(2.11)	(2.06)	(3.05)	(2.89)	(2.87)
Black market premium	−0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(−0.10)	(0.25)	(0.21)	(1.14)	(1.15)	(1.03)	(0.80)	(0.92)	(0.84)
Openness	0.003***	0.003***	0.003***	0.002***	0.002*	0.002	0.003***	0.002**	0.002**
	(3.59)	(2.68)	(2.60)	(2.63)	(1.67)	(1.60)	(3.19)	(2.29)	(2.37)
p-value of Hansen *J*-statistics	0.546	0.654	0.746	0.970	0.901	0.663	0.814	0.945	0.899
N	79	79	79	79	79	79	79	79	79

Note: All regressions include a constant. Figures in parentheses are White (1980) heteroskedasticity-corrected *t*-values. ***, **, and * are 1%, 5%, and 10% significance level, respectively. Columns (1), (4), and (7) control for log of per capita income in 1980, high school enrollment in 1980, and Polity2. Columns (2), (5), and (8) control for log of per capita income in 1980, high school enrollment in 1980, Polity2, fixed factors (landlocked and tropical dummies), and regional dummies. Columns (3), (6), and (9) control for log of per capita income in 1980, high school enrollment in 1980, Polity2, fixed factors (landlocked, tropical, and legal origin dummies), and regional dummies. Private credit = ratio of private credit by deposit banks and other financial institutions to GDP.

4.4. Results for Alternative Measure of Financial Development

To check the robustness of the previous results, we use the value of the stock market capitalization relative to GDP as an alternative measure of financial development.[12] As before, our dependent variables are business-cycle, long-run, and total volatility. We use the initial value of stock market capitalization to account for endogeneity.[13] The sample size now decreases to 52 countries when all controls are included.

Table 9 reports the results for business-cycle volatility. The coefficient of initial stock market capitalization is always negative but significant when possible outliers and country-specific fixed factors except legal origin are controlled for [column (4)]. This result is similar to that in the case of initial private credit. At the disaggregated level, we find that stock market capitalization reduces business-cycle volatility only for the low-income countries [columns (6)–(10)]. This result is robust in all regressions except the one that includes legal origin. Volatility of TOT change is positive and significant in all regressions. The results for long-run volatility are presented in Table 10. The coefficient of stock market capitalization at both aggregate and disaggregated levels is always insignificant except for the low-income countries, for which the results are not robust. The coefficient of volatility of TOT change appears positively significant and weakly robust. The results for total volatility, presented in Table 11, mimic the results for business-cycle volatility.

Although we find support for the mitigating effect on business-cycle volatility of both private credit and stock market capitalization, the results differ across countries for different income levels. Stock market capitalization mitigates business-cycle volatility for the low-income countries, whereas private credit-to-GDP ratio mitigates it for the middle-income countries. It is important to note that the former represents market-based and the latter represents bank-based financial development. Stock markets provide a bundle of financial services different from those provided by banks and other financial intermediaries. For example, stock markets mainly diversify risk and boost liquidity. Banks, on the other hand, reduce the cost of information acquisition and enhance corporate governance. But there are also important overlaps between the services provided by these two types of financial system [Levine (1997, p. 719)]. We do not explore further why the two measures of financial development make such a difference in the results.[14]

4.5. Results for Longer Sample Period

We now focus on the countries for which data for financial development and other variables are available for a longer period. Private credit data date back to 1960, but for a small number of countries. The number of countries can be increased at the expense of a shorter sample period. Given the trade-off, we retain the countries for which the private credit data are available for at least 35 consecutive years; this reduces the sample size to 68.[15] Volatility is calculated for the period 1960–2004.

https://doi.org/10.1017/S1365100512000569 Published online by Cambridge University Press

https://doi.org/10.1017/S1365100512000569 Published online by Cambridge University Press

TABLE 9. Dependent variable: Business-cycle volatility (log) for the period 1980–2004

Explanatory variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Initial stock market cap (log)	−0.023 (−0.52)	−0.055 (−1.13)	−0.076 (−1.45)	−0.109** (−2.03)	−0.088 (−1.63)					
Initial stock market cap (log) (low-income)						−0.127*** (−3.08)	−0.089* (−1.83)	−0.135** (−2.55)	−0.135*** (−2.79)	−0.123 (−2.28)
Initial stock market cap (log) (middle-income)						−0.014 (−0.30)	−0.043 (−0.70)	−0.056 (−0.91)	−0.089 (−1.20)	−0.061 (−0.83)
Initial stock market cap (log) (high-income)						0.139* (1.95)	0.015 (0.13)	0.009 (0.08)	−0.101 (−0.76)	−0.049 (−0.41)
Volatility of TOT change (shock)		1.914 (1.39)	3.646** (2.09)	4.396** (2.13)	4.524** (2.17)		1.736 (1.16)	3.721** (2.03)	4.224* (1.95)	4.338* (1.99)
Black market premium			−0.000 (−0.96)	−0.000 (−0.83)	−0.000 (−0.83)			−0.000 (−1.42)	−0.000 (−1.04)	−0.000 (−1.13)
Openness			0.003*** (3.43)	0.003** (2.60)	0.002* (1.99)			0.003*** (3.68)	0.003** (2.55)	0.003** (2.05)
R^2	0.004	0.347	0.431	0.517	0.561	0.223	0.356	0.451	0.523	0.570
N	75	52	52	52	52	75	52	52	52	52

Note: All regressions include a constant. Figures in parentheses are White (1980) heteroskedasticity-corrected t-values. ***, **, and * are 1%, 5%, and 10% significance level, respectively. Columns (2), (3), (7), and (8) control for log of per capita income in 1980, high school enrollment in 1980, and Polity2. Columns (4) and (9) control for log of per capita income in 1980, high school enrollment in 1980, Polity2, fixed factors (landlocked and tropical dummies), and regional dummies. Columns (5) and (10) control for log of per capita income in 1980, high school enrollment in 1980, Polity2, fixed factors (landlocked, tropical, and legal origin dummies), and regional dummies. Stock market cap = ratio of stock market capitalization to GDP.

https://doi.org/10.1017/S1365100512000569 Published online by Cambridge University Press

TABLE 10. Dependent variable: Long-run volatility (log) for the period 1980–2004

Explanatory variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Initial stock market cap (log)	−0.002	−0.045	−0.053	−0.068	−0.027					
	(−0.04)	(−0.92)	(−1.01)	(−1.18)	(−0.49)					
Initial stock market cap						−0.067	−0.100*	−0.117*	−0.108	−0.074
(log) (low-income)						(−1.37)	(−1.73)	(−1.82)	(−1.71)	(−1.13)
Initial stock market cap						0.002	−0.020	−0.028	−0.032	0.032
(log) (middle-income)						(0.05)	(−0.32)	(−0.42)	(−0.40)	(0.45)
Initial stock market cap						0.105	0.005	−0.008	−0.092	−0.073
(log) (high-income)						(1.22)	(0.05)	(−0.07)	(−0.72)	(−0.64)
Volatility of TOT		3.062**	3.258*	3.461	3.292		2.767*	3.306***	3.097	2.668
change (shock)		(2.31)	(1.74)	(1.64)	(1.48)		(1.87)	(1.69)	(1.38)	(1.16)
Black market premium			0.000	0.000	0.000			0.000	0.000	0.000
			(0.82)	(0.52)	(0.42)			(0.39)	(0.25)	(0.02)
Openness			0.002**	0.001	0.002			0.002***	0.001	0.002
			(2.08)	(1.54)	(1.36)			(2.27)	(1.62)	(1.44)
R^2	0.000	0.217	0.268	0.338	0.448	0.095	0.240	0.296	0.365	0.497
N	75	52	52	52	52	75	52	52	52	52

Note: All regressions include a constant. Figures in parentheses are White (1980) heteroskedasticity-corrected t-values. ***, **, and * are 1%, 5%, and 10% significance level, respectively. Columns (2), (3), (7), and (8) control for log of per capita income in 1980, high school enrollment in 1980, and Polity2. Columns (4) and (9) control for log of per capita income in 1980, high school enrollment in 1980, Polity2, fixed factors (landlocked and tropical dummies), and regional dummies. Columns (5) and (10) control for log of per capita income in 1980, high school enrollment in 1980, Polity2, fixed factors (landlocked, tropical, and legal origin dummies), and regional dummies. Stock market cap = ratio of stock market capitalization to GDP.

https://doi.org/10.1017/S1365100512000569 Published online by Cambridge University Press

TABLE 11. Dependent variable: Total volatility (log) for the period 1980–2004

Explanatory variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Initial stock market cap (log)	−0.024 (−0.55)	−0.071 (−1.54)	−0.085* (−1.72)	−0.108** (−2.14)	−0.083 (−1.62)					
Initial stock market cap (log) (low-income)						−0.130*** (−3.00)	−0.105** (−2.28)	−0.133** (−2.64)	−0.131** (−2.72)	−0.113** (−2.07)
Initial stock market cap (log) (middle-income)						−0.015 (−0.33)	−0.058 (−1.00)	−0.067 (−1.16)	−0.089 (−1.26)	−0.055 (−0.77)
Initial stock market cap (log) (high-income)						0.140* (1.78)	−0.015 (−0.14)	−0.024 (−0.22)	−0.115 (−0.95)	−0.077 (−0.69)
Volatility of TOT change (shock)		2.484** (2.26)	3.385** (2.21)	3.847** (2.14)	3.910** (2.17)		2.306* (1.93)	3.440** (2.13)	3.658* (1.95)	3.651* (1.98)
Black market premium			0.000 (0.07)	−0.000 (−0.09)	−0.000 (−0.19)			−0.000 (−0.45)	−0.000 (−0.30)	−0.000 (−0.51)
Openness			0.002** (2.78)	0.002** (2.04)	0.002* (1.70)			0.003*** (2.90)	0.002* (1.98)	0.002* (1.74)
R^2	0.004	0.429	0.484	0.542	0.587	0.233	0.437	0.498	0.549	0.596
N	75	52	52	52	52	75	52	52	52	52

Note: All regressions include a constant. Figures in parentheses are White (1980) heteroskedasticity-corrected t-values. ***, **, and * are 1%, 5%, and 10% significance level, respectively. Columns (2), (3), (7), and (8) control for log of per capita income in 1980, high school enrollment in 1980, and Polity2. Columns (4) and (9) control for log of per capita income in 1980, high school enrollment in 1980, Polity2, fixed factors (landlocked and tropical dummies), and regional dummies. Columns (5) and (10) control for log of per capita income in 1980, high school enrollment in 1980, Polity2, fixed factors (landlocked, tropical, and legal origin dummies), and regional dummies. Stock market cap = ratio of stock market capitalization to GDP.

The same exercise cannot be replicated for stock market capitalization because of the lack of data for a relatively longer period.

However, this specification, as discussed earlier, will lead to endogeneity for which we do not have valid instruments. We address the problem by employing heteroskedasticity-based identification, discussed in Section 4.3. In the first stage, we regress the ratio of private credit to GDP on initial high school enrollment and Polity2 (based on the Bruesch–Pagan heteroskedasticity tests) and construct the instrument vector $(\mathbf{Z} - \bar{\mathbf{Z}})\hat{\boldsymbol{\varepsilon}}$ for the second-stage regressions. The results are presented in Table 12. Columns (1)–(3) present the results for business–cycle volatility, columns (4)–(6) present the results for long-run volatility, and columns (7)–(9) present the same for total volatility. The results strongly support the previous results with a larger sample for a shorter period. In all specifications, the coefficient of private credit is significant for business-cycle volatility but insignificant for long-run volatility. The magnitude of the coefficient of private credit is smaller than that obtained by the same method reported in Table 8; however, the two sets of results cannot be compared because of the different sample size and time period. On the other hand, volatility of shocks magnifies both business-cycle and long-run volatility in all specifications.[16] The effect of private credit on total volatility is mixed—it is always negative, but the significance is not robust to different combinations of the controls. This finding also suggests why previous studies using total volatility have found a mixed impact of financial development.

The instruments also satisfy the exogeneity condition, as indicated by the p-value for Hansen's J-statistic ranging between 0.3 and 0.9. Shea's partial R^2s are around 0.2 in the first-stage regressions.

4.6. Results for Alternative Volatility Decomposition

In the following, we check robustness further by calculating different components of volatility using the Hodrick–Prescott (1997) filter. We first decompose the growth rate of per capita real GDP into the cyclical and trend components using a smoothing parameter of 6.25, which is recommended for annual data. We then calculate the standard deviations of both the cyclical and trend components, which are the counterparts of business–cycle and long-run volatility, respectively, estimated by the spectral method. We also calculate the standard deviation of the original unfiltered series as the counterpart of total volatility. As mentioned earlier, previous studies measure volatility by the standard deviation either of the unfiltered series or of the cyclical component. This decomposition differs slightly from the one by the spectral method in the case of business-cycle volatility. In the spectral method, we discard both the high- and low-frequency components to calculate the business-cycle volatility, whereas the cyclical components extracted by the Hodrick–Prescott filter discard only the low frequency.[17] In our data, the correlation of business-cycle volatility for the two measures is 0.95, and the same for long-run volatility is 0.98.

https://doi.org/10.1017/S1365100512000569 Published online by Cambridge University Press

https://doi.org/10.1017/S1365100512000569 Published online by Cambridge University Press

TABLE 12. Dependent variable: Volatility (log) at different frequency range for the period 1960–2004 (IV estimation using heteroskedasticity-based identification)

	DV: Business-cycle volatility (log)			DV: Long-run volatility (log)			DV: Total volatility (log)		
Explanatory variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Private credit (log)	−0.436*	−0.474**	−0.396**	−0.165	−0.167	−0.107	−0.201	−0.151	−0.517***
	(−1.89)	(−2.06)	(−2.54)	(−0.95)	(−0.89)	(−0.82)	(−1.59)	(−1.50)	(−2.62)
Volatility of TOT change (shock)	5.457***	4.726***	4.218***	3.535**	3.009**	2.587	5.111***	5.410***	7.978***
	(4.17)	(3.68)	(3.40)	(2.56)	(1.99)	(1.61)	(6.62)	(5.94)	(2.75)
Black market premium	−0.000	0.000	0.000	0.000	0.000	0.000	−0.000	−0.000	−0.000
	(−0.14)	(0.31)	(0.18)	(1.03)	(0.95)	(0.81)	(−0.82)	(−0.87)	(−0.73)
Openness	0.003***	0.003***	0.003***	0.002***	0.002**	0.002*	0.002**	0.003***	0.003***
	(3.57)	(3.34)	(3.21)	(2.60)	(2.22)	(1.66)	(2.41)	(2.82)	(3.86)
p-value of Hansen *J*-statistics	0.346	0.666	0.487	0.810	0.934	0.989	0.787	0.857	0.906
N	68	68	68	68	68	68	68	68	68

Note: All regressions include a constant. Figures in parentheses are White (1980) heteroskedasticity-corrected *t*-values. ***, **, and * are 1%, 5%, and 10% significance level, respectively. Columns (1), (4), and (7) control for log of per capita income in 1960, high school enrollment in 1960, and Polity2. Columns (2), (5), and (8) control for log of per capita income in 1960, high school enrollment in 1960, Polity2, fixed factors (landlocked and tropical dummies), and regional dummies. Columns (3), (6), and (9) control for log of per capita income in 1960, high school enrollment in 1960, Polity2, fixed factors (landlocked, tropical, and legal origin dummies), and regional dummies. Private credit = ratio of private credit by deposit banks and other financial institutions to GDP.

https://doi.org/10.1017/S1365100512000569 Published online by Cambridge University Press

TABLE 13. Dependent variable: Volatility (log) at different frequency range extracted by the Hodrick–Prescott filter for the period 1960–2004 (IV estimation using heteroskedasticity-based identification)

	DV: Business-cycle volatility (log)			DV: Long-run volatility (log)			DV: Total volatility (log)		
Explanatory variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Private credit (log)	−0.198	−0.245*	−0.194*	−0.158	−0.132	0.033	−0.201	−0.223*	−0.120
	(−1.51)	(−1.81)	(−1.76)	(−0.91)	(−0.76)	(0.25)	(−1.53)	(−1.66)	(−1.18)
Volatility of TOT	6.328***	6.344***	6.360***	4.162***	4.334***	4.379***	5.395***	5.592***	5.524***
change (shock)	(7.27)	(6.81)	(6.76)	(3.68)	(3.26)	(3.25)	(6.99)	(6.02)	(5.96)
Black market premium	−0.0002**	−0.0001	−0.0001	0.0002	0.0001	−0.0000	−0.0001	−0.0000	−0.0001
	(−2.04)	(−0.89)	(−1.32)	(0.91)	(0.60)	(−0.16)	(−0.69)	(−0.12)	(−0.83)
Openness	0.002**	0.003***	0.003***	0.002***	0.002**	0.002*	0.002***	0.003***	0.003***
	(2.50)	(3.54)	(3.25)	(2.60)	(2.01)	(1.83)	(2.70)	(3.24)	(2.92)
p-value of Hansen *J*-statistics	0.330	0.758	0.384	0.978	0.998	0.635	0.569	0.876	0.365
N	68	68	68	68	68	68	68	68	68

Note: All regressions include a constant. Figures in parentheses are White (1980) heteroskedasticity-corrected *t*-values. ***, **, and * are 1%, 5%, and 10% significance level, respectively. Columns (1), (4), and (7) control for log of per capita income in 1960, high school enrollment in 1960, and Polity2. Columns (2), (5), and (8) control for log of per capita income in 1960, high school enrollment in 1960, Polity2, fixed factors (landlocked and tropical dummies), and regional dummies. Columns (3), (6), and (9) control for log of per capita income in 1960, high school enrollment in 1960, Polity2, fixed factors (landlocked, tropical, and legal origin dummies), and regional dummies. Private credit = ratio of private credit by deposit banks and other financial institutions to GDP.

We analyze the previous sample of 68 countries for the period 1960–2004, and correct for the endogeneity by exploiting the heteroskedasticity for identification. Estimation in this section differs from that in Section 4.5 only by the construction of the dependent variables, so that the instruments constructed in the first stage are also the same. The results, presented in Table 13, do not qualitatively change from the previous results. Private credit lowers business-cycle volatility, whereas it has no effect on long-run volatility. However, the magnitude of the coefficient now decreases almost by half relative to the comparable estimates in Table 12. Shocks, on the other hand, magnify both business-cycle and long-run volatility, and the results are robust across specifications. The magnitude of the coefficient is larger relative to the previous comparable results. The results for other determinants such as openness and black market premium do not change.

5. CONCLUDING REMARKS

In this paper, we argue that financial development and shocks affect growth volatility through its different components. Specifically, financial development affects only business-cycle volatility, whereas shocks affect both business-cycle and long-run volatility. We find support for both hypotheses. Private credit, our proxy for financial development, dampens business-cycle but not long-run volatility. Volatility of shocks, as measured by volatility of TOT change, magnifies both business-cycle and long-run volatility. The results are robust to an alternative market-based measure of financial development, accounting for endogeneity, and an alternative filtering method of volatility decomposition.

One might argue that other macroeconomic structures, such as trade openness, can also cause different spectral shapes at the business-cycle frequencies. The results also provide qualified support for the conclusion that trade openness increases business-cycle volatility but not long-run volatility, although the latter results are not robust to heteroskedasticity-based identification.

The results have important implications for both business-cycle and growth theories by highlighting the importance of the distinction between the causes of transitory and persistent fluctuations. The spectral method used to decompose volatility has also been found to be useful and can be used in other areas that are concerned with the importance of different frequency ranges.

NOTES

1. Long-run volatility can be a consequence when serial correlation of the output growth rate is very large or an economy does not revert to the original steady state after deviation or exhibits limit cycles. In the latter two cases, the growth rate is nonstationary. The long-run volatility estimated in this paper is more consistent with the former case. We use long-run and persistent volatility interchangeably.

2. 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.

https://doi.org/10.1017/S1365100512000569 Published online by Cambridge University Press

3. Volatility decomposition is important in other areas of economics as well. For example, Adrian and Rosenberg (2008) decompose equity market volatility into short- and long-run components to study the cross-sectional pricing of volatility risk. Chauvet et al. (2010) use different components of asset volatility to predict future economic activity.

4. The basic mechanism in the Aghion and Banerjee (2005) model is the interaction of credit constraints and endogenous changes in the interest rate (or real exchange rate in the context of an open economy). 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. However, 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 long-run volatility; the remaining countries at the intermediate level of financial development are vulnerable to long-run volatility.

5. The difference between the two approaches lies in the treatment of the trend growth rate. The standard deviation of the growth series implicitly assumes a constant trend growth, whereas the standard deviation of the detrended series allows the trend to follow a time-dependent process [Hnatkovska and Loayza (2005, pp. 74–75)].

6. Ahmed et al. (2004, p. 825) exploit this information to compare different components of volatility of U.S. GDP growth and inflation for two distinct periods, and the relative importance of improved monetary policy, exogenous shocks, and improved inventory practices in explaining the change in volatility. Our argument is also based on Ahmed et al. (2004).

7. The long-run component of the variance is equivalent to passing the GDP growth series through a low-pass filter, and then estimating the variance of the resulting series [Levy and Dezhbakhsh (2003, p. 1502)]. Another method is Cochrane's (1988) variance ratio statistic. Similarly, the business-cycle (short-run) component of the variance is equivalent to passing the GDP growth series through a bandpass (high-pass) filter, and then estimating the variance of the resulting series.

8. Engle (1974, p. 3) and Priestley (1981, p. 471) argue that the integrated periodogram is consistent, not because it approaches its spectral value at each frequency, but because the sum (integral) of the periodogram over all frequencies approaches the sum (integral) of the spectral values. Priestley (1981, p. 483) mentions that both approaches—with and without spectral windows—are equivalent as far as their asymptotic sampling properties are concerned.

9. Different components of volatility may not be strictly comparable for different income groups because of different group sizes.

10. This finding contrasts with Levy and Dezhbakhsh (2003, Table 6, p. 1519), the only known study that calculates different variance components of the GDP growth by the spectral method. They find a statistically significant positive relationship between income level and the share of the business-cycle component of the variance. Their sample period (1950–1994) and set of countries are different from ours. For the same set of countries, we find weak support for the conclusion that the mean share of the business-cycle component is marginally increasing with income level for the period 1960–2004 (0.40, 0.41, and 0.43 for the low-, middle-, and high-income countries, respectively). However, total variance and also its long-run and business-cycle components are larger for the middle-income than for the low-income countries (detailed statistics are available from the author upon request). This implies that the results may be driven by the choice of sample countries and time period, because the Levy and Dezhbakhsh sample period excludes some recent crises, such as the East Asian one.

11. Granger–Sims tests by Mendoza (1995, Table 2, p. 110) also document that, except for the United States and a few major fuel exporters, exports and imports do not cause the TOT.

12. Another alternative can be the ratio of the value of private bond market capitalization to GDP. However, that series is only available for a small number of countries for a short period of time.

https://doi.org/10.1017/S1365100512000569 Published online by Cambridge University Press

13. We do not employ the heteroskedasticity-based identification because the first-stage regressions of stock market capitalization on exogenous variable(s) do not satisfy the heteroskedasticity condition.

14. We do not find any evidence that financial development dampens the effects of shocks on (any component of) volatility (results not reported). When we add an interaction term of the volatility of TOT change with private credit or stock market capitalization, the coefficient of the interaction term is not significant.

15. Although the initial period for private credit differs across countries, this should not be a problem because we average over a relatively longer period.

16. Ahmed et al. (2004) argue that the periodogram at low frequencies is subject to greater sampling variation. Our regression results for long-run volatility are robust to varying sample size and period.

17. The business-cycle and low-frequency components can also be extracted by applying the Baxter–King (1999) band- and low-pass filters, respectively. However, this filter, similarly to the spectral method, uses restrictions from the frequency domain to determine the filter weights; therefore, we do not apply it. On the other hand, the Hodrick–Prescott filter allows us to compare with other results in the literature, such as Silva (2002).

REFERENCES

Acemoglu, Daron, Simon Johnson, James Robinson, and Yunyong Thaicharoen (2003) Institutional causes, macroeconomic symptoms: Volatility, crises and growth. *Journal of Monetary Economics* 50(1), 49–123.

Acemoglu, Daron and Fabrizio Zilibotti (1997) Was Prometheus unbound by chance? Risk, diversification, and growth. *Journal of Political Economy* 105(4), 709–751.

Adrian, Tobias and Joshua Rosenberg (2008) Stock returns and volatility pricing: The short-run and long-run components of market risk. *Journal of Finance* 63(6), 2997–3030.

Agénor, Pierre-Richard (2001) Business Cycles, Economic Crises, and the Poor: Testing for Asymmetric Effects. Policy research working paper 2700, World Bank, Washington, DC.

Agénor, Pierre-Richard, Christopher J. McDermott, and Eswar Prasad (2000) Macroeconomic fluctuations in developing countries: Some stylized facts. *World Bank Economic Review* 14(2), 251–285.

Aghion, Philippe, George-Marios Angeletos, Abhijit V. Banerjee, and Kalina Manova (2010) Volatility and growth: Credit constraints and the composition of investment. *Journal of Monetary Economics* 57(3), 246–265.

Aghion, Philippe and Abhijit Banerjee (2005) *Volatility and Growth*. New York: Oxford University Press.

Aghion, Philippe, Abhijit Banerjee, and Thomas Piketty (1999) Dualism and macroeconomic volatility. *Quarterly Journal of Economics* 114(4), 1359–1397.

Aguiar, Mark and Gita Gopinath (2007) Emerging market business cycles: The cycle is the trend. *Journal of Political Economy* 115(1), 69–102.

Ahmed, Shagil, Andrew Levin, and Beth A. Wilson (2004) Recent U.S. macroeconomic stability: Good policies, good practices and good luck. *Review of Economics and Statistics* 86(3), 824–832.

Aizenman, Joshua and Andrew Powell (2003) Volatility and financial intermediation. *Journal of International Money and Finance* 22(5), 657–679.

Backus, David K., Patrick J. Kehoe, and Finn E. Kydland (1994) Relative price movements in dynamic general equilibrium models of international trade. In Fredrick van der Ploeg (ed.), *The Handbook of International Macroeconomics*, pp. 62–96. Cambridge, MA: Blackwell.

Baxter, Marianne and Robert G. King (1999) Measuring business cycles: Approximate band-pass filters for economic time series. *Review of Economics and Statistics* 81(4), 575–593.

Beck, Thorsten, Ashli Demirgüç-Kunt, and Ross Levine (2000) A new database on the structure and development of the financial sector. *World Bank Economic Review* 14(3), 597–605 (updated November 2008).

https://doi.org/10.1017/S1365100512000569 Published online by Cambridge University Press

Beck, Thorsten, Mattias Lundberg, and Giovanni Majnoni (2006) Financial intermediary development and growth volatility: Do intermediaries dampen or magnify shocks? *Journal of International Money and Finance* 25(7), 1146–1167.

Bernanke, Ben S. and Mark Gertler (1989) Agency costs, net worth, and business fluctuations. *American Economic Review* 79(1), 14–31.

Bernanke, Ben S. and Mark Gertler (1995) Inside the black box: The credit channel of monetary policy transmission. *Journal of Economic Perspectives* 9(4), 27–48.

Bernanke, Ben, Mark Gertler, and Simon Gilchrist (1998) The financial accelerator in a quantitative business cycle framework. In John B. Taylor and Michael Woodford (eds.), *Handbook of Macroeconomics* 1C, pp. 1341–1393. Amsterdam: Elsevier.

Breen, Richard and Cecilia García-Peñalosa (2005) Income inequality and macroeconomic volatility: An empirical investigation. *Review of Development Economics* 9(3), 380–398.

Chauvet, Marcelle, Zeynep Senyuz, and Emre Yoldas (2010) What Does Realized Volatility Tell Us about the Macroeconomic Fluctuations? MPRA paper 34104.

Cochrane, John H. (1988) How big is the random walk in GNP? *Journal of Political Economy* 96(5), 893–920.

Denizer, Cevdet A., Murat F. Iyigun, and Ann Owen (2002) Finance and macroeconomic volatility. *Contributions to Macroeconomics* 2(1), Article 7, 1–30.

Easterly, William, Roumeen Islam, and Joseph E. Stiglitz (2002) Shaken and stirred: Explaining growth volatility. In Boris Pleskovic and Nicholas Stern (eds.), *Annual World Bank Conference on Development Economics*, pp. 191–211. Washington, DC.: World Bank and Oxford University Press.

Engle, R.F. (1974) Band spectrum regression. *International Economic Review* 15(1), 1–11.

Fatás, Antonio (2000) Do business cycles cast long shadows? Short-run persistence and economic growth. *Journal of Economic Growth* 5(2), 147–162.

Global Development Network Growth Database (2001). http://econ.worldbank.org/WBSITE/EXTERNAL/EXTDEC/EXTRESEARCH/0,contentMDK:20701055~pagePK:64214825~piPK:64214943~the SitePK:469382,00.html.

Greenwald, Bruce C. and Joseph E. Stiglitz (1993) Financial market imperfections and business cycles. *Quarterly Journal of Economics* 108(1), 77–114.

Heston, Alan, Robert Summers, and Bettina Aten (2006) Penn World Tables, Version 6.2. Center for International Comparisons, University of Pennsylvania.

Hnatkovska, Viktoria and Norman Loayza (2005) Volatility and growth. In Joshua Aizenman and Brian Pinto (eds.), *Managing Economic Volatility and Crises: A Practitioner's Guide*, pp. 65–100. New York: Cambridge University Press.

Hodrick, Robert and Edward C. Prescott (1997) Postwar U.S. business cycles: An empirical investigation. *Journal of Money, Credit and Banking* 29(1), 1–16.

Iyigun, Murat F. and Ann L. Owen (2004) Income inequality, financial development, and macroeconomic fluctuations. *Economic Journal* 114(495), 352–376.

Kiyotaki, Nobuhiro and John Moore (1997) Credit cycles. *Journal of Political Economy* 102(2), 211–248.

Koren, Miklós and Silvana Tenreyro (2007) Volatility and development. *Quarterly Journal of Economics* 122(1), 243–287.

La Porta, Rafael, Florencio Lopez-De-Silanes, and Andrei Shleifer (2008) The economic consequences of legal origin. *Journal of Economic Literature* 46(2), 285–332.

La Porta, Rafael, Florencio Lopez-De-Silanes, Andrei Shleifer, and Robert W. Vishny (1997) Legal determinants of external finance. *Journal of Finance* 52(3), 1131–1150.

Laursen, Thomas and Sandeep Mahajan (2005) Volatility, income distribution, and poverty. In Joshua Aizenman and Brian Pinto (eds.), *Managing Economic Volatility and Crises: A Practitioner's Guide*, pp. 101–136. New York: Cambridge University Press.

Levine, Ross (1997) Financial development and economic growth: Views and agenda. *Journal of Economic Literature* 35(2), 688–726.

Levy, Daniel and Hashem Dezhbakhsh (2003) International evidence on output fluctuation and shock persistence. *Journal of Monetary Economics* 50(7), 1499–1530.

https://doi.org/10.1017/S1365100512000569 Published online by Cambridge University Press

Lewbel, A. (2012) Using heteroskedasticity to identify and estimate mismeasured and endogenous regressor models. *Journal of Business and Economic Statistics* 30(1), 67–80.

Lopez, Jose A. and Mark M. Spiegel (2005) Financial structure and macroeconomic performance over the short and long run. In L.J. Cho, D. Cho, and Y.H. Kim (eds.), *Macroeconomic Implications of Post-Crisis Structural Changes*, pp. 75–103. Seoul: Korea Development Institute.

Mendoza, Enrique (1995) The terms of trade, the real exchange rate, and economic fluctuations. *International Economic Review* 36(1), 101–137.

Mobarak, Ahmed M. (2005) Democracy, volatility and economic development. *Review of Economics and Statistics* 87(2), 348–361.

Polity IV Project (2009) Political regime characteristics and transitions, 1800–2007. http://www.systemicpeace.org/polity/polity4.htm.

Priestley, M.B. (1981) *Spectral Analysis and Time Series,* vols. 1 and 2. London: Academic Press.

Raddatz, Claudio (2006) Liquidity needs and vulnerability to financial underdevelopment. *Journal of Financial Economics* 80(3), 677–722.

Ramey, Valerie A. and Garey Ramey (1995) Cross-country evidence on the link between volatility and growth. *American Economic Review* 85(5), 1138–1151.

Silva, Gisele Ferreira da (2002) The impact of financial system development on business cycles volatility: Cross-country evidence. *Journal of Macroeconomics* 24(2), 233–253.

Stadler, George W. (1986) Real versus monetary business cycle theory and the statistical characteristics of output fluctuation. *Economics Letters* 22(1), 51–54.

Stadler, George W. (1990) Business cycles models with endogenous technology. *American Economic Review* 80(4), 763–778.

Stockman, Alan C. and Linda L. Tesar (1995) Tastes and technology in a two-country model of the business cycle: Explaining international comovements. *American Economic Review* 85(1), 168–185.

Tharavanij, Piyapas (2007) Capital Market and Business Cycle Volatility. Monash University economics discussion paper.

White, Halbert (1980) A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica* 48(4), 817–838.

Wolf, Holger (2004) Accounting for consumption volatility differences. *IMF Staff Papers* 51(Special Issue), 109–125.

Wolf, Holger (2005) Volatility: Definitions and consequences. In Joshua Aizenman and Brian Pinto (eds.), *Managing Economic Volatility and Crises: A Practitioner's Guide*, pp. 45–64. New York: Cambridge University Press.

World Development Indicators (2009) World Bank. http://data.worldbank.org/data-catalog/world-development-indicators.

https://doi.org/10.1017/S1365100512000569 Published online by Cambridge University Press

APPENDIX

A.1. DESCRIPTION OF DATA

Variable	Source	Period
Real per capita GDP (RGDPL)	Penn World Table 6.2 [Heston et al. (2006)]	1960–2004
Private credit by deposit banks and other financial institutions/GDP	Beck et al. (2000; updated November 2008)	1960–2004 (Initial period varies by country)
Value of stock market capitalization/GDP	Beck et al. (2000; updated November 2008))	1960–2004 (Initial period varies by country)
Openness (export + import as % of GDP)	World Development Indicators, World Bank	1960–2004
High school enrollment	World Development Indicators, World Bank	1960–2004
Terms of trade	Global Development Network Growth Database	1960–1999
Black market premium	Global Development Network Growth Database	1960–1999
Institution (revised Polity2)	Polity IV Project: Political Regime Characteristics and Transitions, 1800–2007	1960–2004
Legal origin, landlocked, latitude, income group (low, middle, and high)	Global Development Network Growth Database and World Development Indicators, World Bank	

https://doi.org/10.1017/S1365100512000569 Published online by Cambridge University Press

A.2. VARIANCE AT DIFFERENT FREQUENCY RANGE FOR THE PERIOD 1980–2004 (LOW-INCOME COUNTRIES: WORLD BANK CLASSIFICATION)

Country	Total variance	Long-run variance	Business-cycle variance	Long-run variance share	Business-cycle variance share
Bangladesh	5.47	1.47	2.66	0.27	0.49
Benin	10.96	1.50	3.42	0.14	0.31
Bhutan	34.08	5.39	16.00	0.16	0.47
Burkina Faso	14.82	3.68	7.17	0.25	0.48
Burundi	50.50	10.99	23.59	0.22	0.47
Central African Rep.	37.54	10.93	15.72	0.29	0.42
Chad	60.12	10.14	33.22	0.17	0.55
China	7.99	1.86	3.05	0.23	0.38
Comoros$^{\psi}$	11.31	4.60	3.76	0.41	0.33
Ethiopia$^{\psi}$	91.09	14.19	23.23	0.16	0.25
Gambia	18.39	5.73	8.18	0.31	0.44
Guinea$^{\psi}$	12.64	5.37	4.30	0.42	0.34
Haiti	34.66	5.10	9.72	0.15	0.28
Honduras	9.14	0.78	5.57	0.09	0.61
India	3.80	1.26	1.76	0.33	0.46
Indonesia$^{\psi}$	16.18	5.41	7.62	0.33	0.47
Korea (North)	28.81	19.68	4.25	0.68	0.15
Laos PDR	33.22	5.06	16.77	0.15	0.50
Lesotho$^{\psi}$	33.57	7.66	14.50	0.23	0.43
Madagascar	15.00	1.80	5.90	0.12	0.39
Malawi$^{\psi}$	35.56	7.42	21.41	0.21	0.60
Mali	34.30	3.52	13.40	0.10	0.39
Mauritania	20.62	5.08	4.27	0.25	0.21
Mozambique$^{\psi}$	62.28	21.81	29.67	0.35	0.48
Nepal$^{\psi}$	10.94	1.02	5.24	0.09	0.48
Nicaragua	21.62	8.71	4.64	0.40	0.21
Nigeria$^{\psi}$	27.11	5.04	11.76	0.19	0.43
Pakistan$^{\psi}$	3.24	1.56	1.24	0.48	0.38
Dem. Rep. Congo$^{\psi}$	94.17	26.32	45.82	0.28	0.49
Sao Tome and Principe	45.10	16.21	15.02	0.36	0.33
Senegal	24.16	2.66	12.87	0.11	0.53
Solomon Islands	50.45	22.28	16.01	0.44	0.32
Somalia	46.71	8.17	21.80	0.17	0.47
Sudan	19.17	4.71	11.14	0.25	0.58
Tanzania$^{\psi}$	88.43	25.57	36.15	0.29	0.41
Uganda	27.80	7.90	13.26	0.28	0.48
Zambia$^{\psi}$	32.03	8.74	12.26	0.27	0.38
Zimbabwe	78.05	19.65	25.75	0.25	0.33

Note: Countries in bold are included in the regressions in Tables 2–8 with all controls for the period 1980–2004. $^{\psi}$Countries included in the regressions in Tables 12 and 13 for the period 1960–2004.

https://doi.org/10.1017/S1365100512000569 Published online by Cambridge University Press

A.3. VARIANCE AT DIFFERENT FREQUENCY RANGE FOR THE PERIOD 1980–2004 (MIDDLE-INCOME COUNTRIES: WORLD BANK CLASSIFICATION)

Country	Total variance	Long-run variance	Business-cycle variance	Long-run variance share	Business-cycle variance share
Algeria	8.97	2.01	4.78	0.22	0.53
Barbados	8.99	3.90	3.17	0.43	0.35
Belize	46.48	14.61	16.98	0.31	0.37
Botswana	33.77	5.57	15.68	0.16	0.46
Brazil	12.56	3.15	4.76	0.25	0.38
Cape Verde	19.93	5.08	4.66	0.25	0.23
Chile$^{\psi}$	23.58	10.26	9.16	0.44	0.39
Colombia$^{\psi}$	1.91	1.04	0.63	0.54	0.33
Costa Rica	11.86	4.62	6.12	0.39	0.52
Cuba	69.55	31.88	23.86	0.46	0.34
Dominica	40.00	6.90	17.04	0.17	0.43
Dominican Republic	13.30	5.20	5.81	0.39	0.44
Egypt$^{\psi}$	5.33	0.52	2.25	0.10	0.42
El Salvador$^{\psi}$	7.79	5.08	2.00	0.65	0.26
Fiji	41.95	5.81	23.35	0.14	0.56
Guatemala	3.64	1.88	1.18	0.52	0.32
Iran	50.08	18.30	22.76	0.37	0.45
Jamaica$^{\psi}$	12.05	3.32	5.23	0.28	0.43
Jordan	37.60	22.32	10.62	0.59	0.28
Korea$^{\psi}$ **(South)**	18.55	5.08	8.48	0.27	0.46
Malaysia$^{\psi}$	7.17	2.84	3.31	0.40	0.46
Maldives	31.17	5.15	16.85	0.17	0.54
Mauritius	10.75	2.90	4.77	0.27	0.44
Mexico	12.23	3.06	6.55	0.25	0.54
Micronesia	28.05	6.53	11.06	0.23	0.39
Morocco$^{\psi}$	23.40	0.98	4.02	0.04	0.17
Namibia	25.84	2.33	14.68	0.09	0.57
Oman	17.33	4.05	7.83	0.23	0.45
Panama$^{\psi}$	20.56	5.18	10.42	0.25	0.51
Papua New Guinea	42.85	8.34	19.18	0.19	0.45
Peru	40.81	13.73	21.96	0.34	0.54
Poland	21.13	12.08	7.77	0.57	0.37
Puerto Rico	9.70	3.50	3.36	0.36	0.35
Romania$^{\psi}$	30.33	18.49	9.26	0.61	0.31
Samoa	31.87	10.08	9.21	0.32	0.29
Saudi Arabia	50.38	23.08	19.37	0.46	0.38
South Africa	4.07	1.90	1.58	0.47	0.39

(Continues)

https://doi.org/10.1017/S1365100512000569 Published online by Cambridge University Press

Country	Total variance	Long-run variance	Business-cycle variance	Long-run variance share	Business-cycle variance share
Sri Lanka$^{\psi}$	8.59	0.99	4.84	0.11	0.56
St. Kitts and Nevis	27.27	4.59	11.18	0.17	0.41
St. Lucia	22.21	9.99	6.97	0.45	0.31
Swaziland	10.96	4.28	4.03	0.39	0.37
Syria	35.66	10.38	13.99	0.29	0.39
Thailand	15.91	9.04	4.74	0.57	0.30
Tonga	80.24	30.58	31.13	0.38	0.39
Trinidad and Tobago	81.26	28.30	32.63	0.35	0.40
Tunisia	4.55	0.42	1.44	0.09	0.32
Uruguay$^{\psi}$	41.81	14.13	21.73	0.34	0.52
Vanuatu	68.09	14.79	32.62	0.22	0.48
Venezuela	28.71	3.23	17.47	0.11	0.61

Note: Countries in bold are included in the regressions in Tables 2–8 with all controls for the period 1980–2004.
$^{\psi}$ Countries included in the regressions in Tables 12 and 13 for the period 1960–2004.

https://doi.org/10.1017/S1365100512000569 Published online by Cambridge University Press

A.4. VARIANCE AT DIFFERENT FREQUENCY RANGE FOR THE PERIOD 1980–2004 (HIGH-INCOME COUNTRIES: WORLD BANK CLASSIFICATION)

Country	Total variance	Long-run variance	Business-cycle variance	Long-run variance share	Business-cycle variance share
Australia$^{\psi}$	2.36	0.63	1.02	0.27	0.43
Austria$^{\psi}$	1.36	0.57	0.57	0.42	0.42
Bermuda	9.73	2.22	3.89	0.23	0.40
Brunei	34.65	12.49	16.30	0.36	0.47
Canada	5.29	1.99	2.39	0.38	0.45
Cyprus	6.92	2.06	2.53	0.30	0.37
Denmark	3.09	1.13	1.15	0.37	0.37
Finland$^{\psi}$	12.19	6.18	4.69	0.51	0.38
Germany	2.05	0.84	0.94	0.41	0.46
Greece$^{\psi}$	5.24	2.83	1.74	0.54	0.33
Hong Kong	15.24	5.56	7.00	0.36	0.46
Israel$^{\psi}$	7.27	1.56	4.08	0.21	0.56
Italy$^{\psi}$	1.50	0.62	0.66	0.41	0.44
Japan	3.49	2.02	1.25	0.58	0.36
Macao, China	28.52	14.23	9.31	0.50	0.33
Netherlands	2.80	1.50	1.14	0.54	0.41
Netherlands Antilles	11.58	5.30	3.79	0.46	0.33
New Zealand$^{\psi}$	3.47	1.48	1.08	0.43	0.31
Norway$^{\psi}$	2.86	1.27	1.33	0.44	0.46
Portugal	6.21	3.67	1.98	0.59	0.32
Qatar	51.87	27.94	15.07	0.54	0.29
Singapore	20.86	5.04	9.71	0.24	0.47
Spain	2.60	1.71	0.71	0.66	0.27
Sweden$^{\psi}$	4.05	1.93	1.53	0.48	0.38
Taiwan, China	6.36	3.09	1.85	0.49	0.29
United Kingdom	3.06	1.55	1.29	0.51	0.42
United States$^{\psi}$	3.69	1.19	1.65	0.32	0.45

Note: Countries in bold are included in the regressions in Tables 2–8 with all controls for the period 1980–2004. $^{\psi}$ Countries included in the regressions in Tables 12 and 13 for the period 1960–2004.

https://doi.org/10.1017/S1365100512000569 Published online by Cambridge University Press