On the Link between the Volatility and Skewness of Growth

Abstract

In a sample of 110 countries over the period 1960–2009, we document a positive relation between the volatility and skewness of growth in the cross-section. This novel stylized fact is related to two distinct mechanisms: sudden growth spurts in emerging markets, and sharp financial crises-driven recessions in developed economies. The former phenomenon is driven by industrialization, macroeconomic stabilization, and the exploitation of natural resources. The latter is consistent with recent theories of financial frictions. This contrasts with a negative relation between volatility and skewness in panel data with country fixed effects, driven by business cycle variation in rich countries.

JEL Classification: E32; G10; O10.

Keywords: Volatility; Skewness; Development; Financial frictions; Growth spurts; Business cycles.

I. Introduction

This paper documents a novel stylized fact: in a large cross-section of countries, the volatility and the skewness of GDP growth are positively correlated over the long run. As a concrete example, countries in the highest decile in terms of volatility[1] exhibit an average skewness over the 1960–2009 period of 1.51, while the lowest volatility decile exhibits an average skewness of -0.71. The relation between volatility and skewness is significant and robust across time and space. For example, it holds for the top and the bottom quartile of countries both in terms of 1960 per capita GDP and in terms of subsequent average growth rate, it holds both before and after the Great Moderation, and it holds for both annual and quarterly underlying growth data.

What economic models best explain the positive relation between the volatility and skewness of GDP growth in the cross-section? One potential explanation is that the relation is driven by business cycle dynamics whereby the primary source of fluctuations in GDP growth are transitory fluctuations around a stable trend. However, the most basic version of such a model in the business cycle literature appears inconsistent with the stylized fact because it predicts a negative temporal relationship between volatility and skewness. A large number of papers have empirically established that business cycles are negatively skewed, with recessions occurring suddenly and being sharp, whereas booms occur more slowly (see, e.g., Diebold and Rudebusch, 1990; Hamilton, 1989; and Acemoglu and Scott, 1994). Models explaining this type of behaviour include, for example, Acemoglu and Scott (1997), who relate the business cycle asymmetry to intertemporal increasing returns to investment, and Zeira (1994), Jovanovic (2006), and Van Nieuwerburgh and Veldkamp (2006), whose models rely on a learning process in which either bad signals are more extreme than good signals, or signals are less noisy during booms. Given the recent interest in differences between business cycles in emerging markets and developed countries (see e.g. Aguiar and Gopinath, 2007; Garcia-Cicco, Pancrazi, and Uribe, 2010), an interesting question is whether this stylized fact is universal or restricted to the developed countries for which it has hitherto been documented. We show that in panel data with country fixed effects, volatility and skewness are indeed temporally negatively correlated, especially in very rich (mostly industrialized OECD) countries. Importantly, we show that for the

[1] While in the empirical tests we employ the natural logarithm of the standard deviation of GDP growth, in the text we interchangeably refer to the “volatility” of GDP growth.

same subset of countries, the volatility and skewness of growth are still positively correlated in the cross-section.

A temporal negative correlation between volatility and skewness can only be reconciled with a positive correlation in the cross-section if lower-volatility countries receive on average larger transitory negative shocks. However, business cycle models suggest that the mechanisms which generate business cycle asymmetry are hardwired in the business cycle itself and do not depend on the size of the volatility-generating shocks. This also applies to the new generation growth-business cycle model of Comin and Gertler (2006) which uses technological change to generate medium-frequency oscillations between periods of robust growth and periods of relative stagnation. In short, models capturing the negatively-skewed business cycle of small open economies do not offer a mechanism for the positive cross-sectional relationship between volatility and skewness observed in a large cross-section of countries, and in particular for the large share of high-volatility, high-positive-skewness countries in the data.

Could this stylized fact be generated by models of growth and development? Such models do a good job at explaining how an economy can transition from a period of underdevelopment to a period of rapid growth. For example, Acemoglu and Zilibotti (1997) suggest that under-developed countries, likely prevalent in our sample, are stuck in an equilibrium with high output variability as indivisibilities in the production process limits the economy's ability to diversify idiosyncratic risk. Only when they experience "lucky draws" do they accumulate enough capital to invest in large indivisible high-growth projects, at which point the economy takes off and volatility declines due to diversification. Furthermore, Acemoglu, Johnson, Robinson, and Thaicharoen (2003) identify institutions as the key determinant of the mean and variability of the growth process, and suggest that better institutions come with higher growth, lower volatility, and less severe contractions. Such models seemingly predict a negative cross-sectional relationship between skewness and volatility whereby over the development path, the growth process becomes simultaneously more positively skewed and less volatile. However, we show that the positive cross-sectional relationship we observe holds for all development levels. Theories modelling the transition from a "Malthusian" equilibrium (low economic growth and high population growth) to a "Solowian" equilibrium (high economic growth and low population growth), such as Galor and Weil (2000) and Hansen and Prescott (2002), suggest that at each point in time, a number of countries could be operating under both regimes. However, such models are primarily concerned with the rate of growth at different stages of development and they do not offer explicit predictions for the relationship between volatility and skewness.

The stylized fact we uncover can also be viewed as puzzling from the point of view of traditional models of financial frictions. For example, Bernanke and Gertler (1989), Bernanke, Gertler, and Gilchrist (1996), and Kiyotaki and Moore (1997) present models where microeconomic credit constraints amplify (exogenous) technological shocks. In a world without financial intermediation, volatility is low and growth skewness is zero as no amplification of shocks takes place in the absence of leverage. Financial development initially increases volatility by alleviating the capacity constraints on investment induced by positive technological shocks. As the financial system develops further, the capacity constraint binds only for large negative shocks, and as a result, volatility is reduced and the growth process becomes more negatively skewed.[2] Finally, at very high (infinite) levels of financial development the capacity constraint never binds, reducing volatility further and increasing the skewness of growth. These models of financial frictions are consistent with a temporally negative relationship between volatility and skewness. However, they seem hard to reconcile with a cross-sectional pattern whereby the lowest-volatility countries are the most negatively skewed and where a number of countries are characterized by very volatile, very positively skewed growth process.

This short overview suggests that the main stylized fact established in this article is hard to reconcile with a particular class of models. We argue that the positive cross-sectional relationship between the long-run volatility and long-run skewness of growth is reconciled by two separate mechanisms which are at play at different stages of development. First, for developed countries with sophisticated financial sectors, a positive link between volatility and skewness makes economic sense from the perspective of models developed to explain the recent global financial crisis. Following the Great Moderation, characterized by steady growth and low output volatility, many countries experienced a deep financial crisis, leading to a sharp decline in output growth. The economics profession has responded by building new macroeconomic models of endogenous risk with financial frictions. A prime example in this literature is the

[2] Related to this literature, Ranciere, Tornell, and Westermann (2008) study a model where systemic risk taking in financially liberalized economies with limited contract enforcement, reduces the effective cost of capital and relaxes borrowing constraints. This allows greater investment and generates higher long-term growth, but it raises the probability of a sudden collapse in financial intermediation when a crash occurs. Popov (2014) provides empirical evidence that equity market liberalization worsens the negative skewness of output growth, both directly and through the channel of more frequent banking-crises-driven recessions.

model by Brunnermeier and Sannikov (2014).[3] Their model generates a "volatility paradox", whereby agents respond to a low volatility environment by over-leveraging and creating latent endogenous variability which may then lead to a financial crisis. Conceptually, this model is reminiscent of the work of Minsky (1986) who contends that during good times (characterized by high growth and low volatility) speculative euphoria leads to a borrowing bubble, which leads to a financial crisis and a contraction. We document direct empirical evidence of this mechanism for the most financially developed countries. In particular, we find that protracted periods of low volatility are often followed by a systemic financial crisis, which is consistent with the idea that higher risk taking during periods of low volatility begets large macroeconomic contractions in the future. In such an environment, there is a natural cross-sectional positive relationship between lagged volatility and skewness, which may in turn help explain the long-term positive correlation between skewness and volatility, even though, contemporaneously, the relationship between volatility and skewness is negative because of business cycle variation.

Such evidence alone, however, would not suffice to explain a cross-sectional positive relationship for our sample of 110 countries most of which are not industrialized economies. The second mechanism we uncover is related to sudden growth spurts in a considerable number of developing countries. These growth spurts generate positive skewness and come hand in hand with high growth volatility. For these countries, the temporal relationship between volatility and skewness is consistent with the long-run relationship. A variety of theoretical models of industrialization and early development relate such growth spurts to a transition from an agriculture-based to a manufacturing-based economy as happened during the Industrial Revolution (Murphy, Shleifer, and Vishny, 1991; Acemoglu and Zilibotti, 1997). While in our data over the 1960-2009 period there are a number of cases of growth spurts due to industrialization, most of the large and abrupt expansions we observe are associated with more prosaic developments, like the discovery and subsequent exploitation of natural resources, or post-war economic recovery.

To summarize, the novel stylized fact we present appears to be explained by two separate mechanisms in two different sets of countries. Countries at early stages of development, while occasionally hit by crises and sudden stops, experience periods of very rapid economic growth,

[3] Mendoza (2010), He and Krishnamurthy (2012), and Dewachter and Wouters (2014) also present models of endogenous risk in a macroeconomic context.

generating high long-run volatility and simultaneously positive long-run skewness. Changes to growth trends are fundamental in this story. This mechanism is lacking in more developed economies, giving them the well-known business cycle pattern of a slow boom and a steep bust. Crucially, the latter pattern is exacerbated by the occasional severe financial crisis-driven contraction which follows periods of relatively low volatility, generating a positive correlation between long-run volatility and long-run skewness.

The paper proceeds as follows. In Section II we study the cross-sectional relationship between volatility and skewness, whereas Section III focuses on panel data. In Section IV, we dig deeper into development and financial frictions models that may help explain our results. In Section V, we present a simple statistical data generating process, consistent with our empirical results. Section VI provides concluding remarks.

II. The Cross-Sectional Relationship Between Volatility and Skewness

We first study the cross-sectional relationship between the long-term volatility and long-term skewness of output growth, as follows:

$$Skewness_i = \beta_1 + \beta_2 Log(Volatility)_i + \varepsilon_i \tag{1}$$

Here *Skewness* is calculated as the Fisher-Pearson coefficient of skewness, and *Volatility* is calculated as the square root of the variance, i.e., the standard deviation, of GDP growth rates over the period 1960–2009.[4] To compute the two higher moments of growth, we use data on annual GDP growth from the Penn World Table (PWT) 7.0 for 110 countries that have data on GDP going back at least to 1960. PWT 7.0 reports growth rates calculated as the percentage change in GDP per capita between two periods. Later, we also report results where growth rates are calculated as first differences of log levels.

Volatility over the full sample ranges between 1.9% for Norway and 24.2% for Equatorial Guinea. The cross-sectional distribution of volatility is very right-skewed, which is not surprising. In fact, the skewness of volatility estimates is well documented in the statistics literature and it is well-known that log-volatility shows a more normal distribution (see Andersen, Bollerslev, Diebold and Labys, 2003). To avoid that outliers drive the results, we use the log of volatility throughout our empirical analysis. The main results of the paper are only

[4] Throughout the paper, volatility and skewness are calculated using GDP growth rates rather than the actual shocks that are driving the GDP growth dynamics.

strengthened when we use the level of volatility. Figure 1 plots skewness versus log-volatility for the 110-country sample and a strong positive relationship is readily apparent.

Table 1, column (1) reports the point estimate of β_2 from a bivariate regression of long-term skewness on the logarithm of the long-term standard deviation of GDP growth. The estimate of the coefficient in this bivariate regression is 1.022 and it is significant at the 1% statistical level. The *R*-squared of the regression implies that the variation in log volatility explains a quarter of the variation in skewness in the cross-section. The magnitude of the coefficient implies that a 1-standard-deviation increase in volatility is associated with an increase in skewness representing half the standard deviation of skewness in the sample. The association between volatility on skewness remains unchanged when we control for initial GDP per capita and for average GDP growth over the 1960-2009 period (column (2)), although the magnitude of the association between volatility and skewness decreases by about 10%.

We next wish to establish whether this result is driven by a particular set of countries, or by a particular time period. Columns (3) and (4) examine whether the relationship is a "rich or poor country story." Interestingly, we find that the relationship holds strongly and in a statistically significant manner in both the lowest and the highest quartile of countries in terms of initial GDP per capita. Nevertheless, the OLS estimate is almost twice larger for the poorest quartile of countries relative to the richest quartile of countries, and the R-squared of the regression is 0.42 relative to 0.17. We conclude that the positive association between volatility and skewness is stronger for developing countries, but it is not a feature exclusive to developing countries.

We next split the sample along the growth dimension. We run the main regression on the countries in the bottom quartile (column (5)) and in the top quartile (column (6)) of the distribution of average growth over the 1960–2009 period. We thus juxtapose the 28 slowest growing countries (with an average growth rate of 0.4% over the 50-year period) with the 28 fastest growing countries (with an average growth rate of 4.2%). Strikingly, in both cases the coefficient of the OLS regression has almost the exact same magnitude. The combined evidence in columns (2)-(5) thus suggests that our main result is not fully explained by the fact that growth rates are positively skewed in poor countries, generating a "high growth rate-high volatility" pattern. Higher volatility is associated with higher skewness at all stages of development and at all levels of growth. The fact that the cross-sectional correlation between volatility and skewness is present both *across* income groups and *within* income groups is the most striking fact in the paper.

In columns (7) and (8), we split the sample period in two and re-estimate the cross-sectional relationship between the skewness and volatility of GDP growth over 1960-1984 and 1985-2009, respectively. The cut-off year corresponds to the beginning of the Great Moderation (Stock and Watson, 2002), although the second period includes the 2008-09 global financial crisis. The positive association between volatility and skewness is observed over the two periods, but it is economically stronger in the post-1984 period. This is likely driven by developed countries experiencing particularly low volatility during the Great Moderation combined with negative skewness induced by the global financial crisis of 2008-09.

Our results are reminiscent of but different from Ramey and Ramey (1995) who argue that there is a negative trade-off between output growth and volatility. Interestingly, given the usual utility functions economic agents are endowed with, their stylized fact strongly suggests high volatility is invariably welfare reducing. Our results, in contrast, suggest that, holding average growth constant, there may be a true choice between high volatility-high skewness outcomes and low volatility-low skewness outcomes.

In Table 2, we account for the fact that we have used growth rates based on percentage changes in per capita GDP, as reported by PWT 7.0. This approach by default makes growth volatility and especially growth skewness very sensitive to outliers. We now re-estimate both long-run skewness and long-run volatility using growth rates calculated as the first difference in the log levels of per capita GDP from one year to the next. We then replicate all tests reported in Table 1. We note that in all regressions, the association between skewness and log volatility continues to be positive. Moreover, it is significant at the 1% statistical level in the simplest, bivariate specification (column (1)). In column (2), where we control for initial wealth and for average growth, the coefficient on the initial per capita wealth term is negative and significant, plausibly related to the prior that richer economies experience a naturally more negatively skewed growth pattern. Importantly, the correlation between the volatility and skewness of growth is positive, albeit marginally insignificant at the 10% statistical level. Columns (3) and (4) confirm that, as before, the volatility and skewness of growth are positively correlated both in the poorest and in the richest countries. We also find that the positive correlation is statistically significant and economically meaningful for the fastest-growing countries (column (6)) and after the Great Moderation (column (8)), but it weakens in low-growth countries (column (5)) and in the sample before the Great Moderation (column (7). Overall, the magnitude of the association between skewness and log volatility declines relative to the estimates reported in Table 1, confirming a potentially important role that growth outliers play in that association.

In Table 3, we subject our main stylized fact to a number of robustness checks related to the empirical proxies and to the data sources we employ. First, we account for the fact that while by focusing on the natural logarithm of volatility to account for the presence of outliers, we are departing from the bulk of the literature on the volatility-growth link that has used the *level* of GDP growth volatility as right-hand side variable (e.g., Ramey and Ramey, 1995; Posch and Walde, 2011). In column (1) we show that the positive association between growth volatility and skewness obtains in a regression of long-term skewness on the level of long-term volatility. In column (2), we drop nine countries with long-term standard deviation of GDP growth of more than 10 percent, and show that this positive association is not driven by the presence of a few countries with very volatile average growth rate.

Next, we account for the fact that the annual data we are using may not properly capture business cycle dynamics. In particular, the bust phase may be sharper in annual data. This may systematically bias the results in favour of finding a positive correlation between volatility and skewness if the busts are sharper in low-volatility countries. We download quarterly data on 33 OECD countries from the STAN Dataset for Industrial Analysis, and re-run our main specification. Column (3) indicates that the relationship we have uncovered is not driven by the use of less granular data.

Next, we account for the fact that different updates of the Penn World Table can contain different real GDP growth series for the same country, despite being derived from similar underlying data and using almost identical methodologies.[5] In some cases, there can be large differences. For example, according to the 7.0 update that we are using throughout the paper, Guinea-Bissau recorded a GDP growth rate of 86% in 2005, but according to the 7.1 update the country grew by 2% in 2005. While such differences do not appear to be systematic, we repeat the main exercise with data from PWT 7.1. Column (4) indicates that our main result is robust to this alternative version of PWT. The same is true in column (5) where we calculate volatility and

[5] Katayama and Ponomareva (2010) and Johnson, Larson, Papageorgiou, and Subramanian (2013) document how differences in the GDP growth data across different versions of PWT matter for the cross-country growth literature.

skewness of GDP growth using PWT 7.0, but we use only 50% of the countries, i.e. the ones for which the measure of skewness deviates the least from one version of the Penn Tables to the other.

Finally, the positive association between the volatility and skewness of GDP growth continues to be statistically and economically significant when we use entirely different data sources on GDP growth, such as the World Development Indicators (column (6)) and the International Financial Statistics of the IMF (column (7)).

III. Volatility and Skewness: Fixed Effects Panel Estimates

We now turn to exploiting the panel nature of our cross-country dataset in order to study whether our data are consistent with the prior based on asymmetric business cycles, and how this prior can be reconciled with the strong, positive correlation between volatility and skewness of growth in the cross-section. To that end, we calculate $Skewness$ and $Volatility$ over reasonably long non-overlapping periods. This allows us to control for observable time-varying country-specific effects in a model that includes both time- and country-fixed effects. Specifically, we introduce the following econometric framework:

$$Skewness_{it} = \beta_1 + \beta_2 Log(Volatility)_{it} + \beta_3 X_{it} + \beta_4 \mu_i + \beta_5 \varphi_t + \varepsilon_{it} \qquad (2)$$

where for each variable we compute its value over non-overlapping 5-year periods for each country *i*, yielding a panel of 1110 observations. X_{it} is a set of time-varying country-specific control variables to be specified below; μ_i is a matrix of country dummies; and φ_t is a matrix of year dummies.

In Table 4, we start with the simplest possible panel regression in which the log standard deviation of growth is the only regressor and there are country fixed effects (column (1)) and both country and time fixed effects (column (2)). In these specifications, we record a negative association between volatility and skewness, and this association is significant at the 10% level statistical level. The effect is marginally insignificant (significant at the 13% level) in column (3) where we use a Newey-West adjustment of the standard errors for country-specific autocorrelation (with 4 lags), to address the fact that GDP growth skewness could be serially correlated within countries. However, it is once again significant when we do not adjust the standard errors for autocorrelation, and instead control for 1-period lagged skewness (column (4)).

Furthermore, we confirm the negative temporal association between volatility and skewness with quarterly data in column (5), for a smaller sub-sample of (mostly OECD) countries. Here, we have once again calculated the standard deviation and the skewness of growth over 5-year periods, which in this case yields 20 observations per period.

In columns (6) and (7), analogous to the cross-sectional regression, we split the sample based on initial GDP per capita. We find that the negative effect is entirely driven by the *richer* countries, confirming the result from column (5). This raises the question, at what particular level of development the negative skewness-volatility relationship becomes apparent. Column (8) reports the results of a regression where we include the natural logarithm of beginning-of-period GDP per capita, by itself and interacted with volatility. The coefficient on volatility itself is now significantly positive but the interaction effect is statistically significantly negative. We find that the coefficient on volatility turns negative at a per capita GDP level of $1231 (in 2005 dollars), which is at the 28th percentile of the GDP per capita distribution. Rich countries, controlling for volatility, have significantly lower skewness than poor countries.

How can the negative temporal correlation between volatility and skewness in rich countries, and the lack thereof in less developed ones, be reconciled with the positive long-term correlation that we uncovered in the cross-section and that holds both within and across income groups? We examine a number of potential channels in Table 5 and discuss them in turn.

III.A. Recessions

The first possibility is simply the asymmetric business cycle variation discussed before when growth slowdowns or negative growth coincide with high volatility. Aguiar and Gopinath (2007) argue that in emerging markets trend growth dominates cyclical growth which could explain the lack of a strong negative relationship for less developed countries. However, Garcia-Cicco, Pancrazi, and Uribe (2010), focusing on Argentina and Mexico, have disputed the conclusions in Aguiar and Gopinath (2007), showing that an RBC model driven by permanent and transitory productivity shocks fails to captures business cycle dynamics. Instead, a model with international financial frictions is called for. An even simpler explanation is that crises cause both volatility to increase and skewness to decrease simultaneously. However, it would be somewhat surprising that developed countries experience more and more severe crises than do emerging markets. To examine these two hypotheses, we must measure "crises" and "recessions." To define a recession, we set a dummy variable equal to 1 if the country experiences negative annual growth at any point during each 5-year period, and include it in the regression alongside its interaction with the log of the standard deviation of growth over each 5-year cycle (column (1)). The coefficient on volatility duly turns positive, whereas the coefficients on the recession dummy and on its interaction with volatility are negative and statistically significant. Hence, the negative association between volatility and skewness in the full sample is indeed potentially driven by business cycle mechanisms.

III.B. Banking crises and financial development

A banking crisis simultaneously increases real volatility and causes output to fall, generating negative skewness. We use data from Laeven and Valencia (2010) to define a dummy equal to 1 if the economy is experiencing a systemic banking crisis at any point during each 5-year period, and include it in the regression together with its interaction with volatility (column (2)). The coefficients on the variable and on the interaction are negative but (marginally) insignificant, implying that banking crises do not do fully explain the association between volatility and skewness in the full sample.

Next, we test for the effect of financial development on the trade-off between volatility and skewness. In the Kiyotaki and Moore (1997) model of financial frictions, borrowing capacity is a function of the firm's net worth and of the state of financial development. Because net worth fluctuates over the business cycle, real shocks are amplified when the collateral constraint binds, and whether it does depends on the state of financial intermediation. This model yields three distinct regimes. For very low levels of financial intermediation, the economy is in autarky as no borrowing takes place. Because of the absence of leverage, there is no amplification of shocks and as a result, the growth process is symmetric and characterized by low volatility. Away from autarky, financial development exerts a non-linear effect on volatility and on skewness. As financial markets develop initially, economic agents start accumulating leverage. In this case, the collateral constraint is frequently binding, leading to an amplification of net worth fluctuations which is manifested in higher output volatility. The more developed the financial system is, the less frequently the collateral constraint binds. Collateral amplification takes place only when the negative shocks are sufficiently large, and so the economy is characterized by low volatility and by negative skewness. This model has a hard time explaining our cross-sectional evidence where output growth in the highest-volatility countries is very positively skewed. However, as long as no country in the sample is perfectly financially developed (i.e., the capacity constraint still binds on the downside), the collateral amplification mechanism can explain the negative temporal correlation between volatility and skewness in the richest countries. We test this story by including the ratio of private credit to GDP from Beck, Demirgüç-Kunt, and Levine (2010), on its own and in interaction with volatility. Column (3) confirms that more financially developed economies have more negatively skewed business cycles. The relationship between volatility and skewness becomes negative beyond a Private credit / GDP threshold of 0.14 (the 27th percentile of the sample distribution), suggesting that the negative association between volatility and skewness documented in Table 4 is driven by business cycle dynamics in relatively financially developed countries.

Our evidence is inconsistent with the predictions laid out in a recent paper by Ordonez (2013). He uses a learning model with endogenous flow of information to argue that financial frictions delay the economy's recovery after the bust phase. Using quarterly data on (at most) 52 countries, he finds that the skewness of output growth is more negative in less developed economies, a pattern opposite to what we observe in annual data on 110 countries. In addition, our main results on the positive association between volatility and skewness in the cross section are not driven by the reliance on annual growth frequency, as demonstrated in Table 3, column (3) for a sub-sample of industrialized economies.

III.C. Trade

Next, we investigate the effect of trade openness. Economies more open to trade are in theory more volatile because they are exposed to terms-of-trade risk (e.g., Rodrik, 1998; Epifani and Gancia, 2009). We include in the regression a dummy variable equal to 1 if the country is open to trade at the beginning of each 5-period period, and also an interaction of that variable with 5-year volatility. Data on trade openness come from Wacziarg and Welch (2008). Column (4) confirms that trade openness does contribute significantly to the negative skewness of GDP growth. However, the coefficient on the interaction is (marginally) insignificant, suggesting that openness to trade is not a crucial determinant of the development-dependent temporal negative relationship between volatility and skewness.

In column (5), we test for terms-of-trade risk by including the standard deviation of the first (log) difference of the terms of trade over each respective 5-year period as an independent variable. We find that terms of trade shocks do not explain the variation in the skewness of growth rates.

III.D. Government

We also explore the role of the government sector. Higher government spending can be associated with a smoother business-cycle because transitory fluctuations are reduced through automatic stabilisers or discretionary changes in fiscal policy (e.g., Gali, 1994; Fatas and Mihov, 2006). By making recessions milder, government spending may therefore increase the skewness of growth. Column (6) suggests that government spending increases the skewness of output growth (albeit insignificantly so), suggesting a more stable business cycle with less pronounced busts in countries with high government spending. The coefficient on volatility is significantly negative but the interaction coefficient with government spending is positive and significant, suggesting that for countries with low government spending, there is a negative trade-off between volatility and skewness. The interaction effect implies that the association between volatility and skewness becomes positive beyond a government spending / GDP threshold of 0.18 (the 88th percentile of the distribution). Because government spending excludes social security, it turns out that the countries exceeding this threshold are actually mostly developing countries, not the developed countries with mechanisms in place to mitigate the amplitude of the business cycle. It is therefore also possible that government spending is simply a reverse indicator of development, just as private credit to GDP and trade openness may also indirectly rank countries on development status.

III.E. Growth spurts

We now examine the growth spurt mechanism. Various theories provide endogenous mechanisms for countries to take off and experience growth acceleration after a long period of underdevelopment characterized by low growth. Some of these theories treat population growth as fixed (Goodfriend and McDermott, 1995), others propose an explicit mechanism which considers how population growth and technological growth affect each other (Galor and Weil, 2000; Galor and Moav, 2002). In some models, the economy needs a “lucky draw” to start on an upward path (Acemoglu and Zilibotti, 1997), and in others, co-ordination is required to achieve industrialization because no individual sector can break even by industrializing alone (Murphy, Shleifer, and Vishny, 1989). However, what all these growth theories have in common is a technology-driven transition from a pre-Industrial Revolution equilibrium, characterized by low GDP growth, to a post-Industrial Revolution equilibrium, characterized by high GDP growth. These theories have direct implications for our tests: if such growth spurts are large enough (and thus create volatility), they could induce a large positive temporal correlation between volatility and skewness. If a sufficient number of countries undergo such episodes, this may account for the fact that the negative temporal correlation between volatility and skewness that is prevalent in richer countries is much weaker in the full sample.

To test this prediction, in column (7) we include a variable capturing whether a country is experiencing a growth spurt during a particular 5-year period. We define a growth spurt using a dummy variable equal to 1 if the average growth rate over the 5-year period is more than two standard deviations higher than the sample average, with this average and standard deviation measured across all countries and time periods. To make sure that we exclude growth spurts which are due to an outlier in the data potentially reflecting a data error (like Guinea-Bissau’s 86% growth in 2005 according to PWT 7.0), we also require that during this 5-year period, the country records *during at least two years* a growth rate which is at least twice higher than the sample average. We also include the interaction of this variable with volatility. The evidence confirms the intuition: while volatility and skewness are negatively temporally correlated in the full sample, the coefficient on the interaction term implies that they become positively correlated during periods in which the economy is experiencing a growth spurt. Growth spurts themselves, not surprisingly, contribute significantly to the positive skewness of growth.

III.F. Horse race

Finally, in column (8) we run a horse race where we include all variables[6], as well as their interactions with volatility, simultaneously in the regression. Tellingly, the only effects that remain significant are those of recessions, private credit / GDP, and growth spurts. This suggests

[6] We exclude the terms-of-trade variable which has too many missing observations.

that business cycle mechanisms in rich countries and growth spurts in developing countries go a long way in explaining the development-dependent temporal association between volatility and skewness.[7]

What is the nature of the growth spurts in our dataset? In traditional models of early growth, take-off is due to the process of industrialization, i.e., the transition from an economy based on agriculture to one with a diversified fast-growing manufacturing base. These models are designed to capture the experience of what are now industrialized countries during the 18th and 19th century (Galor and Weil, 2000), but they also aim to capture post-WWII developments which are subsumed in our data period, such as the Big Push in Korea during the 1960s and 1970s (Murphy, Shleifer, and Vishny, 1989). Table 6 lists the growth spurt episodes in our data, alongside the reason for the rapid growth. From 23 such episodes, 7 can indeed be classified as Industrial Revolution-type growth spurts: Hong-Kong in 1960–1964, Japan in 1960–1964, Cyprus in 1965–1969, Malaysia in 1970–1974, Romania in 1975–1979, Singapore in 1970–1974, and China in 2005–2009. However, the majority of the remaining episodes (13) are related to the discovery and exploitation of natural resources (mostly oil) and/or a sudden increase in global demand for such resources or for agricultural products. Three are related to economic stabilisation and/or liberalization in the wake of political independence or a war.

One subtle distinction that we have not made so far is between growth spurts and "growth miracles". While the former are periods of fast growth that may nevertheless be short-lived, the latter are usually understood as sustained periods of economic growth and convergence in per capita income. To verify the effect of such growth miracles, we also run a regression (unreported) including growth miracles in the definition of growth spurts. We define "growth miracles" as country-specific episodes of at least three consecutive five-year periods with annual growth higher than 0.05 (the 75th percentile of growth rates in the full sample), and assign a value of 1 to such episodes. Using this criterion, we add Korea and Taiwan to the sample of growth spurt countries, resulting in the inclusion of all four "Asian tigers". The resulting sample of 21 countries also subsumes the sub-sample of countries which experienced a convergence in per capita income over the sample period: Botswana and Equatorial Guinea (which moved from the bottom quartile to the third quartile of per capita GDP) and Korea and Taiwan (which moved

[7] In an unreported regression, we also include GDP per capita and its interaction with volatility in the horse race. Both coefficients are insignificant, implying that the development channels we test in Table 5 explain the development-dependent relationship between volatility and skewness.

from the bottom quartile to the third quartile of per capita GDP). The main result is robust to this alternative definition of growth spurt episodes.

IV. The Volatility Paradox: Does Low Volatility Breed Negative Skewness?

We are still left with a puzzle. In the cross-section, there is a strong positive association between the volatility and skewness of growth. In panel data, the relationship is overall negative, but becomes positive for less developed countries. We documented that asymmetric business cycles explain the negative coefficient for developed countries in the panel. We also showed that growth spurts in developing countries can explain a temporal positive correlation between volatility and skewness. How can such patterns lead to the strong positive cross-sectional relationship documented in Table 1 for all stages of development? Growth spurts explain the positive relationship in the bottom quartile of countries in terms of GDP per capita. However, the evidence we have presented does not reconcile the strong negative temporal association between volatility and skewness with the strong positive long-term association between the two in the top echelon of countries in terms of per capita wealth (Table 1, column (4)), especially after 1984 (the year of the commonly accepted start of the Great Moderation). If anything, rich countries with deeper recessions should have a higher long-term volatility than rich countries with less deep recessions, inducing a negative cross-sectional variation between long-run volatility and long-run skewness. At the same time, however, some rich countries have experienced large macroeconomic contractions *because* they had low volatility for too long, which led to over-leveraging and a sharp financial crisis. This is a temporal but not a contemporaneous relation between low volatility and negative skewness that can help explain the positive long-run association between the two in the cross-section. By populating the high and low quadrant of the cross-sectional distribution of volatility correctly, the cross-sectional relationship becomes strongly positive. We explore this "story" now in more detail.

A narrative going back to Minsky (1986) suggests that good (high-growth, low-volatility) times give rise to speculative investor euphoria, and soon thereafter debts exceed what borrowers can pay off from their incoming revenues, which in turn leads to a financial crisis. As a result of the collapse of the speculative borrowing bubble, investors—and especially banks—reduce credit availability, even to companies that can afford to borrow, and the economy subsequently contracts. This narrative suggests that *past* volatility and *future* skewness can correlate *positively*.

Building on similar models by Bernanke and Gertler (1989), Bernanke, Gertler, and Gilchrist (1996), and Kiyotaki and Moore (1997), Brunnermeier and Sannikov (2014) formalize this story through a mechanism in which agents react to an exogenous decline in macroeconomic risk by accumulating higher leverage. As a result, a low exogenous risk environment is conducive to a greater build-up of systemic risk. In this setting, instability is higher when aggregate risk is low, implying that a period of low volatility should be followed by a sharp crisis (a period of negative skewness), especially in economies whose financial markets are developed enough as to enable a build-up of leverage beyond the critical threshold. If reaching particular low levels of volatility was associated with an increased propensity for large, abrupt, and rare macroeconomic contractions in the future, this could explain a positive link between volatility and skewness at high levels of financial development. For this to contribute to the positive cross-sectional relationship, it must be the case that the volatility induced by the crisis itself does not push these countries into the upper part of the cross-sectional volatility distribution.

In Table 7, we test these implications of the Brunnermeier-Sannikov model in a number of ways. First, we regress the skewness of GDP growth onto the *lagged* standard deviation of GDP growth and on *lagged* private credit / GDP, plus the interaction between the two. In the full sample, not surprisingly, we do not find any statistically significant coefficient. The Brunnermeier–Sannikov model is only relevant for economies that have sufficiently developed financial sectors. In the second column, we focus on the top tertile of the sample in terms of average private credit / GDP over the 1960-2009 period. Now all three coefficients are significant at a minimum at the 10% level. At relatively low levels of financial development, low past volatility is still negatively associated with future skewness; however, at private credit / GDP levels of more than 1.05, the relationship turns positive. While the threshold may seem somewhat high, there are 23 countries in the sample that experience private credit / GDP levels beyond that threshold during at least one 5-year period. These regressions also include country and time fixed effects and the controls used in Table 5. These tests thus provide strong evidence that periods of low volatility may be causally linked to future periods of crises (negative skewness), especially for countries in later stages of financial development.

In the next two columns, we test an alternative specification. In particular, we define a "low volatility duration" regime, in the following way. We create a variable equal to 1 if the country is experiencing a 5-year GDP growth volatility of less than 0.013 (the bottom 10^{th} percentile of the overall sample distribution of 5-year volatility). If volatility was also less than 0.013 in the previous period, we give the variable a value of 1.75 (1 + 0.75), and a value of 2.31 ($1.75 + .75^2$) if two periods ago volatility was also less than 0.013, and so on. As a consequence, we over-weight longer duration low volatility regimes, decaying the effect by 0.75 per 5 year block.[8] Then we interact this variable with private credit / GDP and replicate the regression reported in the first two columns where instead of volatility we employ this new "low volatility duration" indicator. Columns (3) and (4) of Table 7 indicate that while the association between volatility and skewness does not depend on financial development in the full sample, it does, and significantly so, in the set of countries in the top tertile of the sample in terms of average private credit / GDP over 1960-2009. The magnitude of the coefficients implies that while prolonged periods of low volatility are positively associated with GDP growth skewness, the relation turns negative at private credit / GDP levels of more than 0.98. We note that 26 countries in our sample experienced at least one 5-year period during which private credit / GDP was beyond that threshold. In 12 of these, the combination of a period of low volatility and over-the-threshold levels of domestic credit was followed by a systemic banking crisis, as defined by Laeven and Valencia (2010).[9]

Figures 2 and 3 illustrate the two main mechanisms which are at work in the cross-section in the long run. The evolution of GDP growth in Equatorial Guinea (Figure 2) is marked by the discovery of large oil fields in 1996. As a result of their subsequent exploration, Equatorial Guinea experienced a rapid growth spurt; for example, its GDP tripled between 1996 and 1998. This development is mapped into the highest growth volatility over 1960-2009 in our sample, 0.242, as well as the third highest skewness, 2.676, although prior to 1996 the country's economy was characterized by a symmetric and relatively steady (low) growth process.

At the opposite end of the development cycle is the UK (Figure 3). Characterized by a low-volatility growth all the way up to the recent crisis, its economy experienced a very deep contraction in 2009 following the banking crisis of 2007-08. The resulting skewness of -1.176 is one of the lowest in the cross-section, despite the fact that UK's growth volatility over 1960-2009 is the fourth lowest at 0.020.

[8] The results are robust to alternative weighting schemes.
[9] These countries are: Austria (2008–), Denmark (2008–), France (1998), Japan (1997–1998 and 2008–) Malaysia (1997–1999), Netherlands (2008–), Portugal (2008–), Spain (2008–), Sweden (1991–1995 and 2008–), Switzerland (2008–), the United Kingdom (2008–), and the United States (2008–).

V. A Statistical Growth Model

The empirical findings in this article are not easily reconciled with economic theory, but they also raise statistical challenges. Most growth models assume Gaussian shocks, but we document a relationship between a second and a third moment, which may vary over time within a country and vary across countries, depending on their level of development. There is an empirical literature that attempts to test whether single equilibrium standard development and/or growth models are consistent with the data or whether the data suggests multiple equilibriums. In essence these models test for non-linearities of the type that we also document in the data. For example, Bloom, David, and Sevilla (2003) suggest that GDP per capita follows a two regime process, whereas Owen, Videras, and Davis (2009) find evidence in favour of two regimes estimating a standard growth regression. What we set out to do here is to show that a fairly simple statistical model is potentially consistent with our findings.

The basic framework borrows from the "BEGE" or Bad Environment Good Environment model proposed in Bekaert and Engstrom (2013). The key assumption is that there are two shocks to the growth process, a "good" non-Gaussian shock drawn from a positively skewed distribution, and a "bad" non-Gaussian shock drawn from a negatively skewed distribution. Which of the shocks dominates, and thus determines the conditional volatility and skewness of the growth process, can depend on fundamentals, such as the degree of economic and financial development.

Formally, the model for output growth is given by the following equation:

$$y_{t+1} = \bar{g} + x_t + \sigma_{yp}\omega_{p,t+1} - \sigma_{yn}\omega_{n,t+1} \tag{3}$$

where y_{t+1} is the 1-period change in per capita output. $\bar{g}$ is the unconditional mean rate of output growth, and x_t is the deviation of the conditional growth rate from $\bar{g}$. Because our findings concern higher-order moments, we abstract from the conditional mean for now and focus on the shocks. Both σ_{yp} and σ_{yn} are positive. The shocks $\omega_{p,t+1}$ and $\omega_{n,t+1}$ are zero-mean innovations that come from gamma distributions, as follows:

$$\omega_{p,t+1} = \varphi_{t+1} - p_t \tag{4}$$

$$\omega_{n,t+1} = \phi_{t+1} - n_t \tag{5}$$

Here, φ_{t+1} represents a "good environment" variable and ϕ_{t+1} represents a "bad environment" variable, where $\varphi_{t+1} \sim \Gamma(p_t,1)$ and $\phi_{t+1} \sim \Gamma(n_t,1)$. The first parameter is the shape parameter; the second is the scale parameter of the gamma distribution which is normalized to 1, because the σ-parameters govern the scale of the processes. The shape parameter p_t governs the width of the positive tail, and the shape parameter n_t governs the width of the negative tail of y_{t+1}. Because the mean of the gamma distribution is equal to its shape parameter when the size parameter is one, the terms $-p_t$ in Equation (4) and $-n_t$ in Equation (5) ensure that each shock has a conditional mean of 0.

Bekaert and Engstrom (2013) show that in this framework, the second and the third unscaled conditional moments of y_{t+1} can be rewritten as:

$$E_t\left[\left(y_{t+1}-(\bar{g}+x_t)\right)^2\right]=\sigma_{yp}^2 p_t+\sigma_{yn}^2 n_t=\mathrm{var}_t \tag{6}$$

$$E_t\left[\left(y_{t+1}-(\bar{g}+x_t)\right)^3\right]=2\sigma_{yp}^3 p_t-2\sigma_{yn}^3 n_t=skew_t \tag{7}$$

Equation (6) demonstrates that both p_t and n_t contribute positively to the conditional variance of output. However, Equation (7) demonstrates that they differ in their implications for the conditional skewness of output. Skewness, defined as $\frac{skew_t}{\mathrm{var}_t^{3/2}}$, is positive when $\sigma_{yp}^3 p_t$ is relatively large, and negative when $\sigma_{yn}^3 n_t$ is relatively large. While both the "good environment" and the "bad environment" shocks are on average zero, there is a higher probability of a good shock in a good environment, and vice versa. Importantly, the conditional covariance between skewness and volatility equals $2\sigma_{yp}^5\,\mathrm{var}(p_t)-2\sigma_{yn}^5\,\mathrm{var}(n_t)$. Depending on how the dynamics of p_t and n_t are modelled, this covariance can be positive or negative and change over time. In the Bekaert-Engstrom model, for example, the shape parameters follow autoregressive processes, driven by the same shocks as the growth process.

For our purposes, we are mostly interested in the cross-section of output growth. Therefore, we assume that all countries follow the same process but that the parameters depend on fundamentals and change with economic and financial development. Specifically, we assume that the first shape parameter is a function of economic development, captured by per capita output Y_t, and that the second shape parameter is a function of financial development, F_t, as follows:

$$p_t = \begin{cases} p^L & if \quad Y_t < \overline{Y} \\ p^H & if \quad Y_t \geq \overline{Y} \end{cases} \tag{8}$$

and

$$n_t = \begin{cases} n^L & if \quad F_t \geq \overline{F} \\ n^H & if \quad F_t < \overline{F} \end{cases} \tag{9}$$

where *L* and *H* define low and high economic, respectively, financial development. This gives the potential for 4 different development regimes, with the main transition of interest that of going from early stages of development with low per capita GDP and an under-developed financial sector, to later stages of development where GDP per capita is much higher and the financial sector is more developed. In the first stage, the model must generate positive skewness to make growth spurts more likely. In the second stage, growth variability should decrease and the likelihood of growth spurts should diminish. As the financial intermediation sector develops further, the Minsky and Brunnermeier-Sannikhov mechanisms come into play and growth becomes negatively skewed as severe, banking crisis-driven recessions become possible.

The parameter configurations that can deliver such development cycle are not easily pinned down. While unscaled skewness is increasing (decreasing) in p_t (n_t), because the variance is increasing in p_t and n_t, the derivative of scaled skewness with respect to p_t or n_t cannot be signed. However, if the σ (scale) parameters and n_t and p_t are of similar magnitude, skewness is increasing in p_t and decreasing in n_t. The same is true if the variance contribution of "bad" and "good" variance to the total variance are about equal and the sigma parameters are not too different. Thus, in such a world, low development regimes are characterized by high *p* (or low *n*) and developed regimes by high *n* (low *p*). However, this intuition is no longer valid if either σ_p (in the low development regime) or σ_n (in the high development regime) is relatively large. Importantly, the model is flexible enough to generate such regimes and regime transitions.

We calibrate a BEGE model as in Equations (3)–(9) to our growth data to illustrate how it can fit our key empirical facts. To further introduce flexibility, we assume that the σ- parameters also vary with the regime. That implies that there are a total of 8 parameters. In Table 8, we report the results. To implement the model, we split the sample into 4 bins based on development cut-off values applied to the full cross-country panel distribution of per capita real GDP, as a measure of economic development, and private credit to GDP, as a measure of financial development. We set the threshold for development at the two-thirds point in the distribution. The first column in Table 8 lists standard deviations and skewness coefficients over the 4 bins with 95% percent confidence intervals. Note that the first letter indicates economic development (low or high) and the second letter indicates financial development (low or high). Development, be it economic or financial, invariably lowers the variability of GDP growth rates. More relevant for our story, is that financial development decreases skewness both in low and high economic development states. A GMM test confirms that the decrease is statistically significant at the 1% level in both cases.

Because we have 8 parameters and 8 moments, in principle we should be able to fit the moments exactly. Unfortunately, to obtain a perfect fit, the model selects parameters with very small n^L values. When the shape parameters go to zero, the de-meaned gamma distribution becomes very skewed and at 0 it is degenerate. We therefore opt to conduct an extensive parameter grid search, looking for parameter configurations that fit the statistics laid out above very well, but where the *p* and *n* parameters are bounded away from zero. The first set we report minimizes the sum of squared residuals from the eight moment conditions (using the unscaled skewness rather than the scaled skewness) and imposes the conditions $p^L > 0.25$; $p^H > 0.2$; $n^H > 0.15$. At these parameters, the skewness coefficients are all well within the 95% confidence interval, but standard deviations in financially developed economies are somewhat too high.

In the next column, we report a parameter configuration that satisfies the key fact that skewness decreases with financial development and yields statistics that are insignificantly different from the data for a minimum of 3 out of 4 standard deviations and skewness coefficients. Again the fit with the skewness coefficients is very good, and skewness decreases with higher financial development, reaching -1.84, on average, when an economy is both economically and financially developed. As to standard deviations, economic and financial development lower the standard deviation, albeit by less than they do in the data.

Looking at the parameter estimates, the *p* parameters are similar across regimes, but the *n* parameter is much lower in the high financial development regime. It is this switch in parameters that causes growth to be more negatively skewed with high financial development. In a regime of low economic and financial development, 86.44% of the variance is driven by the good environment, positively skewed shock; in the regime of high economic and financial development, 67.25% of the variance is driven by the bad environment, negatively skewed shock. In the other model, the good environment, positively skewed shocks account for 66.07% of the total variance. Note that the *p*-variable is quite low in that regime, potentially generating large positive skewness. In the high development regime, the bad environment variable only accounts for 43.75% of the total variance, but it is very negatively skewed helping to generate severe recessions.

Of course, this model is extremely parsimonious and cannot fit all empirical facts. Apart from the link between skewness and volatility, useful empirical facts also include the cumulative output loss of banking crises, reported to be 10% in Abiad, Balakrishnan, Brooks, Leigh, and Tytell (2009), or the average annual growth rates of catch-up economies, which Szirmai (2012) reports to be between 6% and 12%. This would also require us to model the mean of the growth process, which is outside the scope of the paper.

VI. Conclusion

In a sample of 110 countries during the 1960–2009 period, the volatility and skewness of GDP growth are positively correlated in the cross-section. This fact is novel and somewhat puzzling, especially when juxtaposed with a negative temporal correlation between volatility and skewness observed in panel analysis with country fixed effects. We argue that existing models have a hard time providing an explanation for this stylized fact. For example, in a number of business cycle theories, the skewness of GDP growth is hardwired in the business cycle due to learning asymmetries and so is orthogonal to the standard deviation of the distribution of real shocks (e.g., Van Nieuwerburgh and Veldkamp, 2006). Theories of early development and industrialization (e.g., Acemoglu and Zilibotti, 1997) do not fully explain the prevalence of low-volatility low-skewness countries in the sample, and financial accelerator-type theories (e.g., Bernanke and Gertler, 1989; Kiyotaki and Moore, 1997) have no mechanism for generating a high-volatility positive-skewness growth profile in developing economies.

We argue that there are two main, disjoint forces at play in the cross-section. First, a number of developing countries experience abrupt economic expansions, which can be short-lived ("growth spurts") or sustained ("growth miracles"). While some are related to industrialization, many are the outcome of the discovery and exploitation of natural resources, and others are due to macroeconomic stabilisation following political conflict. Second, a number of developed countries experience periods of low volatility, followed by systemic financial crises and large macroeconomic contractions, a mechanism consistent with the narrative in Minsky (1986) and Brunnermeier and Sannikov (2014). While such countries experience the highest volatility during the contractions (explaining the temporally negative association between volatility and skewness), the *relative* magnitude of the contraction can be inversely related to the preceding long-term volatility. These two phenomena jointly explain the co-existence of high-volatility positive-skewness and of low-volatility negative-skewness countries in the cross-section. They are illustrated in Figure 4 where the growth spurt countries occupy the upper right quadrant of the data points, and the financially developed countries that experience high levels of aggregate private leverage occupy the lower left quadrant.

While we invoke two separate mechanisms to explain the positive correlation between volatility and skewness in the cross-section, our data contains examples of a single country subject to both mechanisms in the long run. Figure 5 presents the evolution of GDP growth in Japan between 1950 and 2009. The first period, between 1951 and 1973, is characterized by high albeit volatile growth, following rapid industrialization in the wake of WWII. The second period, between 1975 and 2009, is a period of slower economic growth and lower volatility, especially after 1991. This same period contains two systemic financial crises, the one following the dual stock market and real estate boom of the 1980s and the global financial crisis of 2008–09. Thus, Japan illustrates how a country can in a fairly short time period go from an emerging industrializing economy characterized by high, volatile, positively-skewed growth process to a low-growth low-volatility industrialized country with a highly developed financial sector[10] that can accumulate excessive debt and cause a systemic crisis.

Our evidence has implications for the calibration of various business cycle models, especially in emerging markets. Kydland and Zarazaga (2002) and Aguiar and Gopinath (2007), among others, have suggested that a Real Business Cycle (RBC) model driven by permanent shocks to productivity can replicate satisfactorily business cycles in developing countries, in particular the behaviour of output and consumption volatility. Our evidence suggests that in

[10] After Iceland in 2006 and Cyprus in 2009, Japan in 1998 had the highest ratio of private credit to GDP in our sample, at 2.31.

modelling business cycles in emerging markets, it is important to provide mechanisms matching higher order moments, too. In particular, a calibration of RBC models in emerging markets should be simultaneously mindful of the positive relation between volatility and skewness over the long-run and of the lack of a negative short-run relation between the second and third moment of output growth, which is nonetheless prevalent in developed economies.

Recent unified growth models provide an endogenous mechanism for the transition from pre- to post-industrialization based on the accumulation of knowledge (Galor and Weil, 2000; Hansen and Prescott, 2002). However, we are not aware of growth models that also capture the "late" stage of development characterized by low volatility and occasional severe recessions led by financial crises. In Section V, we motivate our empirical findings with a data generating process where per capita growth is subject to two separate non-Gaussian shocks, one positively skewed which dominates at early stages of economic development, and one negatively skewed which dominates at later stages of financial development. However, the evidence presented in this paper calls for thorough model-building endeavors in this direction.

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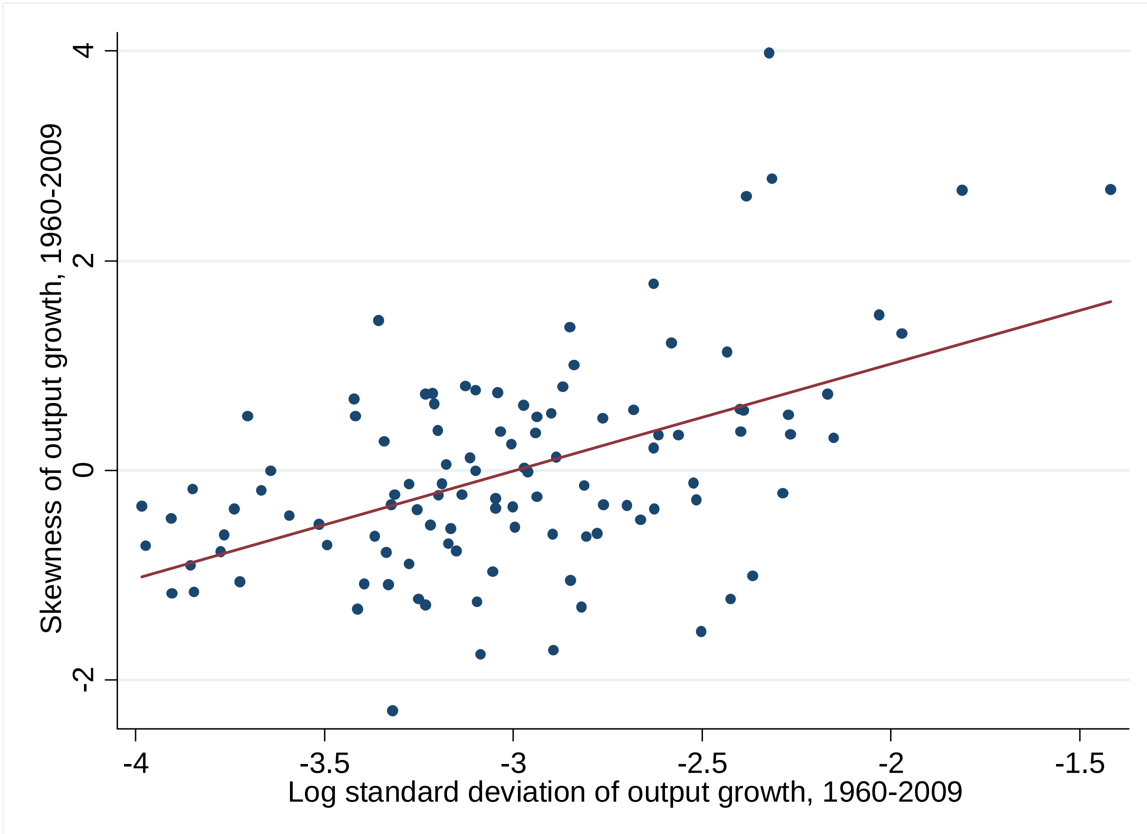
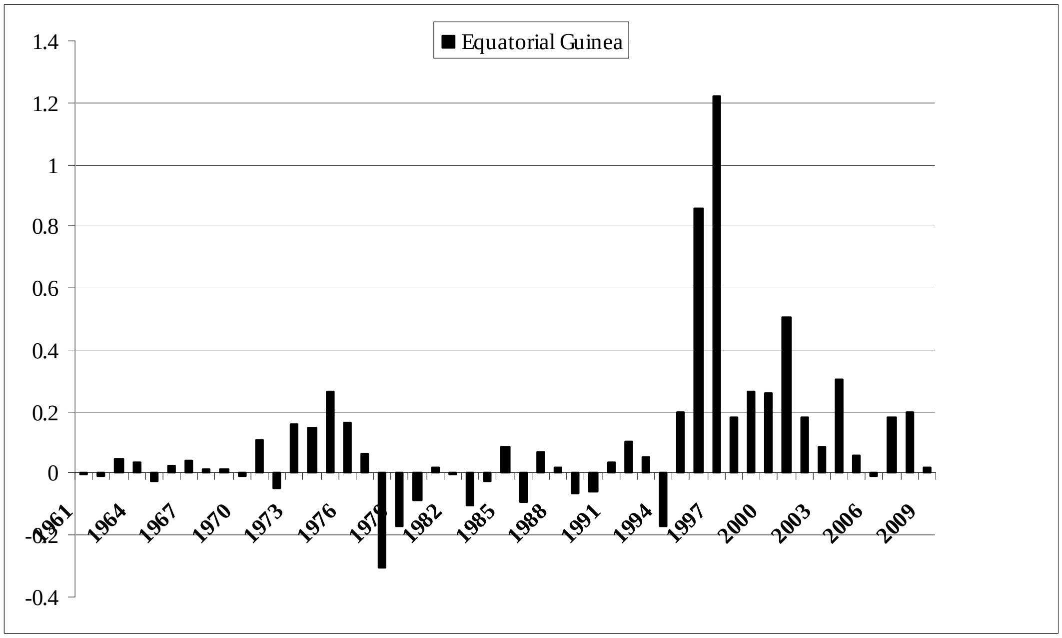
Figure 1 – Skewness of Output Growth against Log Standard Deviation of Output Growth, 110 Countries, 1960–2009

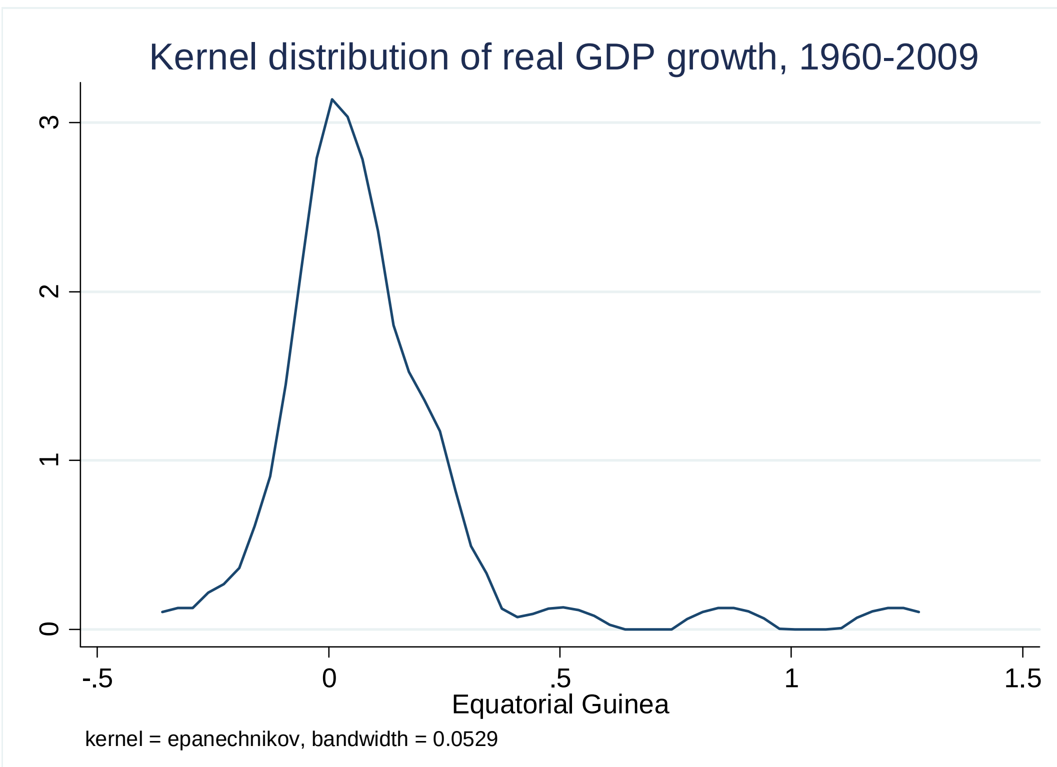


Notes: This figure plots the Fischer-Pearson coefficient of skewness of per capita GDP growth against the natural logarithm of the standard deviation of per capita GDP growth, both calculated over the period 1960–2009, for 110 countries. Data on GDP per capita come from the Penn Tables 7.0.

Figure 2 – Output Growth, Equatorial Guinea

Growth = 0.098; St. dev. = 0.242; Skewness = 2.676

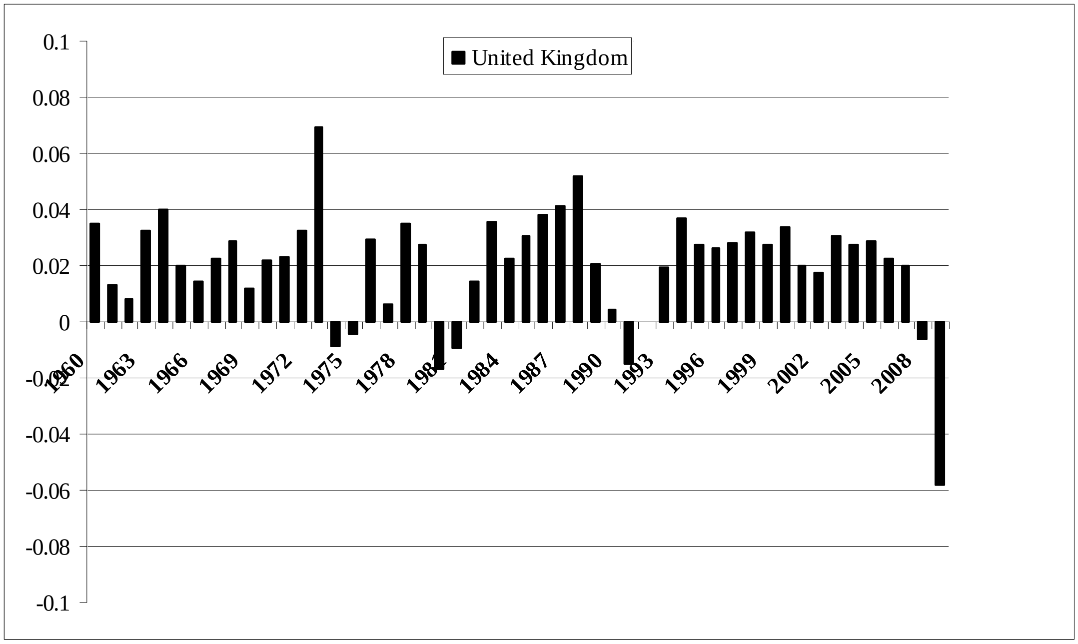


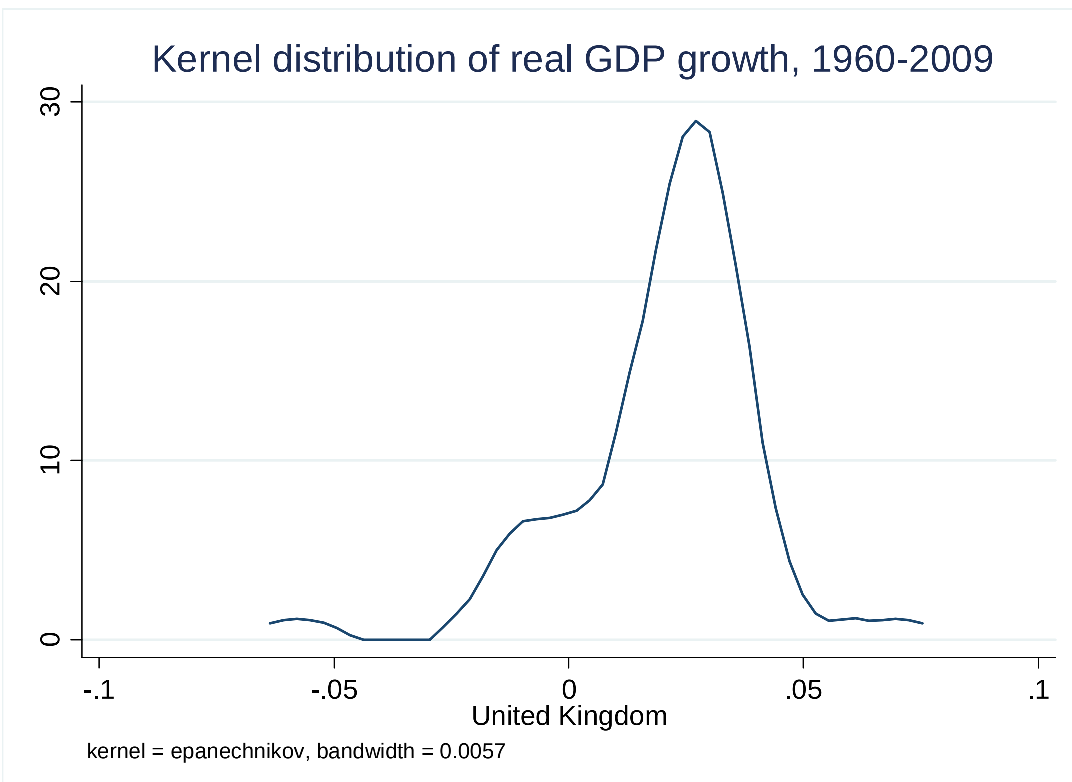


Notes: The figures plot the per capita GDP growth for Equatorial Guinea over the period 1960–2009, and the kernel distribution of the underlying per capita GDP growth rates over the same period. Average growth and the standard deviation and the skewness of growth rates are calculated over the entire period.

Figure 3 – Output Growth, United Kingdom

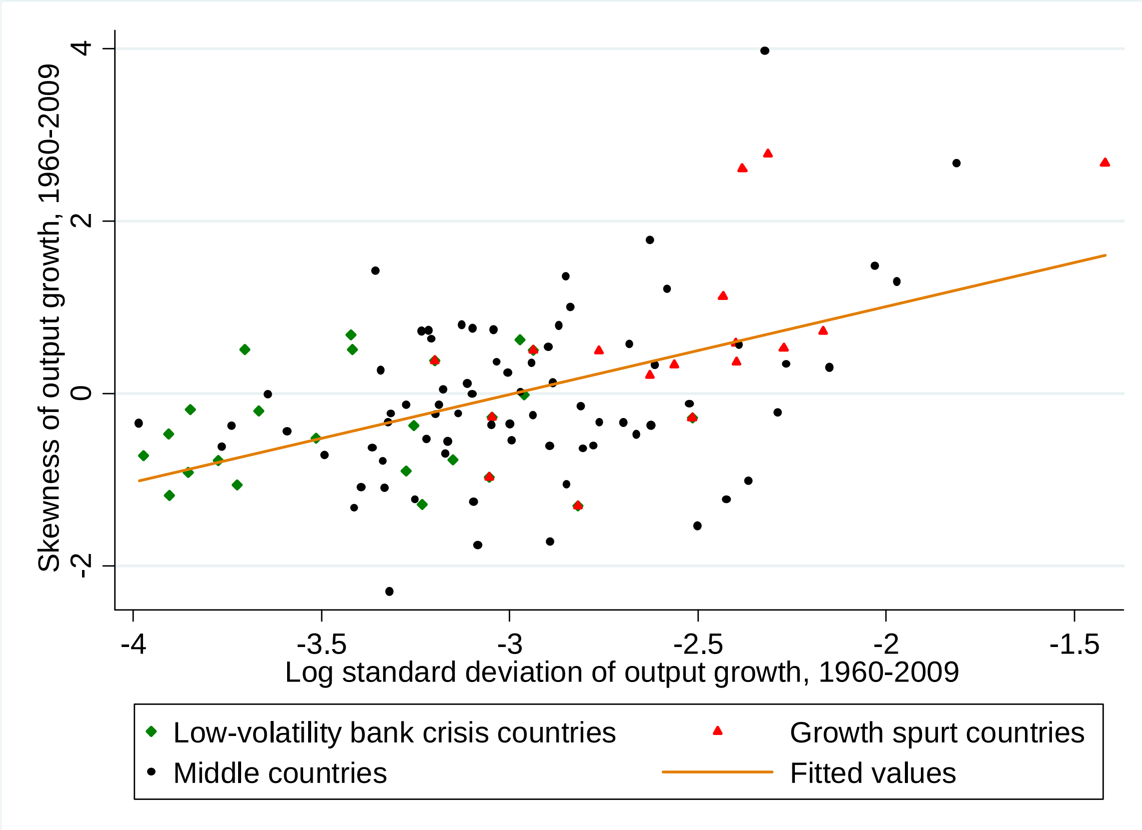
Growth = 0.008; St. dev. = 0.020; Skewness = -1.176





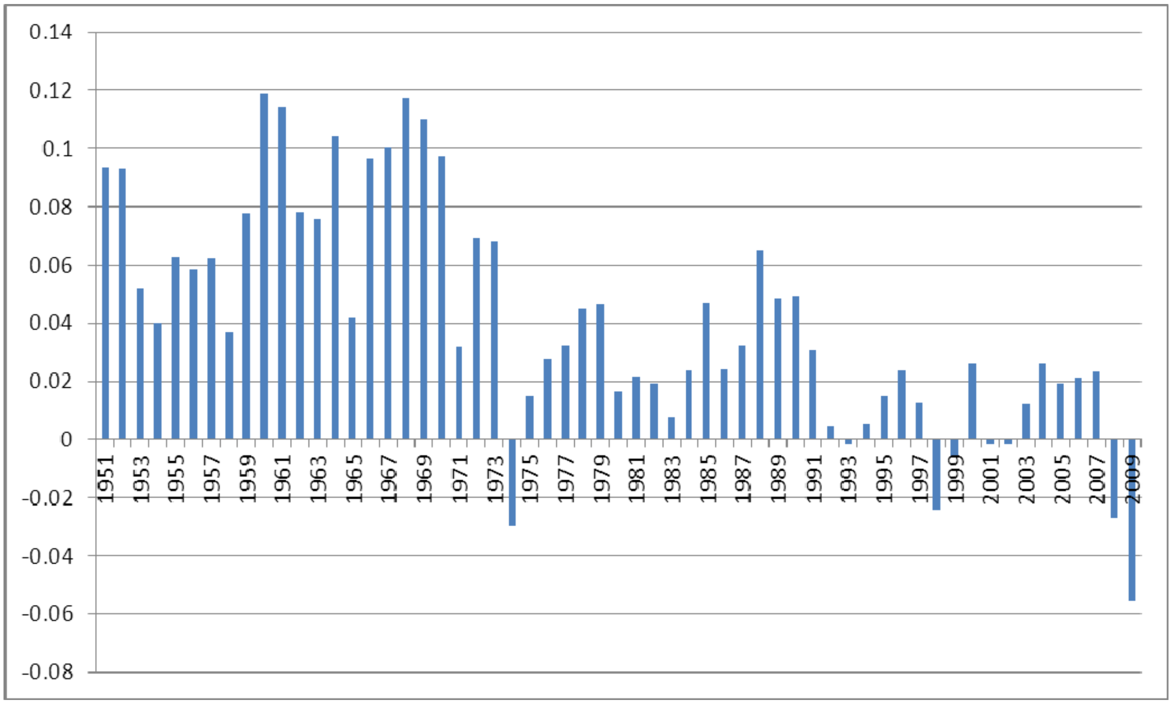
Notes: The figures plot the per capita GDP growth for the United Kingdom over the period 1960–2009, and the kernel distribution of the underlying per capita GDP growth rates over the same period. Average growth and the standard deviation and the skewness of growth rates are calculated over the entire period.

Figure 4 – Low Volatility Bank Crisis Countries and Growth Spurt Countries



Notes: This figure plots the Fischer-Pearson coefficient of skewness of per capita GDP growth against the natural logarithm of the standard deviation of per capita GDP growth, both calculated over the period 1960–2009, for 110 countries. Countries in red experienced at least one growth spurt event (i.e., a 5-year period during which the average growth rate is more than two standard deviations higher than the sample average across all countries and time periods, and during which the country recorded at least two years with a growth rate that is at least twice higher than the sample average) during the sample period. Countries in blue experienced at least one systemic banking crisis, according to the classification in Laeven and Valencia (2010), during the sample period. Data on GDP per capita come from the Penn Tables 7.0.

Figure 5 – Output Growth, Japan



Notes: The figure plots the per capita GDP growth for Japan over the period 1960–2009.

Table 1 – The Skewness of GDP Growth and the Natural Logarithm of the Standard Deviation of GDP Growth: Cross-Sectional Results

	Full sample (1)	Full sample, growth controls (2)	1st quartile, initial GDP per capita (3)	4th quartile, initial GDP per capita (4)	1st quartile, growth (5)	4th quartile, growth (6)	1960–1984 (7)	1985–2009 (8)
Log (St. dev. GDP growth)	1.022***	0.908***	1.398***	0.684**	1.075***	1.104***	0.366**	1.104***
	(0.167)	(0.209)	(0.307)	(0.266)	(0.323)	(0.163)	(0.142)	(0.163)
Initial GDP per capital		-0.088						
		(0.095)						
Average GDP growth		-0.994						
		(5.334)						
Observations	110	110	28	28	28	28	110	110
R-squared	0.25	0.26	0.42	0.17	0.20	0.30	0.06	0.30

Notes: The skewness and the standard deviation of GDP growth are calculated for all countries in the sample for the 1960–2009 period (column (1)–(6)), for the 1960–1984 period (column (7)), and for the 1985–2009 period (column (8)). Data on GDP growth, calculated as percentage change in per capita GDP from one year to the next, from the 7.0 update of the Penn World Table are used. Initial GDP per capita quartiles are determined based on GDP per capita in 1960. Growth quartiles are determined based on average GDP growth over the 1960–2009 period. Standard errors are provided in parentheses. *** indicates a p-value less than 0.01, and ** indicates a p-value less than 0.05.

Table 2 – The Skewness of GDP Growth and the Natural Logarithm of the Standard Deviation of GDP Growth: Log growth

	Full sample (1)	Full sample, growth controls (2)	1st quartile, initial GDP per capita (3)	4th quartile, initial GDP per capita (4)	1st quartile, growth (5)	4th quartile, growth (6)	1960–1984 (7)	1985–2009 (8)
Log (St. dev. GDP growth)	0.533***	0.297#	0.886***	0.671**	0.117	0.576*	0.092	0.722***
	(0.170)	(0.209)	(0.316)	(0.237)	(0.530)	(0.356)	(0.144)	(0.171)
Initial GDP per capital		-0.181**						
		(0.093)						
Average GDP growth		0.960						
		(5.492)						
Observations	110	110	28	28	28	28	110	110
R-squared	0.08	0.09	0.20	0.21	0.01	0.06	0.01	0.13

Notes: The skewness and the standard deviation of GDP growth are calculated for all countries in the sample for the 1960–2009 period (column (1)–(6)), for the 1960–1984 period (column (7)), and for the 1985–2009 period (column (8)). Data on GDP growth, calculated as the difference in the logarithm of per capita GDP from one year to the next, from the 7.0 update of the Penn World Table are used. Initial GDP per capita quartiles are determined based on GDP per capita in 1960. Growth quartiles are determined based on average GDP growth over the 1960–2009 period. Standard errors are provided in parentheses. *** indicates a p-value less than 0.01, ** indicates a p-value less than 0.05, * indicates a p-value less than 0.10, and # indicates a p-value less than 0.15.

Table 3 – The Skewness of GDP Growth and the Natural Logarithm of the Standard Deviation of GDP Growth: Cross-Sectional Results from Alternative Empirical Proxies and Data Sources

	Volatility (1)	Volatility, no outliers (2)	STAN quarterly data (3)	PWT 7.1 data (4)	PWT 7.0 and 7.1 data (5)	WDI data (6)	IFS data (7)
Log (St. dev. GDP growth)			0.864**	0.803***	0.797***	0.688***	0.522***
			(0.428)	(0.178)	(0.221)	(0.221)	(0.148)
St. dev. GDP growth	16.801***	19.633***					
	(2.473)	(4.260)					
Observations	110	101	33	110	55	89	142
R-squared	0.30	0.17	0.12	0.16	0.18	0.09	0.08

Notes: The skewness and the standard deviation of GDP growth are calculated for all countries in the sample for the 1960–2009 period. In columns (1) and (2), the right-hand side variable is the standard deviation of GDP growth over 1960–2009, in levels. In column (2), we exclude countries with long-term volatility of GDP growth of more than ten percent. In column (3), quarterly data on GDP growth from the STAN Dataset on Industrial Analysis are used to calculate long-run volatility and skewness. In column (4), data on GDP growth are from the 7.1 update of the Penn World Table. In column (5), data on GDP growth are from the 7.0 update of the Penn World Tables, and the top 50% of the countries in terms of the difference in skewness between the 7.0 and the 7.1 update are dropped. In column (6), data on GDP growth are from the World Bank's World Development Indicators. In column (7), data on GDP growth are from the IMF's International Financial Statistics. Standard errors are provided in parentheses. *** indicates a p-value less than 0.01, and ** indicates a p-value less than 0.05.

Table 4 – The Skewness of GDP Growth and the Natural Logarithm of the Standard Deviation of GDP Growth: Panel Regression Results

	Full sample (1)	Full sample (2)	Full sample, autocorrelation (3)	Full sample (4)	Quarterly data (5)	1st quartile (6)	4th quartile (7)	Full sample (8)
Log (St. dev. 5-year GDP growth)	-0.059*	-0.058*	-0.058	-0.064*	-0.276*	0.013	-0.213***	0.512***
	(0.034)	(0.034)	(0.039)	(0.036)	(0.165)	(0.063)	(0.075)	(0.199)
1-period lagged 5-year GDP skewness				-0.107***				
				(0.034)				
Log (GDP per capita)								-0.293***
								(0.103)
Log (5-year output volatility)× Log (GDP per capita)								-0.072***
								(0.025)
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Period dummies	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1100	1100	1100	990	169	280	280	280
Countries	110	110	110	110	33	28	28	28
R-squared	0.01	0.03	0.03	0.03	0.33	0.01	0.20	0.06

Notes: The skewness and the standard deviation of GDP growth are calculated for all countries in the sample for five-year non-overlapping periods over 1960–2009. Annual data on GDP growth from the 7.0 update of the Penn World Table are used (columns (1)–(4) and columns (6)–(8)). In column (5), quarterly data on GDP growth from the STAN Dataset on Industrial Analysis are used. GDP per capita refers to the country's per capita GDP in the beginning of each 5 year period. The regressions include country (column (1)) and country and period (columns (2)–(8)) fixed effects. In column (3), a Newey-West adjustment of the standard errors for panel-specific autocorrelation with 4 lags is used. In columns (6) and (7), quartiles are determined based on GDP per capita in 1960. Standard errors are provided in parentheses. *** indicates a p-value less than 0.01, and * indicates a p-value less than 0.10.

Table 5 – The Skewness of GDP Growth and the Natural Logarithm of the Standard Deviation of GDP Growth: Country Heterogeneity

	Recession (1)	Banking crisis (2)	Private credit / GDP (3)	Trade liberalization (4)	Terms of trade (5)	Government spending/GDP (6)	Growth spurt (7)	Horse race (8)
Log (St. dev. 5-year GDP growth)	0.138** (0.056)	-0.037 (0.036)	0.049 (0.048)	-0.017 (0.043)	-0.145** (0.072)	-0.159*** (0.061)	-0.092*** (0.035)	0.147 (0.098)
Recession	-0.837*** (0.241)							-0.843*** (0.290)
Banking crisis		-0.391 (0.323)						-0.225 (0.333)
Private credit / GDP			-1.342*** (0.334)					-0.742** (0.356)
Trade liberalization				-0.396* (0.232)				-0.261 (0.263)
St. dev. (Terms of trade)					6.021 (3.930)			---------
Government spending / GDP						2.389 (1.456)		0.940 (1.586)
Growth spurt							1.775*** (0.504)	1.301** (0.528)
Log (St. dev. 5-year GDP growth)× Recession	-0.111* (0.064)							-0.124* (0.076)
Log (St. dev. 5-year GDP growth)× Banking crisis		-0.056 (0.096)						-0.018 (0.098)
Log (St. dev. 5-year GDP growth)× Private credit/GDP			-0.357*** (0.089)					-0.212** (0.096)
Log (St. dev. 5-year GDP growth)× Trade liberalization				-0.106 (0.065)				-0.023 (0.072)
Log (St. dev. 5-year GDP growth)× Log (Terms of trade)					1.946* (1.138)			---------
Log (St. dev. 5-year GDP growth)× Government spending/ GDP						0.907** (0.453)		0.426 (0.499)
Log (St. dev. 5-year GDP growth)× Growth spurt							0.481** (0.202)	0.432** (0.212)
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Period dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1100	1100	977	1100	569	1100	1100	977
R-squared	0.05	0.05	0.06	0.05	0.03	0.05	0.09	0.09

Notes: The skewness and the standard deviation of GDP growth are calculated for all countries in the sample for five-year non-overlapping periods over 1960–2009. Data on GDP growth from the 7.0 update of the Penn World Table are used. Recession is an indicator variable equal to 1 if the country experiences at least 1 year of negative GDP growth during each respective five-year period. Banking crisis is an indicator variable equal to 1 if the country experiences a systemic banking crisis as defined by Laeven and Valencia (2010) during each respective five-year period. Private credit / GDP is the average of the ratio of credit to the private sector to GDP during each respective 5-year period. Trade liberalization is an indicator variable equal to 1 if the country has liberalized trade according to the Wacziarg and Welch (2008) classification at the beginning of each respective five-year period. St. dev. (Terms of trade) is the standard deviation of the first (log) difference of the terms of trade over each respective 5-year period. Growth spurt is an indicator variable equal to 1 if the country experiences an average growth rate higher than the sample average by two standard deviations or more during each respective five-year period. The threshold corresponds to an average annual growth of 0.095 over five years. All regressions include country and period fixed effects. Standard errors are provided in parentheses. *** indicates a p-value less than 0.01, ** indicates a p-value less than 0.05, * and indicates a p-value less than 0.10.

Table 6 – Growth Spurt Episodes

Country	Period	Average annual GDP growth	GDP skewness, 1960-2009	Event
Botswana	1970–1974	0.194	0.531	In 1966, newly independent Botswana embarks on a program of economic liberalization under Prime Minister (and later President) Khama.
	1985–1989	0.100	0.531	Diamonds are discovered. Diamonds now constitute 62% of Botswana's exports.
Chad	2000–2004	0.112	1.132	Oil production starts in 2003. By 2008, oil revenues constitute 41% of GDP.
China	2005–2009	0.097	-1.304	The economy of China growth by more than 11.5% annually between 2005 and 2007, fuelled by strong foreign demand for its exports.
Republic of the	1970–1974	0.103	0.332	Rapid increase in oil production and exports.
Congo	1980–1984	0.097	0.332	Oil production continues to expand. Per capita GDP more than doubles between 1970 and 1984.
Cyprus	1965–1969	0.104	-0.283	Rapid transition from agriculture to manufacturing in the wake of gaining independence from Great Britain.
	1975–1979	0.102	-0.283	The economy recovers after the 1974-1975 war during which per capita GDP declined by 31% in two years.
Equatorial Guinea	1995–1999	0.545	2.676	Discovery and subsequent exploration of large oil reserves. As a result, Equatorial
	2000–2004	0.266	2.676	Guinea has emerged as the third-largest oil producer in Sub-Saharan Africa.
Gabon	1970–1974	0.113	0.585	Oil was discovered offshore in the early 1970s. At present, the oil sector accounts for 50% of GDP and 80% of exports.
Gambia	2005–2009	0.115	1.780	Strong sustained economic growth driven by tourism and agricultural exports.
Hong Kong	1960–1964	0.119	0.505	Hong Kong continues the policy of rapid industrialization embarked upon in the 1950s.
Japan	1960–1964	0.098	0.383	Rapid industrialization, continuing a trend since the early 1950s.
Malawi	1965–1969	0.136	0.726	Rapid economic growth based on the export of agricultural products.
Malaysia	1970–1974	0.099	-0.269	Rapid industrialization from a mining- and agriculture-based economy to a multisector economy
Mauritania	1960–1964	0.126	2.613	Iron mines start operating in 1963.
Morocco	1960–1964	0.109	0.496	The government embarks on a 5-year plan for the development and modernization of the agricultural sector.
Nigeria	1970–1974	0.102	0.369	Rapid expansion of oil production. In 2000, oil and gas exports represent more than 98% of export earnings and 83% of government revenues.
Romania	1975–1979	0.096	-0.636	Rapid state-enforced industrialization.
Singapore	1970–1974	0.102	-0.969	Following separation from Malaysia in 1965, the government adopts a pro-foreign investment, export-oriented economic policy combined with investment in strategic government-owned companies.
Trinidad and	2005–2009	0.100	0.216	A global demand-driven boom in the production of oil, petrochemicals, and liquefied

Tobago				natural gas.
Zambia	2000–2004	0.150	2.780	Substantial growth in copper exports due to rising world prices. At present, copper and copper products constitutes 69% of Zambia's exports.

Table 7 – The Skewness of GDP Growth and the Natural Logarithm of the Standard Deviation of GDP Growth: Testing for the "Volatility Paradox"

	Full sample (1)	Top 33% private credit (2)	Full sample (3)	Top 33% private credit (4)
1-period lagged log (St. dev. 5-year GDP growth) × 1-period lagged private credit / GDP	0.058	0.201*		
	(0.087)	(0.123)		
1-period lagged log (St. dev. 5-year GDP growth)	-0.011	-0.211*		
	(0.049)	(0.127)		
Low volatility duration × 1-period lagged private credit / GDP			0.049	-0.440**
			(0.146)	(0.210)
Low volatility duration			-0.022	0.431**
			(0.106)	(0.192)
1-period lagged private credit / GDP	0.334	0.957*	0.030	0.211
	(0.371)	(0.508)	(0.113)	(0.164)
Country variables	Yes	Yes	Yes	Yes
Country dummies	Yes	Yes	Yes	Yes
Period dummies	Yes	Yes	Yes	Yes
Observations	901	331	977	331
Countries	108	36	108	36
R-squared	0.08	0.19	0.07	0.18

Notes: The skewness of GDP growth, the standard deviation of GDP growth, and the ratio of private sector to GDP are calculated for all countries in the sample for 10 five-year periods over 1960–2009. Low volatility duration refers to the sum of consecutive periods during which the country experiences volatility of GDP growth lower by two standard deviations or more than the sample average. The current period is given a weight of 1, the previous period a weight of 0.75, the one before a weight of 2.31, etc. (see Section IV for details). Data on GDP growth from the 7.0 update of the Penn World Table are used. The regressions include the rest of the explanatory variables from Table 5, as well as country and period fixed effects. Standard errors are provided in parentheses. ** indicates a p-value less than 0.05, and * indicates a p-value less than 0.10.

Table 8 – Estimating a Bad Environment Good Environment Model

Panel A. Model Parameters

	Criterion 1 (1)	Criterion 2 (2)
σ_{yp}^{L}	0.1577	0.1828
σ_{yp}^{H}	0.1458	0.0905
σ_{yn}^{L}	0.0213	0.0124
σ_{yn}^{H}	0.2413	0.2814
p^{L}	0.1449	0.0919
p^{H}	0.0739	0.2629
n^{L}	1.8456	9.6834
n^{H}	0.0289	0.0174

Panel B. Empirical and Implied Moments of Economic Growth

	Empirical moments (1)	Implied moments, criterion 1 (2)	Implied moments, criterion 2 (3)
St. dev. [LL]	0.0753	0.0712*	0.0676*
Confidence interval	[0.0652, 0.0855]		
St. dev. [HL]	0.0550	0.0546*	0.0604*
Confidence interval	[0.0478, 0.0622]		
St. dev. [LH]	0.0621	0.0839	0.0667*
Confidence interval	[0.0551, 0.0690]		
St. dev. [HH]	0.0386	0.0704	0.0594
Confidence interval	[0.0349, 0.0423]		
Skew [LL]	3.4045	2.7309*	3.5188*
Confidence interval	[1.1997, 5.6094]		
Skew [HL]	0.9344	1.8004*	1.5992*
Confidence interval	[-0.0204, 1.8892]		
Skew [LH]	-0.1046	0.6449*	1.1670
Confidence interval	[-1.1159, 0.9068]		
Skew [HH]	-0.9037	-0.8892*	-1.8447*
Confidence interval	[-1.9691, 0.1617]		

Notes: The table reports the best-fit results that minimize the sum of squared residuals from eight moment conditions for the standard deviation and the unscaled skewness in the BEGE Model formulated in equations (2)–(8). The moment conditions are the differences between the empirical moments calculated using the underlying data, and the theoretical moments implied by the BEGE model. The weighting scheme multiplies unscaled skewness moment conditions by 100. Panel A reports the best-fit parameter estimates, for two criteria. Under Criterion 1, we impose p^{L} > 0.25; p^{H} > 0.2; and n^{H} > 0.15. Under Criterion 2, Skew[LL] > Skew[LH]; Skew[HL] > Skew[HH]; and the parameters yield statistics that are insignificantly different from the data for a minimum of 3 out of 4 standard deviation coefficients and for a minimum of 3 out of 4 skewness coefficients. Panel B reports the comparison between the empirical moments and the theoretical moments implied by the BEGE model at the best-fit parameter estimates, for the two criteria. Scaled skewness is calculated accordingly. * indicates that the model-implied moments are within a 95% confidence interval around the point estimates.

Appendix 1 – Description of Variables

Variable	Description
Standard deviation of GDP growth	Standard deviation of the growth rate of GDP. Calculated over the 1960–2009 in the cross-section regressions, or over non-overlapping 5-year periods in the panel regressions. The underlying data on GDP growth (GRGDPCH) come from the World Penn Tables.
Skewness of GDP growth	The skewness of the growth rate of GDP. Calculated over the 1960–2009 in the cross-section regressions, or over non-overlapping 5-year periods in the panel regressions. The underlying data on GDP growth (GRGDPCH) come from the World Penn Tables.
Initial GDP per capita	GDP per capita (RGDPCH) in 1960, from the Wold Penn Tables, in PPP converted 2005 constant prices.
GDP per capita	Average GDP per capita (RGDPCH) for non-overlapping 5-year periods, from the Wold Penn Tables, in PPP converted 2005 constant prices.
Recession	A dummy variable equal to 1 if the country experiences a negative growth in at least one year during each non-overlapping 5-year period. The underlying data on GDP growth (GRGDPCH) come from the World Penn Tables.
Banking crisis	A dummy equal to 1 if the country experiences a systemic banking crisis during each non-overlapping 5-year period. The underlying data come from Laeven and Valencia (2010).
Private credit / GDP	The value of total credits by financial intermediaries to the private sector in each country, excluding credit by central banks. From Beck et al. (2010).
Trade liberalization	A dummy equal to 0 (that is, a country is judged as “closed”) if any of the following five criteria holds: average tariffs are 40% or more; non-tariff barriers cover 40% or more of trade; the black market exchange rate is at least 20% lower than the official exchange rate; a state monopoly exists on major exports; and the economic system is socialist (see Wacziarg and Welch (2008)’s revision of the original Sachs and Warner (1995) classification of trade openness episodes)
Terms of trade	The percentage ratio of the export unit value indices to the import unit value indices, measured relative to the base year (2000). From the World Bank Development Indicators
Government spending	The share of government consumption of PPP converted GDP per capita at current prices. The underlying data (KG) come from the World Penn Tables.
Growth spurt	A dummy equal to 1 if over a non-overlapping 5-year period the country is experiencing a) average growth higher than 0.095 (which corresponds to growth higher than the average growth for the sample by two standard deviations), and b) at least two years of high growth (more than twice the sample average). The underlying data on GDP growth (GRGDPCH) come from the World Penn Tables.

Appendix 2 – Summary Statistics

Country	St. dev. of GDP growth	Skewness of GDP growth	Initial GDP per capita	GDP per capita	Recession	Banking crisis	Private credit / GDP	Trade liberalization	Government spending	Growth spurt
Algeria	0.082	-1.533	4078.73	4586.25	0.9	0.1	0.308	0.0	0.12	0
Argentina	0.047	-0.360	6243.57	7957.05	0.9	0.5	0.182	0.3	0.08	0
Australia	0.019	-0.721	13116.90	23875.46	0.4	0.0	0.555	0.9	0.10	0
Austria	0.025	0.514	10632.79	23130.55	0.3	0.1	0.753	1.0	0.10	0
Bangladesh	0.039	-1.227	802.07	839.15	0.7	0.1	0.167	0.2	0.02	0
Barbados	0.053	-0.252	7647.78	17739.93	0.8	0.0	0.511	0.8	0.15	0
Belgium	0.023	-0.616	10240.59	22071.37	0.4	0.1	0.429	1.0	0.11	0
Benin	0.057	0.793	801.33	1001.16	0.8	0.2	0.154	0.4	0.10	0
Bolivia	0.036	-2.291	2713.58	3043.50	0.7	0.2	0.252	0.5	0.08	0
Botswana	0.103	0.531	578.04	4047.99	0.8	0.0	0.140	0.6	0.10	0.2
Brazil	0.042	0.053	2581.05	5664.59	0.5	0.1	0.426	0.3	0.11	0
Burkina Faso	0.058	1.364	589.88	662.76	0.9	0.1	0.106	0.2	0.14	0
Burundi	0.076	1.215	258.73	356.28	1.0	0.2	0.104	0.2	0.18	0
Cameroon	0.056	0.128	1241.29	1688.94	0.9	0.3	0.161	0.3	0.06	0
Canada	0.021	-0.911	12987.91	24286.42	0.4	0.0	0.816	1.0	0.10	0
Cape Verde	0.070	-0.471	1052.97	1613.07	0.5	0.1	0.315	0.3	0.13	0
Central African	0.043	-0.234	1073.57	840.03	1.0	0.2	0.103	0.0	0.19	0
Chad	0.088	1.132	818.61	842.15	1.0	0.3	0.076	0.0	0.51	0.1
Chile	0.055	-1.715	3780.41	5990.72	0.8	0.3	0.455	0.6	0.07	0
China	0.060	-1.304	846.79	1931.41	0.5	0.1	0.859	0.0	0.16	0.1
Colombia	0.035	1.427	2478.32	4244.86	0.8	0.3	0.264	0.4	0.05	0
Comoros	0.048	0.744	757.21	1167.24	0.9	0.0	0.123	0.0	0.32	0
Congo, Dem. Rep.	0.131	1.486	1092.26	709.63	1.0	0.3	0.022	0.0	0.06	0
Congo, Rep.	0.077	0.332	791.10	1773.67	0.8	0.0	0.144	0.0	0.11	0.2
Costa Rica	0.033	-1.326	5023.87	7468.50	0.7	0.3	0.246	0.4	0.18	0
Cote d'Ivoire	0.050	0.246	977.11	1417.37	1.0	0.0	0.260	0.0	0.07	0
Cyprus	0.081	-0.283	3335.81	10511.54	0.7	0.0	1.304	1.0	0.09	0.2
Denmark	0.026	-0.196	12122.61	23297.79	0.8	0.1	0.698	1.0	0.10	0
Dominican Republic	0.050	-0.349	2354.83	4584.48	0.6	0.1	0.223	0.3	0.09	0
Ecuador	0.045	-0.006	2806.84	4463.43	0.7	0.4	0.219	0.3	0.07	0
Egypt	0.044	0.801	1036.31	2321.42	0.4	0.1	0.280	0.3	0.11	0
El Salvador	0.034	-1.085	3397.20	4514.40	0.8	0.0	0.304	0.4	0.12	0
Equatorial Guinea	0.242	2.676	567.66	2704.78	0.8	0.1	0.097	0.0	0.16	0.2
Ethiopia	0.069	0.575	388.04	435.67	0.7	0.0	0.151	0.2	0.08	0

Fiji	0.059	1.003	1977.48	3276.75	1.0	0.0	0.250	0.0	0.10	0
Finland	0.036	-1.091	9080.45	19815.52	0.3	0.2	0.571	1.0	0.10	0
France	0.020	-0.463	10101.31	21161.19	0.3	0.1	0.803	1.0	0.10	0
Gabon	0.091	0.585	4518.43	10394.44	0.8	0.0	0.143	0.0	0.04	0.1
Gambia	0.072	1.780	958.06	899.49	0.9	0.0	0.156	0.5	0.19	0
Ghana	0.116	0.308	603.04	820.34	0.8	0.1	0.073	0.5	0.12	0
Greece	0.038	-0.130	6181.45	16073.07	0.5	0.1	0.365	1.0	0.09	0
Guatemala	0.026	-0.008	2986.78	4669.33	0.4	0.0	0.168	0.4	0.10	0
Guinea	0.042	-0.553	977.34	863.45	0.9	0.2	0.043	0.4	0.10	0
Guinea-Bissau	0.163	2.674	344.06	461.82	0.9	0.1	0.093	0.4	0.13	0
Haiti	0.044	0.120	1887.87	1775.71	0.9	0.2	0.134	0.0	0.17	0
Honduras	0.036	-0.233	2235.43	2856.93	0.8	0.0	0.296	0.3	0.18	0
Hong Kong	0.053	0.505	3339.60	16661.88	0.5	0.0	1.492	1.0	0.03	0.1
Iceland	0.052	-0.013	10500.92	23493.54	1.0	0.1	0.706	1.0	0.08	0
India	0.035	0.274	711.38	1288.00	0.4	0.1	0.223	0.3	0.11	0
Indonesia	0.046	-1.755	692.51	1876.05	0.4	0.2	0.308	0.8	0.08	0
Iran	0.089	-1.229	4403.94	7197.16	0.7	0.0	0.227	0.0	0.13	0
Ireland	0.038	-0.895	6970.00	17150.76	0.3	0.1	0.659	0.8	0.07	0
Israel	0.039	0.726	7093.35	16181.94	0.7	0.1	0.559	0.5	0.17	0
Italy	0.028	-0.437	8858.11	20113.62	0.4	0.0	0.655	1.0	0.10	0
Jamaica	0.040	0.636	5609.14	7256.12	0.9	0.1	0.237	0.4	0.13	0
Japan	0.041	0.383	5850.43	20382.80	0.5	0.2	1.496	0.9	0.10	0.1
Jordan	0.080	-0.120	2681.55	3676.70	1.0	0.2	0.524	0.9	0.10	0
Kenya	0.036	-0.327	1020.12	1094.20	1.0	0.2	0.245	0.3	0.05	0
Korea	0.045	-1.257	1782.05	9242.75	0.4	0.1	0.492	0.8	0.10	0
Lesotho	0.073	0.335	400.74	780.33	0.9	0.0	0.132	0.0	0.05	0
Luxembourg	0.039	-0.371	17353.40	37006.07	0.5	0.1	1.026	1.0	0.07	0
Madagascar	0.053	0.356	841.97	840.31	1.0	0.1	0.139	0.2	0.08	0
Malawi	0.115	0.726	329.07	600.62	1.0	0.0	0.044	0.0	0.11	0.1
Malaysia	0.048	-0.269	1470.16	5261.45	0.5	0.1	0.707	0.9	0.05	0.1
Mali	0.063	-0.329	541.37	611.97	0.9	0.2	0.164	0.4	0.12	0
Mauritania	0.092	2.613	586.95	1211.78	1.0	0.1	0.219	0.3	0.22	0.1
Mauritius	0.062	-0.603	2208.24	4261.45	0.5	0.0	0.444	0.8	0.07	0
Mexico	0.042	-0.698	4588.56	8242.05	0.7	0.4	0.223	0.4	0.03	0
Morocco	0.063	0.496	736.76	1973.31	0.9	0.1	0.249	0.5	0.04	0.1
Mozambique	0.050	-0.540	357.70	428.79	0.8	0.2	0.148	0.3	0.07	0
Namibia	0.055	0.541	2481.49	3432.49	1.0	0.0	0.431	0.0	0.08	0

Nepal	0.030	-0.714	632.24	811.82	0.7	0.1	0.142	0.3	0.09	0
Netherlands	0.021	-0.182	13017.26	24037.63	0.5	0.1	0.901	1.0	0.16	0
New Zealand	0.033	0.682	13802.20	19268.00	0.8	0.0	0.557	0.4	0.10	0
Nicaragua	0.094	-1.011	2546.28	2832.29	0.9	0.2	0.251	0.3	0.21	0
Niger	0.072	-0.366	746.19	624.01	1.0	0.2	0.091	0.3	0.15	0
Nigeria	0.091	0.369	1527.86	1381.29	0.8	0.2	0.117	0.0	0.02	0.1
Norway	0.019	-0.343	12283.61	28642.44	0.2	0.0	0.461	1.0	0.08	0
Pakistan	0.035	-0.628	727.62	1518.41	0.7	0.0	0.241	0.1	0.10	0
Panama	0.051	0.623	2170.94	5009.23	0.7	0.1	0.602	0.2	0.18	0
Papua New Guinea	0.098	3.981	886.96	1727.68	0.7	0.0	0.186	0.0	0.22	0
Paraguay	0.040	0.735	1847.32	3006.74	0.8	0.1	0.196	0.4	0.05	0
Peru	0.058	-1.049	3758.60	4938.39	0.9	0.1	0.171	0.3	0.05	0
Philippines	0.041	-0.240	1314.36	1926.18	0.8	0.4	0.272	0.4	0.06	0
Portugal	0.043	-0.770	4002.81	11744.87	0.5	0.1	0.778	1.0	0.05	0
Puerto Rico	0.041	-0.129	5716.37	15094.00	0.6	0.0	--------	0.0	0.09	0
Romania	0.061	-0.636	1511.20	5463.41	0.5	0.1	0.134	0.3	0.08	0
Rwanda	0.139	1.301	860.19	755.88	0.9	0.0	0.062	0.0	0.32	0
Senegal	0.048	0.366	1421.40	1262.30	0.9	0.2	0.218	0.0	0.07	0
Seychelles	0.104	0.343	3677.19	10639.28	0.8	0.0	0.195	0.0	0.31	0
Singapore	0.047	-0.969	4299.92	19227.81	0.5	0.0	0.743	0.9	0.09	0.1
South Africa	0.030	-0.512	3849.71	5467.06	0.6	0.0	0.905	0.3	0.06	0
Spain	0.033	0.516	6294.55	16890.80	0.4	0.3	0.822	1.0	0.07	0
Sri Lanka	0.024	-0.369	765.12	1751.23	0.4	0.2	0.189	0.3	0.09	0
Sweden	0.021	-1.159	13322.57	23531.33	0.5	0.3	0.849	1.0	0.11	0
Switzerland	0.024	-1.062	18955.18	29666.87	0.6	0.1	1.289	1.0	0.05	0
Syria	0.092	0.567	1600.01	2748.23	0.9	0.0	0.105	0.0	0.09	0
Taiwan	0.036	-0.781	1826.40	11174.34	0.2	0.0	--------	0.0	0.18	0
Tanzania	0.045	0.760	481.38	657.20	0.7	0.1	0.089	0.3	0.08	0
Thailand	0.039	-1.283	961.44	3454.02	0.5	0.3	0.655	1.0	0.07	0
Togo	0.067	-0.334	765.23	1020.72	0.8	0.1	0.181	0.0	0.10	0
Trinidad and Tobago	0.072	0.216	6449.94	11359.22	0.7	0.0	0.325	0.3	0.07	0.1
Turkey	0.040	-0.522	3243.48	6011.44	0.9	0.2	0.187	0.4	0.05	0
Uganda	0.051	0.018	655.38	707.63	0.8	0.1	0.062	0.4	0.15	0
United Kingdom	0.020	-1.176	12841.08	21571.85	0.5	0.1	0.770	0.0	0.10	0
United States	0.023	-0.772	15438.08	27701.78	0.6	0.2	1.230	0.0	0.09	0
Uruguay	0.055	-0.609	4753.07	6232.80	0.8	0.4	0.318	0.4	0.06	0
Venezuela	0.060	-0.148	6662.75	8490.63	1.0	0.2	0.281	0.2	0.05	0

Zambia	0.099	2.780	1803.06	1557.82	1.0	0.1	0.114	0.3	0.15	0.1
Zimbabwe	0.102	-0.220	279.80	323.36	0.9	0.1	0.271	0.0	0.06	0