The Emerging Market Great Moderation

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Abstract

We document a Great Moderation in emerging markets, characterized by a dramatic fall in aggregate macroeconomic volatility of more than 40%. However, we show that other distinctive characteristics of emerging business cycles continue to persist. We develop a novel methodology to test canonical emerging market business cycle theories that attribute these distinctive features to differences in income fluctuations (trend vs cycle), finding support for these theories. Our methodology allows us to establish three additional results for emerging markets. First, the moderation stems mainly from a moderation in country-specific and regional shocks. Second, trend shocks imply up to a 10% output loss over the long run. Third, the moderation resulted in a welfare gain of 2% for the median emerging economy.

JEL Classification: E21, E32, E40, F43, O11

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"While business cycle fluctuations in developed markets may have moderated in recent decades, business cycles in emerging markets are characterized increasingly by their large volatility..."

—Aguiar and Gopinath (2007)

"Rich countries are about half as volatile as emerging or poor countries. This is true not only for output, but also for all components of aggregate demand."

—Uribe and Schmitt-Grohé (2017)

1 Introduction

For a long time, emerging markets have been viewed as having excessively volatile business cycles, associated with even larger volatility of consumption and sharp reversals of the current account. The distinctive characteristics of emerging market business cycles have spurred a large research project starting with the seminal work of Aguiar and Gopinath (2007), aimed at understanding the sources of fluctuations in emerging economies. In this paper, we reassess conventional wisdom and document an *Emerging Market Great Moderation*, a dramatic fall in the volatility of business cycles in emerging markets. We connect this moderation to canonical theories of emerging market business cycles and use them to argue that the stabilization of business cycles has resulted in substantial welfare gains for a large part of the world's population.

We begin our analysis by documenting a decline in output volatility in emerging markets of around 40% since the 1980s (Figure 1). We measure volatility as the standard deviation of real annual output growth across a sample of 92 emerging markets for which data is consistently available over multiple business cycles since the 1970s. Figure 1 shows a dramatic decline in volatility in emerging markets, which is falling sharply since the year 2000 and is approaching the level of volatility in advanced economies. The moderation we document for emerging markets is larger than the Great Moderation in advanced economies, as documented, for instance, in Stock and Watson (2005), both in absolute terms and relative to the initial volatility in these countries. This implies large changes in the macroeconomic environment in these economies.

We further establish the moderation and its statistical properties. The decline in volatility holds across groups of emerging markets and is not concentrated in particular regions or at a particular stage of development. It is also not driven by individual countries; we find a moderation at the median or at different quantiles within emerging economies. Looking within countries, of the 92 economies in our baseline sample, 75 have seen a decline in volatility since 1980. Of these, 43 have experienced a statistically significant decline in volatility, while only 5 have seen a statistically significant rise in volatility. The moderation also holds across macroeconomic aggregates, and we document a significant decline in the volatility of all aggregate demand components of GDP: consumption,

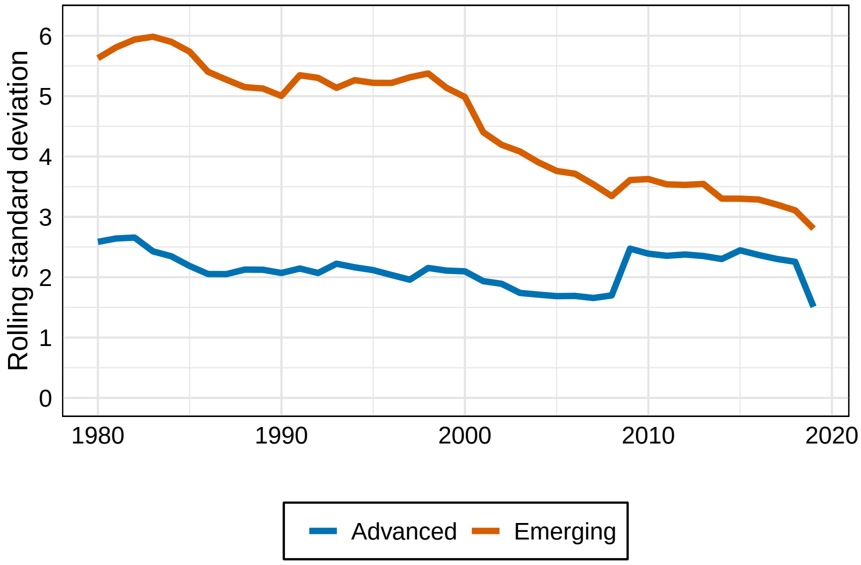

Figure 1. Rolling Standard Deviation of GDP Growth, 1980-2019

Notes: The plot shows the average backward 10-years rolling standard deviation of output growth for 92 emerging markets (solid orange line) and 24 advanced markets (dashed blue line). The rolling standard deviation is computed separately for each country, we show the unweighted averages across emerging and advanced. Details on the data and the sample of emerging and advanced economies are in section 2.

investment, government expenditures, exports, and imports. In terms of timing, we provide evidence of a break in output volatility around the 1990s for most economies; so that since 2000 most countries are in a low-volatility regime. Regarding the mechanisms that led to the moderation, we present evidence on improvements in economic openness, central bank independence, the level of public debt, industrialization, and democracy indices across emerging economies since the 1980s, thus suggesting structural and institutional changes as potential drivers of the moderation.

One interpretation of these facts is that the reduction in volatility is a natural consequence of economic development. However, we find that other properties that have been found to distinguish emerging from advanced economies continue to persist. Importantly, consumption smoothing in these countries remains impaired: Aggregate consumption remains more volatile than income, and the trade balance remains countercyclical (so that countries do not become net borrowers when hit by negative shocks). These properties have *not* moved in line with advanced economies over the course of the moderation.

The facts we document are robust across a number of dimensions. In particular, we use different detrending procedures to construct business cycle fluctuations, as well as various classifications of advanced and emerging economies. Finally, we show that the facts we document hold in quarterly data, which is available for a smaller sample of countries over a long time horizon. Looking at a longer-run sample, we find that volatility in emerging markets was high throughout the second half of the twentieth century and only started to decline in the recent period.

Given these facts, we turn to standard models of emerging market business cycles, which explain precisely the distinctive emerging market properties (alongside high volatility) to study the underlying drivers of the moderation. We introduce new methods to this literature to shed light on the sources of emerging market business cycles and their moderation. Specifically, we test the seminal hypothesis of Aguiar and Gopinath (2007) that shocks to permanent income can explain the properties of emerging business cycles. Concretely, they argue that emerging markets are characterized by business cycles that induce a permanent shift in the growth path, rather than transitory shocks from which the economy eventually recovers. The intuition for this follows from the permanent income hypothesis: Faced with a permanent downward shift in the growth path, households adjust their consumption immediately, causing it to overreact relative to income growth.

This theory stands at the core of business cycle and sovereign debt models of emerging economies; however, it has been subject to substantial controversy (García-Cicco, Pancrazi, & Uribe, 2010; Guntin, Ottonello, & Perez, 2023; Hong, 2023). To test this hypothesis, researchers have generally followed the traditional approach of the business cycle literature, which infers the properties of latent shock processes by targeting all moments of the data (Smets & Wouters, 2007). However, if these models are misspecified, the estimated properties may not accurately reflect the true underlying process.

Our key contribution to this literature is to quantify the importance of these permanent shocks in emerging market business cycles without a fully specified structural model. We develop a flexible Bayesian approach to decompose output fluctuations into trend and cyclical components, incorporating domestic, regional, and global sources of variation. The model nests the specification of Aguiar and Gopinath (2006, 2007). Importantly, our procedure is based purely on the properties of output growth alone and does not need to fit other moments, such as the volatility of consumption or the cyclicality of the current account. We therefore avoid the concern that our estimates are driven by the model's ability to match other moments of the emerging market business cycle. Our model allows for time-varying volatility to investigate the sources of the moderation as well as measurement error. In an extension, we also apply our model to fluctuations in total factor productivity.

We estimate the model using over 60 years of data for the emerging and advanced economies in our sample. We recover well-known events, such as the financial crisis and the persistent output losses associated with it, as well as other crises in emerging markets (Cerra & Saxena, 2008; Hall, 2015; Jordà, Schularick, & Taylor, 2013). Importantly, our model finds a large reduction in volatility, in line with the moderation we document in the first part of the paper.

Consistent with Aguiar and Gopinath (2007), we find an important role for permanent fluctuations in emerging market business cycles using our unobserved components model. Specifically, we attribute 80% of fluctuations in emerging markets to the shifts in the permanent component of output growth. When allowing for stochastic volatility, we find that the volatility of both components has declined roughly in the same proportion over the past years, so this figure remains high also at the end of our sample. This is consistent with the fact that while overall volatility has decreased, the distinctive properties of the emerging market business cycle continue to persist. In contrast, in advanced economies, the share of fluctuations explained by the permanent component decreased from 80% in the 1980s to 60% in the first two decades of the twenty-first century. In the cross-section, we show that countries with a larger contribution of permanent shocks also display higher volatility of consumption relative to output.

Our model successfully captures other salient features of emerging market growth trajectories. Firstly, we use the estimates from the model to show that the sources of volatility stemming from domestic and regional factors fully account for the moderation in emerging economies. Secondly, we find an increasing role for global shocks not only in emerging markets but also in advanced economies as well; a fact that is consistent with the increasing level of trade and financial openness that we document, as well as with the literature on the Global Financial Cycle (Miranda-Agrippino & Rey, 2020). Lastly, we show that the innovations to trend growth (domestic, regional and global) are persistent and have a non-negligible everlasting effect on output; in the words of the finance literature, emerging markets are characterized by long-run risk (Bansal & Yaron, 2004). Similar to Nakamura, Sergeyev, and Steinsson (2017), who study consumption in an international panel, we find that the long-run risk from international sources is the one that is the most persistent, with a half-life of 6.8 years, while the long-run risks from domestic and regional sources have a half-life of 0.96 years and 3.38 years, respectively.

What do these large macroeconomic shifts mean for the people living in these countries? We argue that the Emerging Market Great Moderation has substantially improved welfare in these countries. In standard business cycle models, the welfare costs of business cycles are vanishingly small, such that households would only be willing to give up 0.05% of deterministic consumption to avoid business cycle fluctuations (Lucas, 2003). However, for the permanent shocks we find in our empirical analysis, this is not the case. These shocks change the future consumption growth path, so the economy will never recover to the pre-shock trend. Using a model with an income process calibrated following our estimates of permanent and transitory shocks, we calculate that households in emerging economies would be willing to give up a large fraction of deterministic consumption to avoid these fluctuation, more than one hundred times the 0.05% identified by Lucas (2003).

For every country, we compute the implied welfare gains from moving from the 1980-99 income process to the 2000-19 process, which usually features substantially lower volatility. The resulting welfare gains are large, up to 8% of consumption for the countries with the biggest improvements. Large welfare gains can be found especially in many economies in the Arab World and Sub-Saharan Africa, where permanent shocks played a particularly large role before. For most countries in these regions, welfare gains exceed 3% of consumption. On the other hand, selected countries that did not experience an improvement in their macroeconomic conditions, such as Argentina or Venezuela, fail to see welfare gains and often even see welfare losses.

Related literature. This paper contributes to several strands of the literature. We first contribute to the literature on emerging market business cycles (Aguiar & Gopinath, 2007; Chang & Fernández, 2013; Drechsel & Tenreyro, 2018; García-Cicco et al., 2010; Guntin et al., 2023; Hong, 2023; Koren & Tenreyro, 2007; Neumeyer & Perri, 2005). One key fact in this literature is that emerging markets are far more volatile than advanced economies. We show that this is no longer the case, as there has been a strong convergence in terms of volatility. Moreover, we provide direct tests for the presence of permanent shocks in emerging markets. These shocks are a standard property of many emerging market business cycle and sovereign default models (Aguiar, Chatterjee, Cole, & Stangebye, 2016; Aguiar & Gopinath, 2006; Gordon & Guerron-Quintana, 2018), but their importance has been questioned (García-Cicco et al., 2010; Germaschewski, Horvath, & Rubini, 2024; Hong, 2023; Miyamoto & Nguyen, 2017; Neumeyer & Perri, 2005). Using our approach, we provide estimates of the size and persistence of permanent shocks, which can be used directly as calibration inputs for business cycle or sovereign default models for emerging markets.

Second, we contribute to the literature on the empirical properties of business cycles. A large body of literature dating back to Baily (1978) has identified a moderation in advanced economy business cycles (see for instance Gadea, Gómez-Loscos, and Pérez-Quirós (2018); Kim and Nelson (1999); McConnell and Perez-Quiros (2000); Stock and Watson (2005). We extend this evidence to emerging markets, where we show that the reduction in business cycle volatility is considerably larger than in advanced economies. Krantz (2023) and Casal and Guntin (2023) provide evidence on a moderation of business cycles in Africa and 10 emerging economies from 1978-1995, respectively. Relative to these papers, we cover a far larger sample of countries and connect the moderation to the emerging market business cycle literature.

Finally, we connect the literature on business cycle volatility to the literature on the long-run properties of output fluctuations (Barro & Ursúa, 2008; Campbell & Mankiw, 1987; Cerra, Fatás, & Saxena, 2023; Cerra & Saxena, 2008; Clark, 1987; Cochrane, 1988; Jordà, Schularick, & Taylor, 2024) which focuses on advanced economies. This literature finds evidence in favor of an important persistent component of business cycles, especially outside of the United States. We introduce an empirical model to determine the size of this persistent component and its contribution to the moderation we identify. The persistent component of business cycles is large outside of advanced economies, although we also find evidence in favor of some persistence in advanced economy business cycles. The large persistence of fluctuations in emerging market business cycles informs asset pricing models seeking to explain equity returns in emerging markets using long-run risks (David, Henriksen, & Simonovska, 2024).

Layout. The article is organized as follows. Section 2 discusses the data we use. Section

3 documents the Emerging Market Great Moderation alongside the persistent distinctive features of emerging market business cycles. Section 4 connects our findings to canonical business cycle theories. Section 5 presents the implied welfare gains from the Emerging Market Great Moderation. Section 6 concludes.

2 Data and Measurement

Data sources. We use macroeconomic data on GDP, consumption, government expenditures, investment, exports, imports, capital stock, employment, and the labor share from the *Penn World Tables* (Feenstra, Inklaar, and Timmer (2015)). The advantage of using annual data is that we are able to study a nearly complete set of emerging economies, for which quarterly data often becomes available only after the 1990s (often after emerging market crises, leading to selection problems Barro and Ursúa (2008)). The Penn World Tables are available without breaks throughout our sample.

To complement our baseline analyses, we use quarterly data from Monnet and Puy (2019) as well as other country-specific sources, who provide quarterly data on GDP and other macroeconomic indicators collected from the IMF's archives in a number of emerging markets. Additionally, we use data on financial crises, coups, and armed conflicts from Laeven and Valencia (2020), the coups d'etat database constructed by the Center for Systemic Peace, and Federle, Meier, Müller, Mutschler, and Schularick (2024), respectively. An overview of the data sources and the precise variables is provided in Appendix A.1.

Sample. We classify the world into advanced and emerging economies.[1] Naturally, there is some arbitrariness involved in this procedure, so we explain it in detail below and show the robustness of our results to alternative classifications. Our baseline classification follows the S&P market classification, which is commonly used in the emerging market literature (Aguiar & Gopinath, 2007). Figure 2 provides an overview of the 116 economies in our baseline classification. Advanced economies and emerging markets are represented in blue and orange, whereas countries not included are depicted in black. In recent years, these countries cover more than 90% of the world's population.

Concretely, we start from the full list of countries and exclude two sets of countries from our sample before differentiating advanced and emerging economies. First, we restrict our sample to countries with a population of more than 1,000,000 in 2019 to filter out very small economies with idiosyncratic features. Second, to have a sample with several business cycles, we require countries to have data coverage from 1960 onwards, except for Eastern European and Arab World countries, where the requirement is relaxed to data available from 1970 onwards due to the lack of data before 1970 for most countries in that

[1] Throughout the article, we use the compound words *emerging market* and *emerging economy* as synonyms.

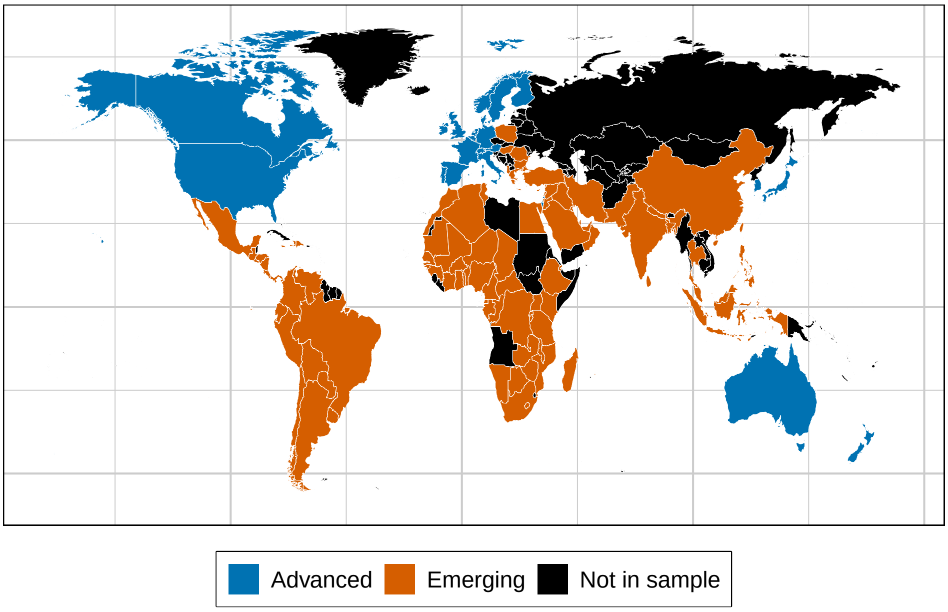

FIGURE 2. COUNTRIES COVERED IN THE SAMPLE

Notes: The figure illustrates our country classification. Advanced and emerging market economies in our sample are represented in blue and orange. Countries not included in our sample are shown in black.

region. These two conditions result in a sample of 116 countries that represent 90.3% of the world population according to the *World Development Indicators* from 2019.

To classify countries into advanced and emerging market economies, we use the S&P Global Ratings' market classification, which divides the world into advanced and emerging. Using this classification, we distinguish all advanced economies; otherwise, we classify the country as an emerging market economy. This results in a sample of 24 advanced economies and 92 emerging countries, depicted in Figure 2.

Measurement of Economic Fluctuations. We measure business cycle fluctuations using growth rates.[2] This approach, although simple and transparent, contrasts somewhat with the practice of filtering the data to recover a measurement of the cycle of the series using an econometric technique such as the Hodrick-Prescott (HP) filter (Aguiar & Gopinath, 2007) or other filters. In practice, these approaches produce similar results, as we show in Appendix B.3.1. However, there are at least two technical reasons to prefer first differences over filtered data.

First, when the trend of a series is not deterministic, overall fluctuations in the series are the sum of trend perturbations and cyclical components. Assuming that the series under study is integrated of order 1, taking first differences ensures that the series does not include any deterministic component in the trend while still containing the information on trend and cycle perturbations. Hence, this approach provides the necessary information to study the fluctuations of the series.

Second, as noted in Hamilton (2018), popular filtering techniques, such as the Hodrick-

[2]Concretely, we first take logarithms of variables and then compute first differences.

Prescott filter and its one-sided version, construct the cycle and trend components of a time series at time t using the estimated innovations ahead of t. This procedure results in estimated trend and cycle components for the series that are highly correlated with the estimated future innovations. Nonetheless, true innovations are unpredictable; hence, the correlation between the estimated components and the estimated innovations is spurious as it is the artifact of the filtering technique, not of the true data generating process.

3 What Has Changed since the Early 1980's?

3.1 The Emerging Market Great Moderation

In Figure 1 in the introduction, we have shown that output growth volatility in emerging markets has fallen sharply in the past two decades. We now document this fact systematically across countries. We first focus on comparing two periods, 1980-99 versus 2000-19. Then, to complement our analysis we provide evidence showing that most emerging economies went through a moderation in their output volatility since the 1980s. The moderation process can be mainly located in the period 1980-99 and has not reverted since, justifying our emphasis on analyzing the 1980-99 and 2000-19 periods separately. Here, and throughout the text, volatility refers to the standard deviation.

We summarize the extent of moderation in Table 1. The average volatility of output growth in emerging markets was 5.32% in the 1980-99 period and 3.43% during the 2000-19 period. This implies a fall in volatility of around 40% over this horizon. Looking at regions, this decline is not driven by economies in specific geographic regions, volatility declines throughout emerging economies. Even for the Americas, where output volatility fell the least, there was a statistically significant decline in output volatility. On the other hand, in advanced economies, output volatility remained fairly constant and fell by only 10%. We report different quantiles of volatility distribution within emerging markets in Table 2. Volatility declines at all quantiles. The least volatile, the median, and the most volatile emerging markets are all substantially less volatile than during the 1980s and 1990s, with the moderation being on the order of 40% for each.

Figure 3 delves into the details of the country-specific moderation in output volatility. It shows the bootstrapped mean and the 70% and 95% —symmetric— confidence intervals for the percent change in output volatility for all countries in our sample computed with data from 2000-19 to 1980-99. For the sake of clarity in the exposition, we truncate our statistics to be equal to a -100% (100%) whenever they fall below (above) such a threshold, corresponding to a decrease (increase) in output volatility of more than 100% (see the note of the figure for details on how we construct the statistics).

We observe that for the vast majority of emerging markets, output volatility is declining. More precisely, we find that output volatility was lower for the period 2000-19 than for the two-decade period that preceded it in 70 out of the 92 emerging economies

Table 1: OUTPUT VOLATILITY: 1980-99 VS 2000-19

Region	1980-99	2000-19	Difference	Log Change
Emerging economies	5.32	3.43	-1.89	-0.44
	(0.23)	(0.19)	(0.30)	(0.07)
Americas	3.98	3.06	-0.92	-0.26
	(0.26)	(0.25)	(0.36)	(0.11)
Arab World	9.11	4.50	-4.62	-0.71
	(0.90)	(0.40)	(0.98)	(0.13)
Asia and the Pacific	2.79	1.71	-1.08	-0.48
	(0.39)	(0.14)	(0.41)	(0.17)
Europe	4.93	2.98	-1.95	-0.50
	(0.69)	(0.36)	(0.78)	(0.19)
Sub-Saharan Africa	5.16	3.77	-1.39	-0.31
	(0.29)	(0.24)	(0.37)	(0.08)
Advanced economies	2.12	1.97	-0.15	-0.09
	(0.14)	(0.34)	(0.37)	(0.19)

Notes: This table reports the average output volatility for the periods 1980-99 and 2000-19, together with the difference in volatility in levels and in logs. Standard errors in parenthesis are computed via a bootstrap procedure with 5000 iterations.

(roughly 75% of them). The confidence bars reveal that the reduction in output volatility is statistically significant for 60 (41) emerging economies at the 70% (95%) confidence level. Hence, at the 70% (97.5%) confidence level, we cannot reject the null hypothesis that output volatility in 2000-19 was lower than it was during the period 1980-99 for roughly 65% (45%) of emerging economies. In contrast, only 9 (5) of such economies saw a statistically significant increase in output volatility, as inferred from their 70% (95%) confidence interval.

It is well known that many advanced economies experienced a moderation in volatility starting in the early 1980s (Stock & Watson, 2005). We find that this process is continuing despite the Global Financial Crisis in 2008, consistent with Gadea et al. (2018). For 12 out of 24 advanced economies, the mean estimate of relative change in output volatility was below zero (on average). However, in most cases, the decline in volatility is small and not statistically significant. Thus, the moderation seems to be continuing, but at a slower pace, as suggested by Figure 1.

Finally, we compare business cycle volatility in advanced and emerging economies. We notice that although the mean of the relative change in output volatility is negative for 75% of emerging economies and 50% of advanced economies, the decrease is more pronounced for the former group. Specifically, we observe that the median 1980-99 to

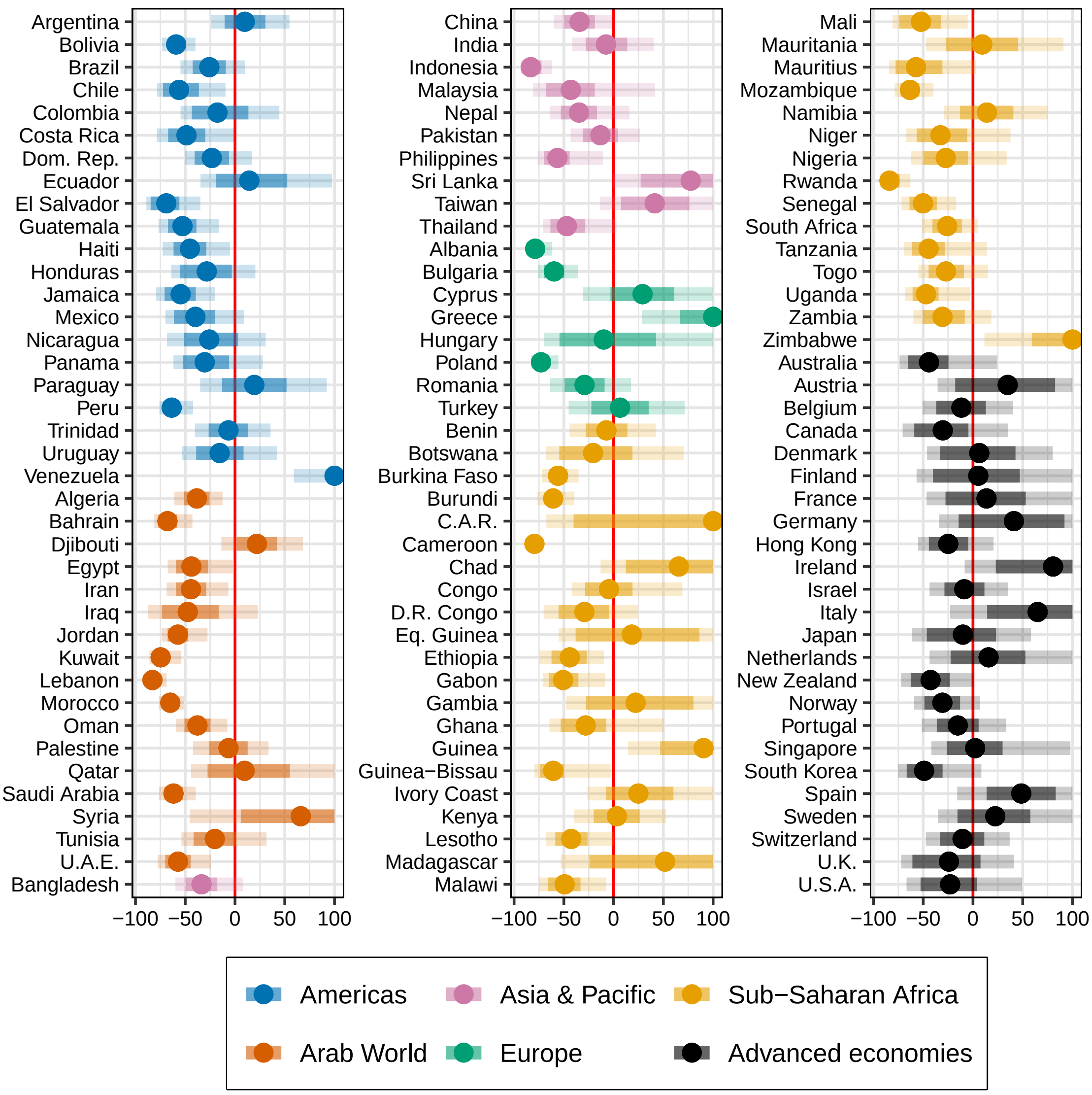

Figure 3. Change (%) in Output Volatility, 1980-99 vs 2000-19

Notes: The figure reports the relative change (in percentage points) of output volatility from 1980-99 to 2000-19. For a given country, the dot represent the mean estimate, and the light (dark) bars represent the 95% (70%) confidence interval. The three statistics were computed using bootstrap with replacement and were truncated to -100% or 100% whenever they were outside these boundaries. Specifically, we repeated a three-step process $B = 5,000$ times for each country. First, we drew 20 growth rates from the period 1980-99 with replacement and did the same for the period 2000-19. Second, we estimated the output standard deviation for both periods using the data that we drew. Third, we took the relative change between the estimate of output volatility from 1980-99 to 2000-19. Repeating this process provided us with an estimate of the empirical distribution of the relative change in output volatility. We used the empirical distribution to compute the mean and the 70% and 95% confidence intervals.

2000-19 relative change in output volatility was -32.7% in emerging economies and -9.4% in advanced economies. Furthermore, when we restrict the sample to countries that had a decrease in their output volatility, the median corresponds to -44.4% in emerging economies and -24.1% in advanced economies. These figures provide evidence that not only was there a moderation of output volatility in emerging economies, but also that for these economies, their output volatility levels are approaching those that are observed in advanced economies.

We summarize these observations as follows:

Fact 1. The Emerging Market Great Moderation. *Output volatility has fallen since the 1980's for around 80% of emerging markets. On average, volatility declines by around 40% and is currently approaching the volatility observed in in advanced economies.*

3.2 The Moderation Extends to Other Macro-Aggregates

Have other macroeconomic aggregates experienced a moderation similar to that observed for output? The panels in Figure 4 show the cross-country distribution of average log-inflation and of the log-volatility of subcomponents of output (output, consumption, government expenditure, investment, exports, and imports) and production fundamentals (capital and Solow residual) for the periods 1980-99 (in orange) and 2000-19 (in blue).[3] The moderation we have documented for output holds across other aggregates.

Figure 4 shows the difference between the mean of the distribution during the 2000-19 and 1980-99 periods for each macroeconomic quantity under consideration (d-value in the upper-right corner of its respective panel). In all cases, average volatility drops significantly.

Further examining the change in volatility, one way to cluster macroeconomic quantities based on their degree of moderation is as follows. The volatility of the capital stock, which across countries decreased on average by -0.21 log-points (a reduction of one fifth in levels), decreased the least. Next, the volatility of output, consumption, government expenditures, investment, exports, imports, and the Solow residual, quantities for which the moderation in their volatility ranged from -0.28 to -0.53 log-points, which is equivalent to a 24.4% to 41.1% decrease in levels, or about a reduction of one third in levels. Finally, the average inflation has decreased most strongly by -0.65 log-points (half of what is was during the 1980-99 period).

As in the case of output volatility, which we analyzed in section 3.1, the observed shift to the left in the distributions also holds across regions and countries, indicating a consistent fall in macroeconomic volatility (see Appendix B.1 for the details). Therefore, the moderation observed in emerging markets extends beyond output volatility.

Fact 2. Macroeconomic Extent of the Emerging Market Great Moderation. *The EMGM can be understood as a phenomenon in emerging economies that encompasses: (i) a reduction in the volatility of aggregate demand (output, consumption, government expenditure, investment, exports, and imports) and the fundamentals of production (capital and the Solow residual); and (ii) a decrease in average inflation levels.*

[3] We show the distributions in log-levels for the sake of visualization since the distributions in levels tend to be highly skewed to the right. Our choice does not affect any of our findings.

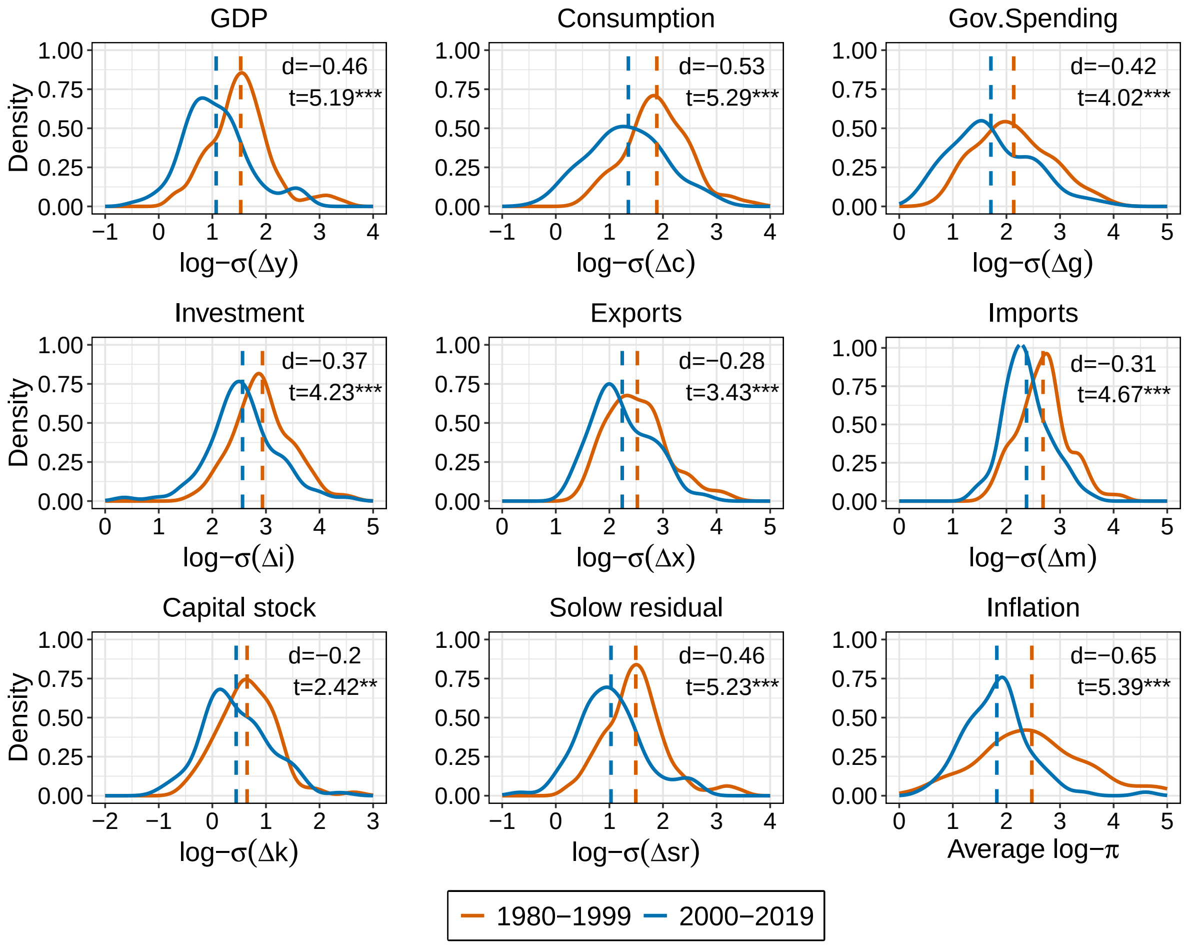

FIGURE 4. MACROECONOMIC MOMENTS ACROSS EMES, 1980-99 VS 2000-19

Notes: The figure shows the cross-country distribution (solid lines) and the mean (dashed lines) of the (log) standard deviation of the first log-differences of output (y), consumption (c), government expenditure (g), investment (i), exports (x), imports (m), capital stock (k), and Solow residual (sr); as well as the average of the log inflation (π). The values in the upper-right corner of each panel are the differences between the mean from periods 2000-19 and 1980-99 (d-values) and the t-values obtained from Welch's t-tests. *** and ** denote statistical significance at the 99% and 95% confidence levels, respectively. All logs were taken after multiplying the concerning quantities by one hundred; except for inflation, for which we first truncated four cases at zero (Ecuador and Zimbabwe in the 1980-99 period and Taiwan and Mali in the 2000-19 period), then added 0.01, and next multiplied the result by one hundred before computing the logarithm. In the case of investment, we had to drop Nicaragua in the 1980-99 period and Venezuela in the 2000-19 period due to their negative investment rates.

3.3 Business Cycles: Emerging vs Advanced Economies

By how much are the gaps between emerging and advanced economy business cycles closing? One could be tempted to interpret the EMGM as a natural consequence of the economic growth —emerging economies in the 2000-19 period look more like advanced economies because that is the natural path of development. However, in this section we show that other properties of emerging business cycles have not yet converged to advanced economies. We focus on two key business cycle moments that have been argued to distinguish emerging and advanced economies (Aguiar & Gopinath, 2007; Uribe & Schmitt-Grohé, 2017):

i) *Excess Consumption Volatility:*
Consumption is more volatile than output in emerging markets; the opposite is true in advanced economies.

ii) *Countercyclicality of the Trade Balance:*
The ratio of net exports to output is countercyclical in emerging markets and acyclical (or mildly procyclical) in advanced economies.

Table 2 shows these moments across emerging and advanced economies for the two periods we consider. The facts documented in the prior literature continue to hold not only for the period 1980-99 but also for the 20-year period that follows. First, in the periods 1980-99 and 2000-19, the volatility of consumption relative to output (denoted by σ_c/σ_y) was greater than one in most emerging economies and only declined slightly from an average value of 1.59 to 1.53 in the latter period. On the other hand, in advanced economies, consumption was on average only slightly more volatile than output in the initial period and is considerably less volatile than output in the modern period. Second, the cyclicality of the trade balance has remained relatively constant in both emerging and advanced economies. In emerging markets, it is slightly negative, at around -0.06, whereas in advanced economies it is slightly positive at around 0.10.

Fact 3. *The excess consumption volatility and the countercyclicality of the trade balance, which have been argued to differentiate the emerging markets business cycle from that of advanced economies, continue to hold.*

One aspect worth noting is that in advanced economies, the distributions of the consumption-output volatility ratios shifted left. At the same time, the correlations between output and the net exports to output ratio became mildly less negative, as one can infer by looking at the 25% quantile figures. We cannot say the same happened across emerging economies. While it is true that the lower half of the emerging markets distribution of consumption-output volatility ratios shifted left by about 0.10 units (in contrast to nearly 0.25 units in advanced economies), it is also true that there were not many changes in the upper half of the distribution. Additionaly, in emerging markets, the distribution of the correlations between the net exports to output ratio and output was almost identical during the two periods under analysis. Hence, advanced economies have become *less emerging* while emerging economies are *as emerging as before* in the sense that the business cycle contrasting facts are now more marked than they were before.

3.4 Correlates of the Moderation

Next, to shed light on the sources of the moderation, we document changes in economic and political fundamentals that the literature has regarded as relevant for economic devel-

Table 2: Business Cycles: 1980-99 vs 2000-19

Statistic	Period	Emerging Markets						
		Mean	Median	S.D.	p5	p25	p75	p95
$\sigma(y)$	1980-99	5.63	4.62	4.68	1.94	3.29	6.15	13.00
	2000-19	3.51	2.65	2.73	1.21	1.92	3.89	9.65
$\sigma(c)/\sigma(y)$	1980-99	1.59	1.35	0.91	0.75	1.07	1.79	3.16
	2000-19	1.53	1.23	0.86	0.57	0.97	1.87	3.25
$\sigma(i)/\sigma(y)$	1980-99	4.56	4.33	2.17	1.74	3.07	5.70	8.78
	2000-19	5.10	4.32	2.68	2.01	3.30	5.93	10.73
$\sigma(NX/Y)$	1980-99	0.07	0.05	0.07	0.02	0.03	0.09	0.20
	2000-19	0.06	0.04	0.05	0.02	0.03	0.09	0.15
$\rho(NX/Y, y)$	1980-99	-0.06	-0.09	0.33	-0.56	-0.33	0.18	0.50
	2000-19	-0.06	-0.08	0.34	-0.58	-0.29	0.14	0.50
$\rho(c, y)$	1980-99	0.58	0.64	0.28	0.01	0.47	0.77	0.94
	2000-19	0.55	0.55	0.29	0.11	0.34	0.85	0.93
$\rho(i, y)$	1980-99	0.51	0.56	0.32	-0.24	0.40	0.76	0.89
	2000-19	0.49	0.54	0.31	-0.03	0.25	0.78	0.88
Statistic	Period	Advanced Economies						
		Mean	Median	S.D.	p5	p25	p75	p95
$\sigma(y)$	1980-99	2.21	1.95	0.88	1.21	1.66	2.53	4.07
	2000-19	2.08	1.92	0.99	1.23	1.48	2.19	3.48
$\sigma(c)/\sigma(y)$	1980-99	1.08	1.00	0.34	0.76	0.86	1.28	1.53
	2000-19	0.84	0.76	0.34	0.42	0.57	1.03	1.27
$\sigma(i)/\sigma(y)$	1980-99	4.06	3.98	0.91	2.58	3.58	4.73	5.59
	2000-19	3.64	3.56	0.91	2.57	3.08	3.97	5.34
$\sigma(NX/Y)$	1980-99	0.02	0.01	0.01	0.01	0.01	0.03	0.05
	2000-19	0.03	0.02	0.02	0.01	0.01	0.03	0.06
$\rho(NX/Y, y)$	1980-99	0.07	0.13	0.31	-0.37	-0.17	0.26	0.46
	2000-19	0.06	0.09	0.27	-0.42	-0.07	0.29	0.35
$\rho(c, y)$	1980-99	0.75	0.80	0.17	0.37	0.67	0.87	0.90
	2000-19	0.72	0.77	0.19	0.33	0.64	0.84	0.92
$\rho(i, y)$	1980-99	0.79	0.84	0.14	0.51	0.74	0.89	0.95
	2000-19	0.76	0.80	0.20	0.51	0.66	0.91	0.94

Notes: The table reports business cycle moments for emerging and advanced economies for periods 1980-99 and 2000-19. Variables refer to first-difference filtered real aggregates. The table reports the mean, median, standard deviation, 5th, 25th, 75th, and 95th percentiles of the statistics across the countries in each category.

opment and volatility. Specifically, we examine the frequency of crises, economic openness, monetary and fiscal policy indicators, and political regimes, and find that the decrease in

Table 3: Relative frequency (%) of Crises

	1980-99					2000-19				
	Bank	Currency	Sov.Debt	War	Coup	Bank	Currency	Sov.Debt	War	Coup
Emerging economies	4.3	5.2	2.2	0.7	5.4	0.7	1.2	0.7	0.2	2.0
Americas	6.0	8.3	3.8	0.5	5.0	1.0	2.1	1.7	0.0	1.2
Arab World	3.8	4.4	2.5	0.0	2.5	2.5	0.6	1.2	0.0	0.6
Asia & the Pacific	4.5	6.8	2.3	0.3	9.7	0.3	2.4	0.4	0.0	5.1
Europe	2.5	3.1	1.2	1.9	4.1	0.0	0.9	0.0	0.3	0.6
S.S. Africa	5.0	3.2	0.9	0.9	5.9	0.0	0.0	0.0	0.5	2.3
Advanced economies	1.5	2.0	0.0	0.2	0.2	3.0	0.0	0.0	0.0	0.0

Notes: The table reports the relative frequency (in percentage points) of four types of crises. For emerging economies, we report the simple average across regions. For banking crises, we use banking crisis dates from Laeven and Valencia (2020) and restrict a banking crisis event to the year when the crisis started. For political crises, we concentrate on wars (fought within the territory) and coups d'état (successful and unsuccessful). We classify wars using Federle et al. (2024) and coups using Polity International V data.

macroeconomic volatility in emerging economies is associated with an *improvement* in all these fundamentals. Although these associations require further study to be established formally as causes of the moderation, we view them as plausible channels that could help explain the Emerging Market Great Moderation.[4]

Frequency of Crises. Table 3 shows the relative frequency (in percentage points) of financial and political crises during the periods 1980-99 and 2000-19. Specifically, the table shows the frequency of banking, currency, and sovereign debt crises, wars within the country, and coups d'état. Overall, in emerging economies, crises were much less frequent during the latter period.

The relative frequency of banking crises during the 2000-19 period was one-sixth of what it was during the previous 20-year period, going from 4.3% to 0.7%, respectively. For currency crises and sovereign debt crises, the relative frequency went from 5.2% to 1.2% and from 2.2% to 0.7%. Hence, during the 2000-19 period, the probability of emerging markets experiencing any of the three types of financial crises was less than 30% of what it was during the 1980-99 period.

Also, emerging markets experienced a pronounced decline in political crises. Coup attempts (including successful and unsuccessful attempts) occurred with a 6.2% probability in 1980-99; this number decreased to 2.1% in 2000-19. The marked decline in the relative frequency of wars (fought within the territory) in emerging economies is perhaps the most positive implication from Table 3; it went from 0.71% to 0.15% —a quarter of what it used to be.

It is worth noting that, in contrast to emerging markets, advanced economies were

[4]More importantly, since our article is the first to document the EMGM, we regard it as a first order priority to look at the broader picture of potential channels through which economic volatility in emerging economies has decreased.

Table 4: ECONOMIC AND POLITICAL FUNDAMENTALS, 1980-99 VS 2000-19

	Economic fundamentals					Political fundamentals	
	Trade Openness Index	Financial Openness Index	Central Bank Independence	Debt to Output	Agriculture Share of Output	Democracy Index	Autocracy Index
Panel A. 1980-99							
Emerging economies	0.60	0.34	0.51	0.62	0.18	3.6	3.8
Americas	0.48	0.36	0.53	0.68	0.14	6.2	1.3
Arab World	0.89	0.57	0.52	0.63	0.10	0.2	7.9
Asia & the Pacific	0.44	0.36	0.44	0.48	0.25	4.0	2.7
Europe	0.66	0.17	0.58	0.55	0.13	5.8	2.4
S.S. Africa	0.52	0.22	0.49	0.78	0.26	1.9	4.7
Advanced economies	0.51	0.75	0.52	0.61	0.04	9.2	0.3
Panel B. 2000-19							
Emerging economies	0.74	0.51	0.64	0.52	0.11	5.7	1.8
Americas	0.65	0.71	0.64	0.46	0.08	8.0	0.2
Arab World	0.95	0.62	0.56	0.49	0.06	1.2	5.6
Asia & the Pacific	0.66	0.28	0.55	0.50	0.15	5.8	1.4
Europe	0.85	0.67	0.80	0.62	0.07	9.1	0.2
S.S. Africa	0.62	0.30	0.62	0.55	0.21	4.3	1.5
Advanced economies	0.85	0.97	0.73	0.71	0.02	9.2	0.2

Notes: This table reports the average of economic and political fundamentals. We constructed the Trade Openness Index ($[0, \infty)]$) as the sum of exports and imports divided by output, constructed using the Penn World Tables. To construct the average Financial Openness Index, we used the Chinn and Ito (2006) index ([0,1]) extended through 2019 by the authors. For the average Central Bank Independence Index ([0,1]), we used the data from Romelli (2022). The average debt-to-output ratios ($[0, \infty)]$) were computed using Abbas, Belhocine, ElGanainy, and Horton (2010)'s database on public debt extended until 2022. The average agriculture share of output was computed using the *agriculture, forestry, and fishing values added* time series in the World Bank Data database. The average democracy and autocracy were computed using the democracy and autocracy indices ([0,10]) in the Polity V database.

subject to almost no political crises, did not experience any sovereign default crises, and currency crises were much less likely. Nonetheless, the likelihood of an advanced economy experiencing a banking crisis during the 2000-19 period was four times that observed for emerging economies. The underlying reason is the Great Financial Crisis. While most advanced economies experienced a banking crisis in 2008, emerging economies did not.

Economic fundamentals. In Table 4 we report the average of five economic indicators and two political indices for the two periods under study. Focusing on the economic dimensions, we find that emerging economies have become more open to trade and financial flows, their central banks enjoy more independence, and their output relies less on agriculture. This is generally true for all regions (except for Asia and the Pacific in terms of financial openness). With regard to debt, the average public debt to output ratio decreased for the Americas (68% to 46%), the Arab World (63% to 49%), and Sub-Saharan Africa (78% to 55%); whereas for Europe and Asia and the Pacific, this ratio increased slightly —respectively from 55% to 63% and from 48% to 50%.

One interpretation of the increase in trade and financial openness is that emerging economies have been able to increase their degree of substitutability. If so, firms can reduce the impact of production spillovers from supply shocks to domestic providers by substituting domestic inputs with foreign inputs. At the same time, firms are less affected by demand shocks in other economies since they are exporting to a wider spectrum of economies. With regard to monetary policy, a higher degree of independence of the central banks could be linked to greater economic confidence in terms of price stability, which makes it easier for economic agents to make less variable prospective demand and supply decisions. On the fiscal policy side, a decrease in the level of indebtedness is potentially related to improvements in international credit ratings; thus making these economies more attractive for sustained investment from abroad. Finally, the fact that these economies have become less reliant on agriculture implies that their output is less subject to a sector that —as Koren and Tenreyro (2007) document— is more volatile than manufacturing and services.

Political regime and institutions. Table 4 also reports average democracy and autocracy indices from the Polity V dataset. These indices range from 0 to 10; the higher the index, the more democratic (or autocratic) the economy is. In general, we observe that every emerging economy region became more democratic while simultaneously exhibiting fewer autocratic characteristics, as measured by the polity indices. The average democracy (autocracy) index increased from 3.6 to 5.7 (decreased from 3.8 to 1.8). In the case of advanced economies, on average, they have been close to being a full democracy (democracy index equal to 10) since the 1980s, and they do not share characteristics typical of autocratic regimes, as shown by the near-zero average autocracy index.

In Panel A of Figure 5 we show the 10-year rolling standard deviation of output for emerging economies. These economies are grouped based on their democratic status during the period 1980-2018: democracies for more than 30 years, between 10 and 30 years (inclusive), and for less than 10 years.[5] Indeed, emerging economies that are more democratic see lower volatility than countries that those not classified as democracies in most years. The former were at least 1% less volatile than the latter, with the gap being around 2% before 2000.

Despite this, output volatility fell for all three groups. In Panel B we track the democracy score —measured by the *polity2* score— for the same three groups. We observe that the democracy score increased for all three groups since 1980, including the group of economies classified as democracies for less than 10 years. Thus, output volatility fell for all three groups of countries at the same time that they became more democratic. One interpretation of this, although not based on causal estimates, is that an increasing degree of democratization could be at the heart of the moderation in emerging economies.

[5]We follow the Polity IV convention of categorizing a year-country observation as a democracy if their *polity2* score ([-10,10]) is greater than or equal to 6. Also, we base our criteria on the period 1980-2018 instead of 1980-2019 due to the Polity V dataset being available up to 2018.

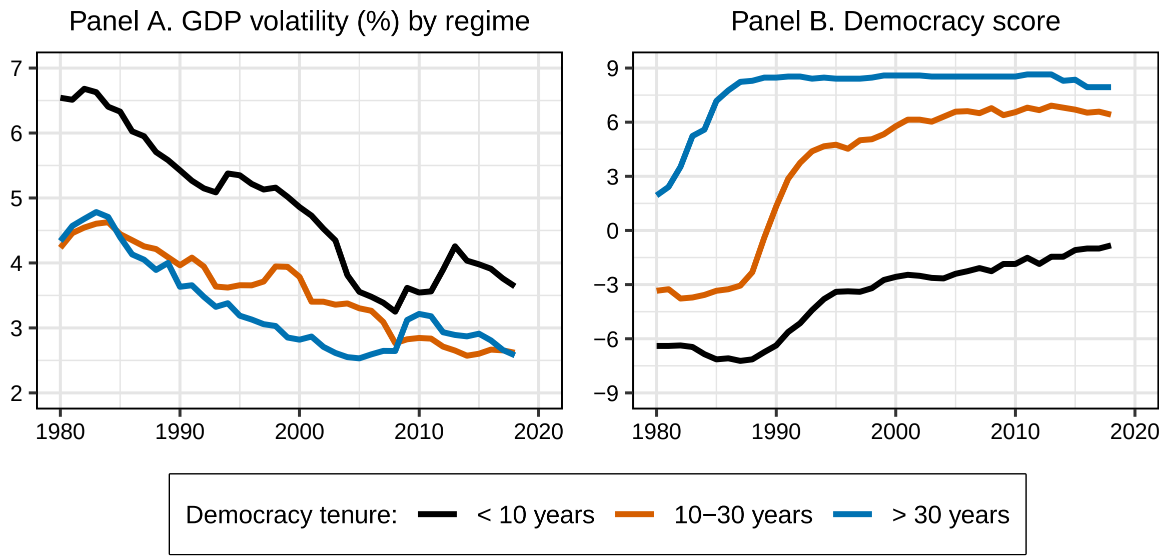

Figure 5. Democracy and the Moderation

Notes: The figure reports the average rolling output standard deviation and average democracy score, as measured by the *polity2* index ([-10,10]) in the Polity V dataset, for the emerging economies in our sample. These economies were clustered into three groups based on the number of years (out of the 39 in the period 1980-2018) that they can be regarded as democracies: less than 10 years, between 10 and 30 years (inclusive), more than 30 years.

3.5 Additional Facts

Dating the Moderation. The evidence above supports a decline in volatility across countries and macroeconomic aggregates. However, it does not reveal when this moderation began. We shed further light on this question in Appendix B.2.1, using the structural break testing procedure developed by Bai and Perron (1998, 2003). Using these methods, we test for an unknown number of breaks in the volatility of emerging markets. We briefly summarize the procedure here and provide details in Appendix B.2.1.

We follow McConnell and Perez-Quiros (2000), who document the Great Moderation for the United States, by modeling output growth as an AR(1) process. Then, we test for structural breaks in the standard deviation of the innovations. Applying this procedure across all countries in our sample yields, for each country, an estimate of the structural breaks along with an estimate of the level of volatility between breaks.

Our estimation procedure reveals that the most noticeable changes in the distribution of emerging market output volatility occurred before the year 2000. Roughly speaking, latent output volatility shrank mainly during the years covered by the period 1980-99. After the year 2000, output volatility stabilized in Asia & the Pacific, continued to decrease at a slower pace in the Americas, the Arab World, and Sub-Saharan Africa, and remained below the 1980-99 levels in Europe. Hence, not only were there marked reductions in output volatility during the 1980s and 1990s, but the moderation has not reversed in the last two decades and, in some cases, has become more pronounced.

The Gradient of Volatility and Development. Another way of viewing the Great Moderation documented for emerging economies in this article is by considering the gradient between economic development and volatility. We do so in Appendix B.2.2, where we examine the relationship between volatility and development, by regressing output volatility on output per capita, as in Koren and Tenreyro (2007). The regression coefficient, i.e., the volatility-development gradient, has considerably flattened over time. Quantitatively, the regression coefficient has decreased by 50% from -0.47 to -0.24 for the two time periods we consider. In turn, there is a large decline in the intercept, which reflects that emerging markets have become considerably less volatile, beyond what would be predicted by economic growth alone. This underscores that the emerging market moderation is not just a natural consequence of the process of economic development, but that volatility has fallen beyond economic growth in emerging markets.

A Long View on Volatility. In this article, we focus on the decline in volatility since the 1980s, as economic data for many emerging markets only starts in the 1970s. However, we can also extend our sample further back in time for many countries. We do so in Table B2 in the Appendix, where we study output volatility in emerging and advanced since the 1960s. As suggested by the rolling standard deviation in Figure 1, output volatility in emerging markets only fell very slightly from the 1960s to the period 1980-99. This contrasts with advanced economies, who see large declines in volatility from 1960-1980 to the 1980-2000 period during the Great Moderation. In magnitude, the moderation in emerging economies is larger, with volatility declining by around 40% in emerging economies, but by around 25% in advanced economies. In absolute terms, the reduction in volatility is around three times as larger, because initial volatility is much higher in emerging markets.

3.6 Robustness

Appendix B.3 demonstrates that the change in business cycle properties we identify is robust to alternative data treatments. There are four key inputs into our results: the measurement of the business cycle, country classification and sample, economic data on output, and the frequency at which we measure business cycles. We vary each input in order.

First, we vary the measurement of the business cycle. In our baseline analysis, we measure the size of cyclical fluctuations using the volatility of growth rates. This offers a transparent approach that maps directly into our model estimation in Section 4. However, we can also compute the volatility of deviations from a Hamilton (2018) or Hodrick and Prescott (1997)-filtered trend as is common in business cycle analysis. We do so in Tables B3 and B4. Again, this leads to similar results for the decline in volatility as well as the co-movement of other variables over the business cycle.

Second, we use different definitions of emerging markets. In our baseline analysis, we use the S&P emerging market classification following Aguiar and Gopinath (2007). In an extension, we consider alternative country classifications. We use the World Bank's classification (Table B7), which also allows us to distinguish further between *middle-income* and *low-income* countries (Tables B9 and B8). We show that the moderation holds for emerging markets at all stages of development, not just highly developed emerging countries. In fact, higher-income emerging economies (*upper-middle income* countries) experience more economic volatility than less developed ones (*lower-middle-income* countries).

Third, our main measure of output is real GDP from the Penn World Tables, but in a robustness check, we also use data from alternative sources and country classifications and samples. Our results continue to hold. Table B6 shows the results using the World Bank's World Development Indicators (WDI), which cover a slightly smaller sample. We also check that our results are not driven by outliers, by dropping observations in which output growth exceeds 15% in absolute value in Table B5. The World Bank classification goes back in time, allowing us to construct a 'moving' classification, in which countries are allowed to switch between advanced and emerging (Table B12). Table B10 employs the commonly used classification by Uribe and Schmitt-Grohé (2017), while table B11 replicates the findings in the sample of Aguiar and Gopinath (2007). Throughout, our findings of a Great Moderation in emerging markets, as well as a lack of convergence of other business cycle properties, continue to hold.

Fourth, and finally, we employ quarterly data in table B13. This reduces our sample of emerging markets to 18 countries, as quarterly data only becomes available post 2000 in most emerging economies.[6] The moderation holds in quarterly as well as annual data. Similarly, quarterly data also continue to display the characteristic facts of the emerging market business cycle (such as the excess volatility of consumption), however these tend to become somewhat weaker (the emerging economies covered in the quarterly developed are relatively more developed countries).

4 Linking Business Cycle Developments to Theory

Why are economic volatility levels in emerging economies converging towards those observed in advanced economies, yet distinctive patterns of emerging market business cycles continue to persist? Are emerging market business cycle theories consistent with the fact that advanced economies increasingly behave as *less emerging*? Is the moderation driven by a reduction in idiosyncratic, regional, or global volatility? How long-lived are the shocks to emerging economies?

In this section, we first present an econometric framework with the necessary elements to answer these questions (subsection 4.1). Specifically, we formulate an econometric

[6] We source quarterly data from Monnet and Puy (2019) and add other countries for which long-run quarterly data is available; see Table A1 for the sample.

model of output fluctuations that nests domestic, regional, and global shocks of two types: trend and cycle. In subsection 4.2 we link our estimates to Aguiar and Gopinath (2007)'s *Cycle is the Trend Hypothesis* (CTH). We find that, in line with the CTH, emerging economies show a higher share of output variance explained by trend shocks compared to advanced economies. This coincides with the excess volatility of consumption relative to output and the more pronounced countercyclicality of the trade balance observed for the former economies. In subsection 4.3 we document that in emerging economies, output variance is largely influenced by domestic sources of variation and that the moderation can be traced back to a reduction in the magnitude of domestic and regional shocks. Subsection 4.4 connects our estimates to those in the literature on long-run risk and provides an assessment of the long-run effects of trend shocks on output. Finally, in subsection 4.5, we discuss the robustness of our results, as well as additional results, under an alternative enriched model described in Appendix C.

4.1 A Model for Economic Fluctuations

To model output, we assume a functional form with cycle and trend shocks following Aguiar and Gopinath (2006, 2007). If the contribution of trend shocks to overall output fluctuations has remained constant in emerging economies while it has decreased in advanced economies, this would be evidence that the dominance of trend shocks in emerging economies is capable of explaining part of the excess volatility in consumption and trade balance countercyclicality in emerging economies, as suggested by Aguiar and Gopinath. To explore emerging market business cycle properties, we include domestic, regional, and global factors to help clarify the geographic source of the moderation in emerging economies —a necessary step before digging into the fundamental causes of the moderation. Furthermore, we allow trend shocks to be persistent study *long-run risks* literature and to assess the long-run consequences of trend shocks in output.

In what follows we specify the model we use and describe our estimation procedure.

Model. Output $Y_{i,t}$ of country i in region $R \equiv R(i)$ is composed of a trend and a cycle:

$$Y_{i,t} = \underbrace{\Gamma_{i,t-1} \exp(g_{i,t} + \psi_i g_{R,t} + \zeta_i g_{W,t})}_{\equiv \text{Trend } \Gamma_{i,t}} \cdot \underbrace{\exp\left(z_{i,t} + \psi_i z_{R,t} + \zeta_i z_{W,t}\right)}_{\equiv \text{Cycle } Z_{i,t}}, \tag{1}$$

This specification encompasses domestic innovations $g_{i,t}$ and $z_{i,t}$, regional innovations $g_{R,t}$ and $z_{R,t}$ common to all countries in region R (scaled up to a constant $\psi_i \geq 0$), and global innovations $g_{W,t}$ and $z_{W,t}$ common to all countries in the sample (scaled up to a constant $\zeta_i \geq 0$).[7] Our multi-country model nests the single-country model of Aguiar and Gopinath (2006) by turning off regional and world shocks, i.e. setting ψ_i and ζ_i to 0. We also compare the more general model against this benchmark, which we then refer to as the *AG model*.

[7]The type of process we assume can be traced back to Harvey and Todd (1983) and Watson (1986).

We impose an autoregressive structure on trend and transitory innovations; that is,

$$g_{i,t} = (1-\rho_{R,g})\mu_{i,p} + \rho_{R,g}\cdot g_{i,t-1} + \sigma^g_{i,p}\eta^g_{i,t}, \tag{2}$$
$$z_{i,t} = \rho_{R,z}\cdot z_{i,t-1} + \sigma^z_{i,p}\eta^z_{i,t}, \tag{3}$$
$$g_{R,t} = \gamma_{R,g}\cdot g_{R,t-1} + \sigma^g_{R,p}\eta^g_{R,t}, \tag{4}$$
$$z_{R,t} = \gamma_{R,z}\cdot z_{R,t-1} + \sigma^z_{R,p}\eta^z_{R,t}, \tag{5}$$
$$g_{W,t} = \delta_{W,g}g_{W,t-1} + \sigma^g_{W,p}\eta^g_{W,t}, \tag{6}$$
$$z_{W,t} = \delta_{W,z}z_{W,t-1} + \sigma^z_{W,p}\eta^z_{W,t},. \tag{7}$$

Our specification allows the volatility of innovations to vary by period, consistent with the shift in volatility documented in the previous section.[8] Here, $p \equiv p(t)$ indicates the period to which year t belongs among periods pre-1980, 1980-99, and 2000-19, implying that the non-stochastic growth rate μ and the shock standard deviations σ^g_i, σ^g_R, σ^g_W, σ^z_i, σ^z_R, and σ^z_W are period-varying. The quantities $\eta^g_{i,t}$, $\eta^g_{R,t}$, and $\eta^g_{W,t}$ are unit variance shocks that we call trend (or permanent) shocks. Similarly, $\eta^z_{i,t}$, $\eta^z_{R,t}$, and $\eta^z_{W,t}$ are unit variance shocks that we call transitory shocks. Finally, the autocorrelation of domestic, regional, and global innovations is captured, respectively, by parameters $\rho_{R,g}$ and $\rho_{R,z}$, $\gamma_{R,g}$ and $\gamma_{R,z}$, and $\delta_{W,g}$ and $\delta_{W,z}$ that lie in the interval $(-1,1)$ to ensure the effect of structural shocks (i.e., the η's) on reduced-form innovations z and g fade out over time.

Measurement equation. We allow for measurement error and write

$$\Delta y^{obs}_{i,t} = \Delta y_{i,t} + \nu_{i,t} \tag{8}$$

to account for the fact that observed output growth rates may differ from actual growth rates. We assume that measurement error $\nu_{i,t}$ follows a mean-zero normal distribution with standard deviation $\phi_i\sigma^\nu_{W,p}$, where $\sigma^\nu_{W,p}$ is a period-varying constant common across all countries in the world and ϕ_i regulates its influence on country i. This is especially important in the context of emerging economies, where the quality of national accounts data is compromised by the presence of a non-negligible informal economic sector which makes it difficult to measure output accurately, and delays in the adoption of state-of-the-art national accounting methodologies —Devarajan (2013) emphasizes the latter problem for countries in Sub-Saharan Africa.

Identification assumptions. To reduce the dimensionality of the model, we make two pooling assumptions on parameters. First, we assume that the autocorrelations $\rho_{R,z}$ and $\rho_{R,g}$ of domestic innovations are the same across countries in the same region. Second, to estimate the domestic standard deviations $\sigma^z_{i,p}$ and $\sigma^g_{i,p}$, we impose the linear relation

$$\sigma^g_{i,p} = \theta^{(1)}_{R,p} + \theta^{(2)}_{R,p}\cdot\sigma^z_{i,p}, \quad \theta_{1,p}, \theta_{2,p} \geq 0, \tag{9}$$

[8] In Appendix C, we allow for year-to-year stochastic volatility and show that the main results in this section are unchanged. For our purposes, we prefer to keep things as parsimonious as possible in the main discussion since there is not much to gain from discussing the results under a more complex model.

with the period-varying $\theta_{1,p}$ and $\theta_{2,p}$ being regionally pooled in the estimation procedure.

The two assumptions stem from the difficulty of precisely estimating the autocorrelations at the country-specific level and the standard deviation of the two types of domestic innovation. The first pooling assumption has been used in other branches of literature on macroeconomic volatility (Nakamura et al., 2017; Nakamura, Steinsson, Barro, & Ursúa, 2013), whereas we impose the second assumption for our specific setting having in mind the belief that the level of trend shocks volatility must be positively related to that of transitory shocks volatility.

Estimation. We estimate the model jointly for all countries in our sample while considering six regions/groups: advanced economies and the five geographic-based clusters of emerging economies we have analyzed so far. We use Hoffman and Gelman (2014)'s Hamiltonian Monte Carlo (HMC) with No U-Turn Sampler (NUTS), a Bayesian estimation technique designed to overcome the well-known random-walk behavior and sensitivity to correlated parameters problems of other Markov Chain Monte Carlo (MCMC) techniques that are popular amongst practitioners —e.g., the Gibbs sampler and Metropolis algorithm used by Nakamura et al. (2017) and Schorfheide, Song, and Yaron (2018) in the long-run risks literature. We implement the HMC-NUTS estimation of our model using Stan: a probabilistic programming language developed and supported by a community of academic statisticians (Carpenter et al., 2017).

To complete the list of ingredients for the estimation of the model, we assume weakly informative priors on the parameters by considering dispersed priors. Table C1 in Appendix C.1 summarizes the priors for the parameters. For autocorrelations, we use uniform priors covering the interval $(-1, 1)$. For standard deviations, sensitivity parameters, and the coefficients linking $\sigma^g_{i,p}$ to $\sigma^z_{i,p}$, we use normal priors truncated at zero, implying a prior median for output volatility of about 8.8%. For trend growth, absent trend shocks, we assume a normal prior with a mean and standard deviation of 2% and 3%, respectively.

4.2 Is the Cycle the Trend?

The excessive consumption volatility and higher countercyclicality of the trade balance in emerging markets, compared to advanced economies, led to the development of Aguiar and Gopinath (2007)'s *Cycle is the Trend* hypothesis (CTH). The CTH posits that in emerging markets, the share of output variance explained by fluctuations around trend growth is higher than in advanced economies. Therefore, emerging market households' consumption reacts more strongly to income shocks than that of advanced economy households; thus explaining the excess consumption volatility observed in emerging economies. Furthermore, because households can borrow from abroad, the trade balance will deteriorate more, which rationalizes the ratio of net exports to output being more countercyclical in emerging economies.

Taking the first log-differences of both sides of (1) results in the output growth rate

$$\Delta y_{i,t} = \underbrace{g_{i,t} + \psi_i g_{R,t} + \zeta_i g_{W,t}}_{\text{Trend growth}} + \underbrace{\Delta z_{i,t} + \psi_i \Delta z_{R,t} + \zeta_i \Delta z_{W,t}}_{\text{Cyclical growth}}, \tag{10}$$

which shows that the uncertainty in economic growth can be broken down into trend shocks and transitory shocks.

Plugging processes (2)-(7) into expression (10) and iterating forward ad infinitum, it follows that output variance is

$$\left(\sigma_{i,p}^{\Delta y}\right)^2 = \frac{\left(\sigma_{i,p}^{g}\right)^2}{1-\rho_{R,g}^2} + \frac{\left(\psi_i \sigma_{R,p}^{g}\right)^2}{1-\gamma_{R,g}^2} + \frac{\left(\zeta_i \sigma_{W,p}^{g}\right)^2}{1-\delta_{W,g}^2} + \frac{2\left(\sigma_{i,p}^{z}\right)^2}{1+\rho_{R,z}} + \frac{2\left(\psi_i \sigma_{R,p}^{z}\right)^2}{1+\gamma_{R,z}} + \frac{2\left(\zeta_i \sigma_{R,p}^{z}\right)^2}{1+\delta_{W,z}}, \tag{11}$$

so the share of output variance explained by trend shocks is

$$\text{SVETC}_{i,p} = \frac{\frac{\left(\sigma_{i,p}^{g}\right)^2}{1-\rho_g^2} + \frac{\left(\psi_i \sigma_{R,p}^{g}\right)^2}{1-\gamma_g^2} + \frac{\left(\zeta_i \sigma_{W,p}^{g}\right)^2}{1-\delta_g^2}}{\frac{\left(\sigma_{i,p}^{g}\right)^2}{1-\rho_g^2} + \frac{\left(\psi_i \sigma_{R,p}^{g}\right)^2}{1-\gamma_g^2} + \frac{\left(\zeta_i \sigma_{W,p}^{g}\right)^2}{1-\delta_g^2} + \frac{2\left(\sigma_{i,p}^{z}\right)^2}{1+\rho_z} + \frac{2\left(\psi_i \sigma_{R,p}^{z}\right)^2}{1+\gamma_z} + \frac{2\left(\zeta_i \sigma_{R,p}^{z}\right)^2}{1+\delta_z}}. \tag{12}$$

This measure is a generalization of the one advocated by Boz, Daude, and Durdu (2011) in an environment without regional and global innovations. Moreover, this measure takes into account the persistence of structural shocks.

The average SVETC figures in Table 5 provide us with an input that allows us to make a preliminary assessment of the validity of the CTH.[9] Through the lens of the CTH, advanced economies should show, on average, a decrease in the consumption-output volatility ratio and an increase in the correlation between their trade balance and output from 1980-99 to 2000-19 because their SVETC decreased. In contrast, emerging economies should show no changes in the aforementioned business cycle moments because their SVETC remained unchanged. This prediction is in line with the average behavior in consumption smoothing that we document in section 3.3 for periods 1980-99 and 2000-19, but only partially with that of the trade balance cyclicality —the prediction is violated for advanced economies. Hence, the average SVETC figures suggest that the CTH predicts correctly that shifts in the contribution of trend shocks to output matter for explaining the changes in consumption smoothing across the globe. At the same time, such figures indicate that the CTH may be an insufficient mechanism to explain the differences in the cyclical nature of the trade balance between emerging and advanced economies.

It is also worth noting that during the period 1980-99, the SVETC in advanced and emerging economies was virtually the same. However, as noted in section 3.3, advanced economies were better at smoothing consumption and had a less countercyclical trade balance during both periods under study. Thus, it is tempting to argue that the CTH does not hold because, under such a hypothesis, economies with a similar SVETC should

[9]The corresponding levels of output volatility for the full model are shown in Table 7.

Table 5: Share (%) of Output Variance Explained by the Trend Component

	Full model			AG model		
	1980-99	2000-19	Change	1980-99	2000-19	Change
Emerging economies	80.37	79.05	-1.32	83.42	82.51	-0.91
	(0.94)	(0.84)	(1.10)	(1.10)	(1.18)	(1.35)
Americas	78.95	74.52	-4.43	83.03	84.52	1.49
	(1.69)	(1.03)	(1.46)	(1.89)	(1.64)	(1.69)
Arab World	92.75	86.77	-5.98	94.63	91.70	-2.93
	(0.63)	(1.02)	(1.29)	(0.34)	(1.08)	(0.89)
Asia and the Pacific	79.03	73.16	-5.87	79.27	67.03	-12.25
	(1.80)	(3.40)	(3.23)	(1.93)	(5.24)	(5.79)
Europe	81.10	82.14	1.04	88.59	86.91	-1.67
	(2.58)	(2.32)	(4.30)	(1.56)	(2.57)	(3.62)
S.S. Africa	75.71	79.52	3.80	78.67	81.07	2.40
	(0.78)	(1.34)	(1.53)	(1.51)	(1.68)	(1.94)
Advanced economies	78.45	64.05	-14.40	82.84	60.77	-22.06
	(1.31)	(1.71)	(1.33)	(2.37)	(3.57)	(3.60)

Notes: This table reports the average posterior mean of the share of output variance explained by the trend component in emerging and advanced economies. Standard deviations are in parenthesis and were constructed using $5,000$ bootstrap iterations.

have had a similar level of consumption smoothing and trade balance countercyclicality. Nonetheless, one should be cautious about rejecting the CTH on that basis since averages alone ignore potential confounders that must be accounted for to test the CTH properly.

To adequately evaluate the CTH, we use of our estimates of the SVETC at the country-period level and estimate the regressions

$$y_{i,p} = \alpha + \beta \cdot \text{SVETC}_{i,p} + \gamma' X_{i,p} + u_{i,p}. \tag{13}$$

In this specification, $y_{i,p}$ corresponds to one of the two outcome variables: the log of the consumption-output volatility ratio, which measures consumption smoothing, and the correlation between the trade balance and output, which measures the cyclicality of the trade balance. The vector $X_{i,p}$ corresponds to a vector of controls that changes depending on the specification. The $u_{i,p}$ are the error terms of the regression. The coefficients α, β, and γ correspond to the linear regression coefficients.

Specification (13) serves the purpose of controlling for country variation in outcome variables that stems from sources other than the trend component. This is an important feature of our specification because the original evidence presented by Aguiar and Gopinath (2007) to argue in favor of the CTH was based on a controlled setting. Specifically, for Mexico and Canada, they calibrated a dynamic stochastic general equilibrium

Table 6: TESTING THE CYCLE IS THE TREND HYPOTHESIS

	Consumption smoothing $y_{i,p} \equiv \log(\sigma_c/\sigma_y)_{i,p}$			Net exports cyclicality $y_{i,p} \equiv \text{corr}_{i,p}(NX/Y, \Delta y)$		
	Simple OLS (1)	Simple OLS + FE (2)	Macro controls (3)	Simple OLS (1)	Simple OLS + FE (2)	Macro controls (3)
$\text{SVETC}_{i,p}$	0.936***	0.710**	0.761**	-0.095	-0.297	-0.228
	(0.280)	(0.348)	(0.375)	(0.217)	(0.248)	(0.261)
Region FE	✗	✓	✓	✗	✓	✓
Period FE	✗	✓	✓	✗	✓	✓
R-squared	0.041	0.234	0.236	0.001	0.115	0.127
Observations	232	232	232	232	232	232

Notes: This table reports the regression coefficients of regressing the level of consumption smoothing (σ_c/σ_y) and the correlation between the net-exports-to-output ratio and output growth ($\text{corr}(NX/Y, \Delta y)$) on the share of variance explained by the trend component (SVETC). Robust standard errors are shown in parentheses. *** and ** indicate significance at the 1% and 5% levels, respectively. The x-marks (✗) and check-marks (✓) stand for *no* and *yes*, respectively.

model using the same values for the structural parameters (debt, labor share, preferences, depreciation rate, etc.) and concluded that their model replicates the business cycle differences when the SVETC is higher for the emerging economy (i.e., Mexico).

In Table 6 we show the results of our regressions for three different specifications of the vector of controls $X_{i,p}$, each nesting the previous.[10] First, we consider a simple regression of the outcome variables on the SVETC. In the second specification, we add region fixed effects to soak up variation from period-invariant factors that affect all countries in a region (taking advanced economies as one region itself), as well as period fixed effects that absorb the variation from factors that are common across all countries but that vary by period. In the third specification, we add the median period-values of the trade openness index, inflation, and growth rate as macroeconomic controls.

Roughly speaking, our mean estimates of the coefficient of the SVETC on the outcome variables provide evidence in favor of the CTH. The regression results reveal that at the country level, there is a statistically significant positive relationship between the degree of consumption smoothing in an economy and its SVETC. An additional 100 basis points in the SVETC of an economy are related to a 0.7% increase in the consumption smoothing coefficient σ_c/σ_y. With regard to the trade balance cyclicality, we find a

[10]Before estimating the regression equation we first winsorize the lower and upper 5% tails of the SVETC and the outcome variables at the regional level. We do this to ensure that our results are not driven by outliers. Table C2 in Appendix C.1 shows that our results hold for unwinsorized data as well as for alternative winsorization schemes.

negative relationship between it and the SVETC. Although such a relationship is not statistically significant at the usual significance levels of less than 10%, our figures indicate that a 100 basis point increase in the SVETC is related to a 0.23 basis point decrease in the cyclicality of the trade balance.

Our estimates indicate that shocks to the trend are important for explaining the excess consumption volatility observed in emerging markets. To a lesser degree, they may also provide information about movements in the trade balance. Hence, these estimates lend external validity to the predictions of the CTH. This does not mean —in any way— that our estimates rule out other mechanisms presented in the literature to explain the differences between the business cycles of advanced and emerging economies.

4.3 Locating the sources of the moderation

Similar to how we derive the share (5) from (10), we can iterate forward and derive the share of output variance explained by domestic, global, and regional shocks:

$$\pi_{i,p}^{\text{dom}} = \left(\frac{\left(\sigma_{i,p}^{g}\right)^2}{1-\rho_{R,g}} + \frac{\left(\sigma_{i,p}^{z}\right)^2}{1+\rho_{R,z}} \right) \Big/ \left(\sigma_{i,p}^{\Delta y}\right)^2, \tag{14}$$

$$\pi_{i,p}^{\text{reg}} = \left(\frac{\left(\psi_i \sigma_{R,p}^{g}\right)^2}{1-\gamma_{R,g}} + \frac{\left(\psi_i \sigma_{R,p}^{z}\right)^2}{1+\gamma_{R,z}} \right) \Big/ \left(\sigma_{i,p}^{\Delta y}\right)^2, \tag{15}$$

$$\pi_{i,p}^{\text{glob}} = \left(\frac{\left(\zeta_i \sigma_{W,p}^{g}\right)^2}{1-\delta_{W,g}} + \frac{\left(\zeta_i \sigma_{W,p}^{z}\right)^2}{1+\gamma_{R,z}} \right) \Big/ \left(\sigma_{i,p}^{\Delta y}\right)^2. \tag{16}$$

Table 7 reports our estimates of output volatility (as measured by (11)) and the shares $\pi_{i,p}^{\text{dom}}$, $\pi_{i,p}^{\text{reg}}$, and $\pi_{i,p}^{\text{glob}}$ for emerging and advanced economies during the two periods under study. For reasons that will become clear momentarily, the values of the shares through both periods imply that most of the Emerging Market Great Moderation is accounted for by a reduction in the volatility of domestic and regional shocks. Furthermore, the figures in the table confirm that output volatility in emerging economies is mainly driven by country-specific sources of variation and to a lesser extent, by regional and global variation.

For emerging economies, except for Sub-Saharan African economies, the share of output variation explained by domestic shocks decreased between 10% and 20% from 1980-99 to 2000-19. This indicates that the volatility of domestic shocks decreased by more than output volatility. On the other hand, the share of output variance explained by regional shocks remained relatively constant. Even in the Arab World, where such a share doubled from 1980-99 to 2000-19, the decrease in output volatility was so pronounced that, in level terms, regional shocks also experienced a decrease in their volatility. All in all, these observations imply that the EMGM resulted from the moderation in the magnitude of country-specific and regional shocks.

Table 7: Output Variance Decomposition by Origin of the Shocks

	Output Volatility		Domestic (%)		Regional (%)		International (%)	
	1980-99	2000-19	1980-99	2000-19	1980-99	2000-19	1980-99	2000-19
Emerging economies	6.12	3.98	72.18	65.29	21.07	18.27	6.75	16.43
	(0.42)	(0.23)	(1.61)	(2.11)	(1.47)	(1.45)	(0.84)	(1.72)
Americas	4.46	3.44	72.29	61.06	18.81	15.04	8.90	23.90
	(0.24)	(0.42)	(1.95)	(4.91)	(1.71)	(2.16)	(1.36)	(3.93)
Arab World	9.77	4.98	86.27	70.17	10.25	16.75	3.48	13.08
	(1.74)	(0.78)	(2.59)	(5.05)	(2.27)	(3.74)	(0.71)	(3.22)
Asia & the Pacific	3.97	2.96	68.01	52.86	18.45	21.46	13.54	25.68
	(0.39)	(0.24)	(4.24)	(5.46)	(2.64)	(4.12)	(4.76)	(7.30)
Europe	5.64	3.44	69.82	56.98	22.90	28.77	7.28	14.25
	(0.71)	(0.36)	(7.05)	(7.26)	(6.84)	(6.96)	(2.01)	(2.51)
S.S. Africa	6.14	4.27	67.11	71.25	28.03	17.44	4.86	11.31
	(0.42)	(0.37)	(2.56)	(2.82)	(2.45)	(2.08)	(0.98)	(2.08)
Advanced economies	2.53	2.37	56.53	34.48	23.26	33.18	20.20	32.34
	(0.19)	(0.18)	(4.05)	(4.54)	(4.10)	(5.11)	(2.28)	(4.31)
United States	2.27	1.75	66.04	27.58	3.56	9.05	30.40	63.37
	(0.64)	(0.58)	(20.78)	(12.94)	(5.75)	(11.47)	(20.72)	(19.01)

Notes: The table reports the average posterior mean of the measure of output volatility (11) for the periods 1980-99 and 2000-19, as well as the average posterior mean of the share of output variance explained by domestic, regional, and global shocks. Standard deviations of these averages are shown in parentheses and were constructed using 5,000 bootstrap iterations.

Regarding the influence of global shocks in emerging economies, their contribution to output variation tripled, meaning that, in level terms, the standard deviation of global shocks influencing emerging economies was higher during the 2000-19 period than in the preceding 20-year period. This implies that the variance from global shocks did not contribute to the moderation of output. On the contrary, if it had remained the same, the moderation would have been sharper than what we observe.

Qualitatively speaking, country-specific shocks have been less important for advanced economies than for emerging economies, and such shocks were even less relevant during the 2000-19 period. The share of output variance explained by domestic shocks decreased from 55.9% in the 1980-99 period to 33.9% in the 2000-19 period. Moreover, global variation became more prominent from one period to the next, averaging 20% in the 1980-99 period and 33.4% in the 2000-19 period.

Our estimates provide an interesting connection to the literature on globalization. Specifically, we include the United States in Table 7 and observe that, for this economy, global variation was more relevant than in the average advanced economy in both periods, representing two-thirds of total output variance during the 2000-19 period. One interpretation of these statistics, consistent with recent evidence showing that monetary shocks in the United States generate movements in real macroeconomic aggregates (Boehm & Kroner, 2023; Miranda-Agrippino & Rey, 2020), is that shocks to the output of the United

States could be responsible for a large part of the shocks observed in the global factor.

Our findings on the contribution of domestic and global shocks to output variance during the 1980-99 period are in line with the estimates of other researchers. Kose, Otrok, and Whiteman (2003) use a model with country-specific, regional, and global dynamic factors and find that country-specific (global) shocks explained about two-thirds (one-tenth) of output variation in a sample of 32 emerging economies during the period 1960-1990. These figures are close to the ones we find for the 1980-99 period.

4.4 Long-run Risk in Output

Emerging market business cycle models, like ours, feature persistence parameters in trend and cycle innovations that have helped researchers measure the share of variance explained by the trend component or by location-specific factors. Given the median correlation of about 60% between consumption and output in emerging economies, one may use these estimates to establish a connection to the long-run risks literature in asset pricing, which posits that if growth is persistent enough, several asset pricing puzzles may be resolved (Bansal & Yaron, 2004). Specifically, as in the long-run risks literature, we focus on our estimates of the persistence parameters of the g-processes, known as *long-run risks*, which determine the trend component and thus reflect the long-run effect of a trend shock.

Table 8 reports summary statistics of our estimates for ρ_g, γ_g, and δ_g, which represent the long-run risks that stem from country-specific, regional, and global shocks, respectively. It also shows the implied half-life for each of the three types of shock. Overall, the amount of long-run risk is not trivial at any of the three location levels nested in our model.

Concretely, we make four observations. Firstly, for all economic regions —including advanced economies— and at all origin levels (domestic, regional, and international), the persistence parameters are identified to be above zero with a confidence level of more than 90%. These estimates contrast with those of Aguiar and Gopinath (2007), who cannot reject persistence in trend growth shocks being different from zero when estimating their persistence parameter using a Generalized Method of Moments. On the other hand, the sign of our estimates is in line with that of the estimates of García-Cicco et al. (2010) and Drechsel and Tenreyro (2018), who find positive persistence in trend growth.

Secondly, regardless of the origin of the shock, trend shocks have a lasting effect on growth. For the average emerging economy, trend shocks that are born out of domestic sources of variation have a half-life close to one year, trend shocks influenced by regional factors decrease to half of their original magnitude after 3.4 years, and international shocks reduce their influence by half after 6.8 years —García-Cicco et al. (2010) and Drechsel and Tenreyro (2018) do not specify the origin of trend shocks and find estimates that imply trend shocks have half-lives equal to 3.7 years and 1.1 years, respectively.

Thirdly, one way to rank the duration of trend shocks based on their origin is by clustering regional and global shocks into a single group. Our estimates imply that for

Table 8: Estimates of Persistence of g-Shocks

		Domestic g-shocks		Regional g-shocks		International g-shocks	
		Persist.	Half-Life	Persist.	Half-Life	Persist.	Half-Life
Emerging economies	Med.	0.49	0.96	0.81	3.38	–	–
	10%	0.45	0.87	0.73	2.22	–	–
	90%	0.53	1.09	0.88	5.43	–	–
Americas	Med.	0.59	1.30	0.61	1.39	–	–
	10%	0.52	1.04	0.34	0.64	–	–
	90%	0.66	1.66	0.82	3.59	–	–
Arab World	Med.	0.24	0.49	0.82	3.50	–	–
	10%	0.18	0.41	0.62	1.44	–	–
	90%	0.31	0.59	0.95	13.09	–	–
Asia & the Pacific	Med.	0.66	1.65	0.98	36.58	–	–
	10%	0.51	1.04	0.70	1.91	–	–
	90%	0.96	19.14	0.99	97.09	–	–
Europe	Med.	0.52	1.05	0.71	2.02	–	–
	10%	0.42	0.81	0.50	0.99	–	–
	90%	0.61	1.40	0.89	5.80	–	–
S.S. Africa	Med.	0.48	0.94	0.96	17.55	–	–
	10%	0.42	0.80	0.86	4.63	–	–
	90%	0.53	1.09	0.99	63.07	–	–
Advanced economies	Med.	0.59	1.31	0.54	1.13	–	–
	10%	0.53	1.09	0.28	0.54	–	–
	90%	0.65	1.62	0.76	2.47	–	–
All economies	Med.	0.51	1.02	0.64	1.56	0.90	6.76
	10%	0.48	0.94	0.68	1.77	0.71	2.05
	90%	0.54	1.13	0.82	3.50	0.97	26.89

Notes: The table reports the posterior median and the 10% and 90% quantiles of the persistence parameters (and the implied half-life) of domestic, regional, and global trend shocks for emerging markets, disaggregated into geographic regions, as well as for advanced economies.

all emerging market regions, the regional and international components of the trend are much more persistent than the country-specific component. This finding is in line with Nakamura et al. (2017), who find that the long-run risk deriving from international sources of variation is larger than that from idiosyncratic shocks. For them, the half-life of trend shocks (in consumption) equals 8.5 years in their baseline specification.

Fourth and finally, our estimates add to the literature on hysteresis effects (e.g., Cerra et al. (2023); Cerra and Saxena (2008)). Regardless of the origin of a trend shock, one can measure the long-run influence of a unitary trend shock from the geometric series

$$\sum_{k=0}^{\infty} \chi^k = \frac{1}{1-\chi}$$

where χ is the persistence parameter of the shock. Hence, by taking the inverse of one minus the autocorrelation of the trend innovation, we obtain that a 1% domestic shock to the trend in an average emerging economy increases long-run output by 1.96%. Similarly, a 1% shock to the trend stemming from a regional source of variation has a long-run effect on output of 5.26%, while if it stems from a global source of variation, the long-run effect on output is equivalent to 10%.

4.5 Robustness and additional results

The results presented in Sections 4.2-4.4 were derived from the estimates of our baseline model. A natural question is whether the same results hold under an alternative model. In Appendix C.2, we specify a different model that embodies stochastic volatility as well as trend and transitory shocks. Consistent with our baseline model, the alternative model leads to similar results to the ones we presented in this section. As will be discussed shortly, the alternative model also provides us with the necessary inputs to estimate the dynamic response of volatility to crises.

Specifically, the alternative model nests stochastic volatility that varies at a higher frequency (year-to-year instead of period-to-period). The model is simplified by not explicitly accounting for domestic, regional, and global sources of output variation.[11] With this model, we find evidence going in the same direction as that from our baseline model. First, the model shows a clear decline in volatility for emerging economies. Second, the share of output variance explained by the trend component that we identify under the alternative model is lower for advanced economies than for emerging economies (see Table C3). This aligns with the rationale of the CTH and with our findings in subsection 4.2. Third, the year-to-year stochastic volatility model also finds evidence of long-run risk in output (see Table C4). To be precise, the model identifies the persistence of trend shocks to output to be above zero (half-life of around 2 years, a figure similar to that implied by García-Cicco et al. (2010) and Drechsel and Tenreyro (2018)). Besides, the model identifies a non-negligible role for the persistence of shocks to volatility.

The full stochastic volatility model in Appendix C.2 has the advantage over our baseline model of providing researchers with the yearly time series of volatility for each country. We use these estimates to compute the dynamic response of volatility to three types of crises: financial (including banking and currency crises), sovereign debt, and political (including coups and wars within the country). Specifically, we estimate a local projection (Jordà, 2005) that controls for the correlates of the moderation described in subsection

[11] This simplification is necessary to avoid overburdening the HMC, given the limited number of observations relative to the total parameters in the model.

3.4. We find that crises produce a statistically significant increase in volatility at the 95% confidence level during the year the crisis starts and the following year.[12] Two years after the crisis starts, the effects remain significant at the 70% confidence level. See Figure C14 for details.

5 Welfare Cost of Business Cycles

We have shown that emerging market business cycles have moderated significantly over the past decades, with most of this moderation driven by a decline in the volatility of trend shocks to output. In this section, we argue that this moderation has led to substantial welfare gains in emerging economies.

5.1 Welfare Analysis

Lucas (1987, 2003) famously argued that the implied welfare losses from macroeconomic volatility and crises are small when considering benchmark models of economic fluctuations. We show that this does not hold in benchmark models of fluctuations in emerging economies. Relative to standard models, and inspired by our evidence on the presence of long-run risks in emerging market output, we allow for recessions to leave permanent scars from which the economy is unable to recover, so that macroeconomic fluctuations are not neutral for long-run growth. We calibrate the size of permanent shocks using our estimates from section 4.

In particular, we model a consumption-savings problem for a small open economy that faces income risk using the process described in section 4.1 and has access to a one-period bond for borrowing and saving. We calibrate the model to annual frequency and standard parameters in the emerging market business cycle literature (Aguiar & Gopinath, 2007; García-Cicco et al., 2010). Table D1 summarizes our calibration. We use a CRRA utility function with a relatively low level of risk aversion of 2. Despite the simplicity of the model, we show in appendix D.2 that it is able to match core properties of the emerging market business cycle, such as the high volatility of consumption relative to output and the countercyclicality of the current account.

In contrast to this literature, we do not estimate the shock process to match all moments of the data. Rather, our estimation in section 4 targets solely the statistical properties of output fluctuations. We hold all parameters fixed and calibrate the process for transitory and permanent shocks using our empirical estimates.

[12] Here, we have used language loosely, as sovereign debt crises do not spark volatility with high significance in the same year they start.

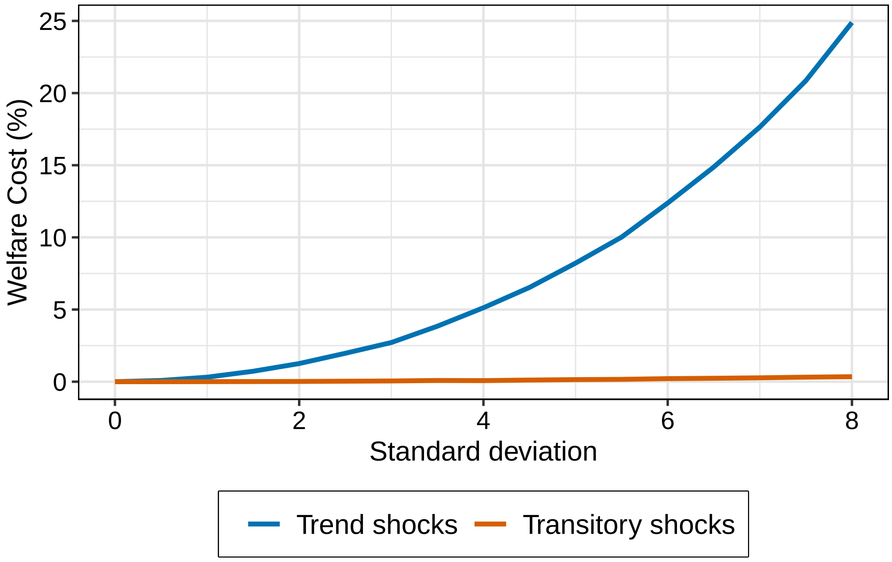

Figure 6. Welfare Cost of Business Cycles by Type of Shock

Notes: This figure shows the welfare cost of business cycles λ as defined in equation 17 for different levels of the standard deviation of permanent and transitory fluctuations. The blue line shows the welfare costs. The calibration of the income process and the utility function is as explained in the text.

5.2 Welfare and the Emerging Market Great Moderation

Within this model, we evaluate the welfare cost of business cycle. Given a risky consumption path C_t and a deterministic path $\bar{C}$ the welfare cost of business cycles λ is defined as the solution to

$$\mathbb{E}_0 \left\{ \sum_{t=0}^{\infty} \beta^t U \left[(1+\lambda) C_t \right] \right\} = \sum_{t=0}^{\infty} \beta^t U \left(\bar{C} \right), \tag{17}$$

i.e., the fraction of annual consumption the country would be willing to forgo in order to eliminate all fluctuations. For simplicity, we omit the country indices.

We solve for the value of λ in equation 17 for different levels of standard deviation of the permanent and transitory shocks. Figure 6 shows the implied welfare costs for different values of the standard deviation of permanent shocks, σ_g and transitory shocks, σ_z. In both cases, the standard deviation of the other shock is set to 0 when computing welfare gains.

The figure shows that the welfare cost of business cycles can be large for permanent shocks, which contrasts starkly with transitory shocks, which deliver small welfare costs on the order of 0.05%, as computed by Lucas (1987).[13] Welfare costs from permanent shocks are an order of magnitude larger. The intuition is that the growth path never recovers from these shocks. As a result, these shocks imply a far larger dispersion in potential consumption growth paths compared to transitory shocks.

[13] Reis (2009) similarly notes that the persistence of consumption fluctuations has strong implications for the welfare costs of business cycles.

Welfare gains around the world. We calculate the welfare cost of business cycles using the volatility of trend and transitory shocks, σ_g and σ_z, during the 1980-99 and 2000-19 periods based on the estimates that we obtained from the model in section 4.[14] In addition to the parameters from the empirical model, we calibrate the discount factor to the standard value in the emerging markets literature of $\beta = 0.95$, the average growth rate $\mu = 3\%$ (close to the median estimate of $\mu_{i,p}$ for both periods under study), and use a CRRA utility function with a coefficient of relative risk aversion of $\gamma = 2$. This gives us a measure of the welfare cost of business cycles in each period, λ_{1980} and λ_{2000}. We then calculate the implied welfare gains from the moderation in each country as

$$\text{Welfare Gain from Moderation} = \lambda_{1980} - \lambda_{2000}.$$

Table 9 reports key percentiles of the distribution of welfare gains for emerging markets and advanced economies. We emphasize three results. First, the median emerging market experienced around a 2% increase in welfare since the 1980-99 period. This figure hides the fact that welfare gains in the upper half of the distribution are quite high, especially for economies located in the Arab World and Sub-Saharan Africa. To put this into perspective, we observe that the welfare improvement of four Arab World economies surpasses the 25% threshold. Second, our estimates indicate that for 80 of the 92 emerging economies in our sample (i.e., almost 90% of emerging economies), welfare increased.[15] This implies that the Emerging Market Great Moderation nests a general improvement in emerging market welfare. Third, although volatility remained relatively constant in advanced economies, all these economies also experienced increases in welfare —although at a much smaller magnitude than emerging economies.

To delve into country-specific details, we plot the implied welfare gains from the moderation across countries in Figure 7. The figure shows that, with some exceptions, the great majority of emerging economies experienced an improvement in welfare, while for advanced economies, welfare remained quite stable. Examples for large gainers in terms of welfare (more than 5% of deterministic consumption) include Albania, Chile, Iraq, Morocco, and Togo. This corresponds to strongly reduced uncertainty about the long-term growth path, which used to be extremely unstable before the 2000s.[16]

[14]For simplicity, we hold the persistence fixed across countries at a level of $\rho_g = 0.6$ and $\rho_z = 0.8$. These figures are based on our estimates of the parameters in the simplified version of our full model from section 4, i.e., they are based on the AG model.

[15]The countries for which welfare decreased are: Argentina (-0.8%), Central African Republic (-15.5%), Chad (-6.4%), Greece (-0.5%), Guinea (-0.6%), Madagascar (-2.4%), Namibia (-0.2%), Paraguay (-1.4%), Sri Lanka (-0.1%), Syria (-8.4%), Venezuela (-15.3%), and Zimbabwe (-16.3%).

[16]In Appendix D.3, we compute welfare gains across countries when assuming higher steady state growth. This mechanically lowers welfare changes, but still results in sizeable gains in most economies.

Table 9: Distribution of Welfare Gains

	Min.	p25	p50	p75	Max.
Emerging economies	-16.27	0.58	1.90	4.45	41.40
Americas	-15.28	1.03	1.58	2.52	5.64
Arab World	-8.44	1.25	8.81	23.83	41.40
Asia and the Pacific	-0.10	0.29	1.09	1.75	3.53
Europe	-0.54	1.40	2.07	6.39	23.16
S.S. Africa	-16.27	0.27	2.04	4.35	40.44
Advanced economies	0.00	0.09	0.23	0.39	1.59

Notes: The table reports five summary statistics for the distribution of welfare gains, λ, across different clusters of countries: minimum, quantiles 25%, 50%, and 75%, and maximum. The figures for emerging markets were computed based on all emerging economies in our sample.

6 Conclusion

We document a Great Moderation in emerging markets, characterized by a fall in output volatility by around 40% since the 1980s. This period coincides with emerging economies gradually becoming more economically open and democratic, and experiencing fewer crises. We find that the moderation holds across countries and macroeconomic indicators in emerging markets. However, other distinctive characteristics of the emerging market business cycle, such as the excess volatility of consumption relative to output, persist.

Linking our empirical findings to the canonical account of Aguiar and Gopinath (2007), we find strong support for the presence of shocks to the trend in emerging economies using a theory-based econometric model of economic fluctuations. This model can be estimated using output data alone and nests the sources of variation stemming from domestic, regional, and global shocks. An advantage of our estimation procedure is that it does not force the model to fit business cycle moments. We highlight four key findings. Firstly, over the course of the moderation, shocks to the trend have decreased in volatility roughly at the same rate as transitory shocks. Thus, while overall volatility has decreased, the distinctive properties of emerging market business cycles persist. Secondly, the moderation is mainly explained by a reduction in the volatility of domestic and regional sources of variation. Thirdly, we find strong support for the view that shocks to the trend can have a long-lasting effect on output. Fourth, and finally, we explore the gains from the moderation using a standard open economy real business cycle model that takes our parameter estimates as inputs. We find that economies in the Americas, the Arab World, and Sub-Saharan Africa benefited the most from the moderation.

Our analysis emphasizes the decrease in macroeconomic volatility across emerging economies. Additionally, it underscores the differences in the composition of overall fluc-

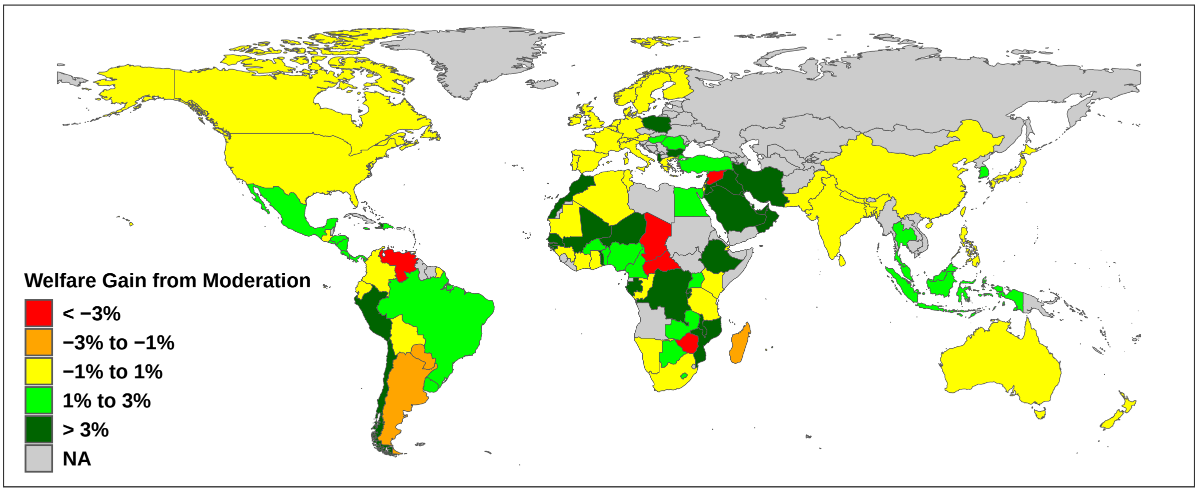

Figure 7. Welfare Gains from Moderation

Notes: This map plots the implied welfare gains from moving from the 1980-99 volatility regimes to the 2000-19 volatility regime. For details see text. Table D3 provides the numbers underlying the figure.

tuations between emerging and advanced economies. These differences align with the view that emerging economies are more susceptible to trend shocks, which in turn lead to higher consumption volatility and a more countercyclical trade balance compared to advanced economies. Yet, our analysis is —in a causal sense— agnostic about the forces that led to the moderation, as well as about the reasons why output fluctuations in emerging economies are mainly explained by shocks to the trend. Future research should focus on understanding the deeper sources of the causes of the moderation as well as the determinants of the trend component.

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Appendices

A Appendix to Section 2

A.1 Annual Data

We obtain annual data on GDP, population, consumption, investment, government consumption, and productivity for the countries in our sample from the Penn World Tables (Feenstra et al., 2015). Our measures of economic activity are in constant 2017 prices (variables q_{gdp}, q_c, q_g, q_i, q_x, q_m). Inflation data also comes from the national accounts. We construct total factor productivity as the Solow residual using the GDP, capital stock, and population (data on the labor force is not available for most countries in our sample) and a labor share of 2/3. The sample of countries is given, by region, in the following list:

- **Americas:** Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, El Salvador, Guatemala, Haiti, Honduras, Jamaica, Mexico, Nicaragua, Panama, Paraguay, Peru, Trinidad and Tobago, Uruguay, Venezuela. All these countries have data available since at least 1960.
- **Arab World:** Algeria, Bahrain, Djibouti, Egypt, Iran, Iraq, Jordan, Kuwait, Lebanon, Morocco, Oman, Qatar, Saudi Arabia, Palestine, Syria, Tunisia, United Arab Emirates. Data for these countries start in 1970.
- **Asia and the Pacific:** Bangladesh, China, India, Indonesia, Malaysia, Nepal, Pakistan, Philippines, Sri Lanka, Taiwan, Thailand. Data for these countries are available since at least 1960.
- **Europe:** Albania, Bulgaria, Cyprus, Greece, Hungary, Poland, Romania, Turkey. For these countries (except for Greece and Turkey) data start in 1970.
- **Sub-Saharan Africa:** Benin, Botswana, Burkina Faso, Burundi, Cameroon, Central African Republic, Chad, Congo, Democratic Republic of the Congo, Ethiopia, Gabon, Gambia, Ghana, Guinea, Guinea-Bissau, Ivory Coast, Kenya, Lesotho, Madagascar, Malawi, Mali, Mauritania, Mauritius, Mozambique, Namibia, Niger, Nigeria, Rwanda, Senegal, South Africa, Togo, Tanzania, Uganda, Zambia, Zimbabwe. For all these countries, data start since at least 1960.
- **Advanced economies:** Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Ireland, Israel, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Singapore, South Korea, Spain, Sweden, Switzerland, United Kingdom, United States. Data for these economies start since at least 1960.

The PWT dataset are recognized in the literature for their high quality. Nonetheless, we also incorporate data from the World Bank as an alternative source in table B6.

A.2 Quarterly Data

We assemble quarterly data on macroeconomic aggregates in Emerging Markets. Table A1 presents the emerging markets we are able to cover using quarterly data. We start with the long-run historical data of Monnet and Puy (2019), which contains data on output, and add to this national accounts for emerging markets where quarterly data is available before the 2000s. Many emerging countries only recently started producing quarterly data, so our sample is considerably smaller and contains richer emerging countries.

Data. Using the data of Monnet and Puy (2019), we study quarterly output volatility in many emerging markets since the 1950s. Monnet and Puy (2019) collected previously unavailable data from the IMF archives on macroeconomic aggregates in a number of economies. To this, we add GDP from quarterly national accounts for six other important emerging markets, for which longer-run data is available: Colombia, the Dominican Republic, Ecuador, Malaysia, Peru and Thailand.

Table A1: Country Sample – Quarterly Data

Country	Start GDP	Start Accounts	Country	Start GDP
Argentina	1957Q2	1993Q2	Finland	1950Q2
Brazil	1991Q1	1991Q2	France	1950Q2
Chile	1950Q2	1986Q2	United Kingdom	1950Q2
Colombia	1994Q2	1994Q2	Greece	1950Q3
Dominican Republic	1991Q2	1991Q2	India	1950Q2
Ecuador	1990Q2	1990Q2	Ireland	1950Q2
Malaysia	1991Q3	1991Q3	Iceland	1995Q1
Mexico	1950Q2	1980Q2	Israel	1957Q2
Peru	1980Q2	1980Q2	Italy	1950Q2
Philippines	1963Q2	1981Q2	Japan	1950Q2
South Africa	1957Q2	1960Q2	South Korea	1957Q2
Thailand	1993Q2	1993Q2	Luxembourg	1950Q2
Turkey	1987Q1	1987Q1	Morocco	1957Q2
Uruguay	1983Q1	1983Q2	Netherlands	1950Q2
Australia	1957Q2		Norway	1950Q2
Austria	1950Q2		New Zealand	1987Q1
Belgium	1950Q2		Pakistan	1950Q2
Canada	1950Q2		Portugal	1955Q2
Switzerland	1955Q2		Sweden	1950Q2
Germany	1950Q2		Taiwan	1957Q2
Denmark	1950Q2		United States	1950Q2
Spain	1950Q2			

Notes: The table shows the starting year for the data on GDP and National Accounts data for each country. We only use quarterly data other than GDP only for emerging economies.

Table A1 presents the data coverage. In a few cases, the series display excessively smooth behavior in the early years and appear to be interpolated. In these cases, we start our sample after these anomalies subside and when the national accounts on the national websites begin. Concretely, this means that we start in 1991.Q1 for Brazil, 1987.Q1 for New Zealand, 1995.Q1 for Iceland, 1983.Q1 for Uruguay, and 1987.Q1 for Turkey. Additionally, we construct quarterly data on other components of GDP (consumption, government spending, etc.) using country-specific sources from national statistical institutes and central banks.

B Appendix to Section 3

B.1 Moderation Beyond GDP

B.1.1 Moderation in macroeconomic aggregates

In Panel A of Figure B1, we show the average rolling standard deviation of first log-differences across the 92 emerging economies in our baseline sample. In Panel B, we show the median inflation rate for the same group of economies. The lessons from this plot are that in emerging markets: i) volatility fell for all macroeconomic aggregates —between 30% (imports) and 50% (productivity); ii) median inflation decreased from around 20% in the 1980s to near 5% in the 2010s.

B.1.2 Regional Changes from 1980-99 to 2000-19

Panel A of Table B1 shows the 1980-99 volatility of the first log-differences of consumption (c), government spending (g), investment (i), exports (x), imports (m), and total factor productivity (a, measured by the Solow residual from a Cobb-Douglas production function). It also shows the average inflation. Panel B does the same for the period 2000-19, and Panel C presents the relative change (in percentage points) between the two periods for these statistics. Bootstrapped standard deviations for these quantities are shown in parenthesis.

From Table B1, it follows that real macroeconomic aggregates in emerging economies experienced a decrease in volatility, as did average inflation. Moreover, the decrease in these statistics is significant at the 95% confidence level, as can be inferred from the standard deviations in parentheses that were constructed using a bootstrap procedure.[17] Hence, this piece of evidence at the regional level supports our claim that the Emerging Market Great Moderation holds across a wide range of real macroeconomic aggregates in all regions. It is worth mentioning that for advanced economies, there is a trend towards a decline in the volatility of real macroeconomic aggregates, but such a trend is only significant for consumption and government spending.

Examining the specific value of changes at the regional level, we observe from Panel C in Table B1 that in emerging economies, the volatility of consumption, government spending, investment, exports, imports, and total factor productivity fell by 31.5%, 30.8%, 20.9%, 25.4%, 27.3%, and 35.9%, respectively. Furthermore, average inflation fell by 63.2%. Roughly speaking, and in line with our findings on the moderation of output these numbers reveal that macroeconomic volatility fell by about a 30% while inflation shrank by 60%.

[17]The assertion on the statistical significance of our finding holds true not only at the aggregate level of emerging markets, but region by region, except for investment in the Americas and Asia and the Pacific, and for exports and imports in Sub-Saharan Africa.

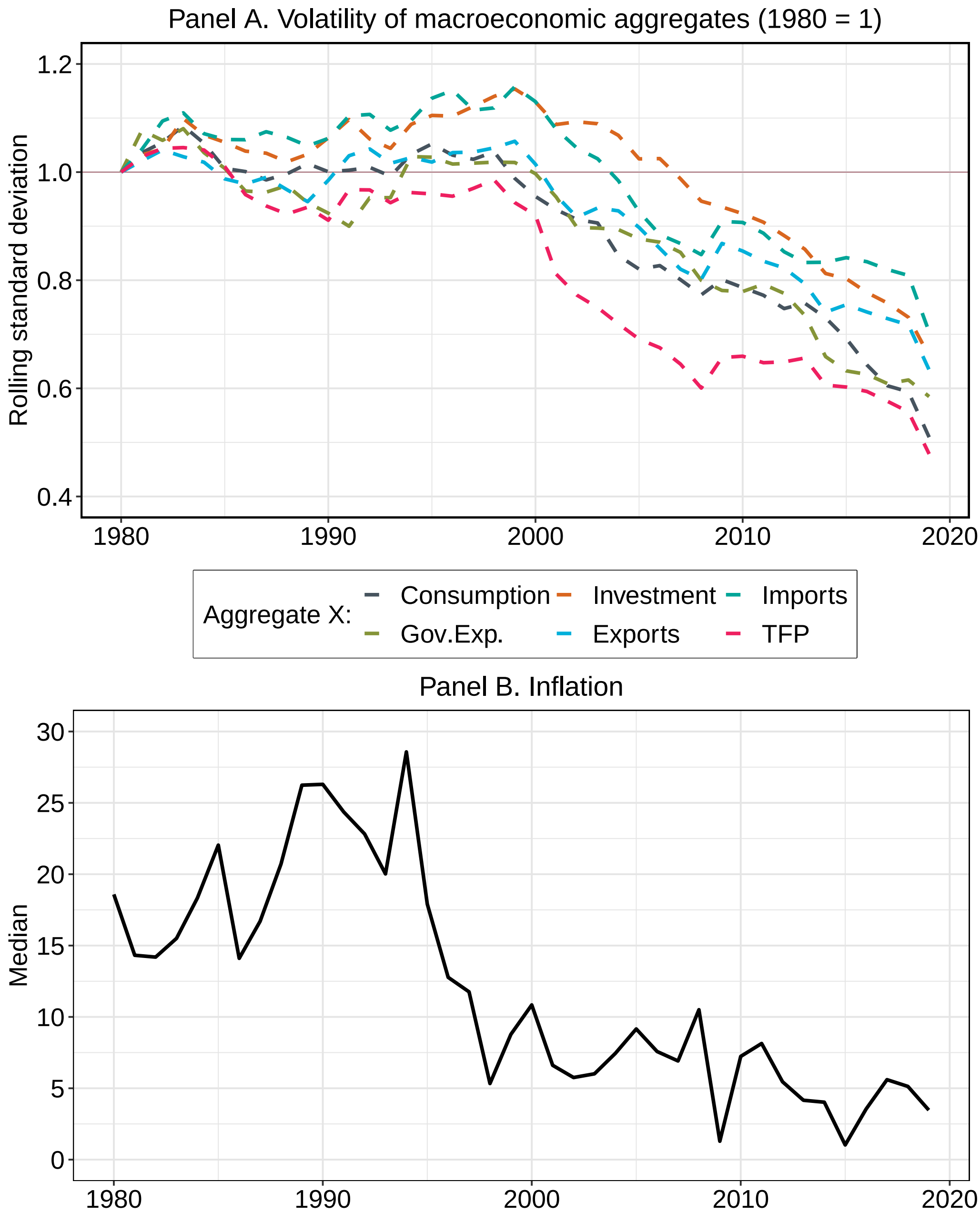


FIGURE B1. MODERATION IN MACROECONOMIC AGGREGATES

Notes: In Panel A, we report the average 10-year rolling standard deviation of first log-differences in macroeconomic aggregates. In Panel B, we report the median inflation across emerging economies. For both panels we use the baseline sample of 92 emerging economies described in Section 2. TFP stands for total factor productivity, which we measure using the resulting Solow residual from a Cobb-Douglas production technology with the respective labor share for each country.

For advanced economies, the two macro aggregates that have moderated their volatility since the 1980-99 period are consumption and government spending. This fact aligns with the improvement in consumption smoothing that we document in section 3.3: average GDP volatility has remained unchanged in advanced economies and the consumption-GDP volatility ratio decreased, which, given the former, can only follow from a moderation in consumption. Last, it is also worth noting that although in advanced economies average inflation has rarely hit the levels observed in emerging economies due to a longer tradition of price stability, average inflation has moderated quite a bit. Specifically, we observe from Panel C that in advanced economies, average inflation went from 6.4% in the 1980-99 period to 1.68% in the 2000-19 period.

Table B1: Macroeconomic Volatility and Inflation, 1980-99 vs 2000-19

Region	c	g	i	x	m	a	π
Panel A. 1980-99							
Emerging economies	7.59	10.40	20.96	14.22	15.60	5.14	19.16
	(0.24)	(0.45)	(0.66)	(0.54)	(0.62)	(0.21)	(1.46)
Americas	5.71	6.78	18.39	10.17	15.49	3.79	35.60
	(0.35)	(0.45)	(1.22)	(0.52)	(1.31)	(0.30)	(1.42)
Arab World	11.01	12.53	21.80	18.47	17.01	9.23	8.86
	(0.60)	(1.27)	(1.20)	(1.92)	(1.36)	(0.88)	(1.42)
Asia & the Pacific	3.54	5.97	11.10	9.01	11.24	2.62	7.61
	(0.30)	(0.36)	(1.52)	(0.53)	(0.64)	(0.35)	(0.41)
Europe	5.99	9.05	23.30	16.25	15.86	4.88	26.09
	(0.85)	(0.99)	(3.76)	(2.39)	(2.21)	(0.68)	(3.82)
S.S. Africa	8.49	12.74	24.47	15.55	16.41	4.87	15.94
	(0.40)	(1.03)	(1.18)	(0.71)	(1.04)	(0.28)	(1.46)
Advanced economies	2.24	2.14	8.19	4.41	5.70	2.05	6.39
	(0.15)	(0.10)	(0.50)	(0.21)	(0.34)	(0.12)	(1.05)
Panel B. 2000-19							
Emerging economies	5.13	7.11	16.36	10.43	11.23	3.26	6.94
	(0.27)	(0.40)	(0.99)	(0.58)	(0.70)	(0.19)	(0.68)
Americas	4.06	4.10	17.28	6.82	9.96	2.95	10.99
	(0.36)	(0.29)	(3.19)	(0.62)	(1.14)	(0.25)	(1.21)
Arab World	6.48	8.14	16.33	10.83	11.99	4.39	5.65
	(0.44)	(0.63)	(1.07)	(0.52)	(0.57)	(0.35)	(1.21)
Asia & the Pacific	1.94	4.10	8.01	7.54	8.70	1.65	4.71
	(0.14)	(0.34)	(0.67)	(0.63)	(0.73)	(0.15)	(0.36)
Europe	3.73	3.28	12.00	6.75	9.01	2.79	5.26
	(0.42)	(0.23)	(1.30)	(1.13)	(1.50)	(0.39)	(0.85)
S.S. Africa	6.45	10.17	19.86	14.29	13.19	3.62	6.49
	(0.44)	(0.66)	(1.31)	(0.87)	(0.56)	(0.21)	(0.70)
Advanced economies	1.58	1.54	6.78	5.07	5.45	1.87	1.68
	(0.17)	(0.10)	(1.01)	(1.11)	(1.09)	(0.38)	(0.12)
Panel C. Change (%) from 1980-99 to 2000-19							

Table B1: MACROECONOMIC VOLATILITY AND INFLATION, 1980-99 VS 2000-19

Region	c	g	i	x	m	a	π
Emerging economies	-31.46	-30.75	-20.94	-25.38	-27.30	-35.93	-63.15
	(4.26)	(4.91)	(5.42)	(5.33)	(5.21)	(4.82)	(4.64)
Americas	-28.54	-38.67	-9.00	-33.25	-35.34	-22.94	-69.40
	(7.76)	(6.88)	(18.83)	(7.03)	(9.37)	(8.29)	(17.74)
Arab World	-40.51	-35.28	-24.10	-40.95	-29.12	-52.29	-35.72
	(5.34)	(9.06)	(5.96)	(7.97)	(7.01)	(6.67)	(17.74)
Asia & the Pacific	-43.66	-30.88	-25.82	-14.55	-20.97	-35.51	-37.51
	(6.57)	(7.26)	(12.29)	(9.26)	(7.99)	(10.80)	(6.28)
Europe	-36.17	-63.99	-47.13	-56.84	-42.37	-41.57	-79.19
	(11.64)	(4.57)	(10.85)	(10.15)	(12.95)	(11.34)	(4.22)
S.S. Africa	-24.99	-20.26	-18.42	-8.39	-19.44	-26.21	-58.97
	(7.09)	(7.93)	(6.62)	(7.06)	(5.72)	(6.63)	(5.52)
Advanced economies	-29.89	-27.79	-16.23	15.77	-4.01	-7.85	-72.25
	(8.82)	(5.95)	(13.08)	(23.86)	(18.84)	(17.84)	(4.83)

Notes: Columns 2 through 7 refer to the volatility of consumption (c), government spending (g), investment (i), exports (x), imports (m), and total factor productivity (a) computed for the periods 1980-99 (Panel A) and 2000-19 (Panel B). For total factor productivity, we use the Solow residual computed based on a Cobb-Douglas production technology. Column 8 shows the period average inflation. Panel C takes the difference between the figures in Panel B and those in Panel A.

B.1.3 Country-Specific Changes from 1980-99 to 2000-19

Figures B2-B7 show the relative change (%) in the volatility experienced from 1980-99 to 2000-19 for all countries in our baseline sample. Figure B8 serves a similar purpose for average inflation. In what follows, we summarize the results for each macroeconomic aggregate:[18]

- *Consumption.* For 82 out of the 92, emerging economies we observe a decrease in consumption volatility since the 1980-99 period. Such a decrease is statistically significant at the 95% (70%) level for 41 (64) emerging economies. In advanced economies, consumption volatility decreased for 21 out of 24 countries, and such a decrease was statistically significant at the 95% (70%) level for 8 (15) of them.

- *Government spending.* Government spending volatility decreased for 74 emerging economies. Out of those, the decrease was statistically significant at the 95% (70%)

[18]Throughout the discussion, recall that our baseline sample consists of 92 emerging economies and 24 advanced economies. Also, keep in mind that the dots in Figures B2-B7 represent the mean estimate —from a bootstrap procedure— of $\log(X_{2000-19}/X_{1980-99})$, where X_p represents a volatility of a macroeconomic aggregate or average inflation in period p, while the light (dark) shaded bars represent the 95% (70%) confidence intervals that were recovered from the bootstrap procedure.

confidence level for 28 (52) of them. For advanced economies, government spending volatility decreased for 16 out 24 countries, and was significant for 8 (14) of them at the 95% (70%) confidence level.

- *Investment.* Investment volatility fell for 66 emerging economies and 18 advanced economies. Such decreases were statistically significant at the 95% (70%) confidence level for 34 (43) emerging economies and 2 (10) advanced economies.

- *Exports.* Exports volatility went down for 68 emerging economies, a decrease that is statistically significant at the 95% (70%) level in the case of 29 (47) of these economies. In the case of advanced economies, exports volatility fell for 8 countries and this was significant at the 95% (70%) confidence level only for 2 (3) of these economies.

- *Imports.* Imports volatility decreased for 68 emerging economies; this being statistically significant for 28 (53) of them at the 95% (70%) confidence level. For advance economies, imports volatility fell for 11 countries but only slightly, as can be inferred from the fact that the decrease was significant the 70% level only for 2 of them.

- *TFP (Solow residual).* TFP volatility fell for 72 emerging economies, the decrease being statistically significant at the 95% (70%) confidence level for 38 (58) of these economies. Fourteen advanced economies experienced a decrease in TFP volatility, with it being statistically significant at the 95% (70%) level only for 1 (7) economy.

- *Inflation.* Average inflation decreased for 76 emerging economies and all but one advanced economy (Norway). These decreases were significant at the 95% (70%) confidence levels for 56 (65) emerging economies and for 17 (23) advanced economies.

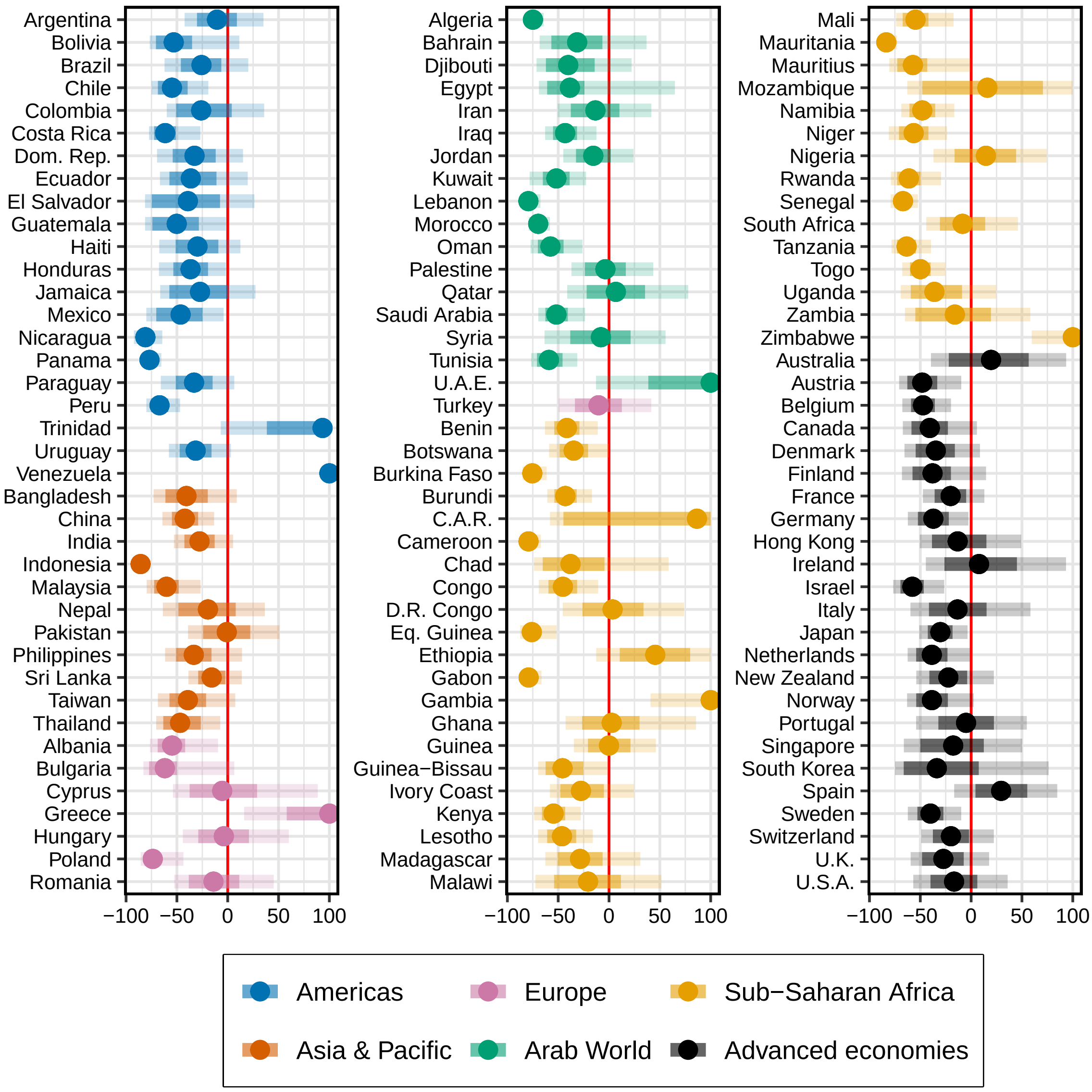


FIGURE B2. CHANGE (%) IN CONSUMPTION VOLATILITY, 1980-99 VS 2000-19

Notes: The figure reports the relative change (in percentage points) of consumption volatility from 1980-99 to 2000-19. For a given country, the dot represent the mean estimate, and the light (dark) bars represent the 95% (70%) confidence interval. The three statistics were computed using bootstrap with replacement and were truncated to -100% or 100% whenever they were outside these boundaries. Specifically, we repeated a three-step process $B = 5,000$ times for each country. First, we drew 20 growth rates from the period 1980-99 with replacement and did the same for the period 2000-19. Second, we estimated the consumption standard deviation for both periods using the data that we drew. Third, we took the relative change between the estimate of consumption volatility from 1980-99 to 2000-19. Repeating this process provided us with an estimate of the empirical distribution of the relative change in consumption volatility. We used the empirical distribution to compute the mean and the 70% and 95% confidence intervals.

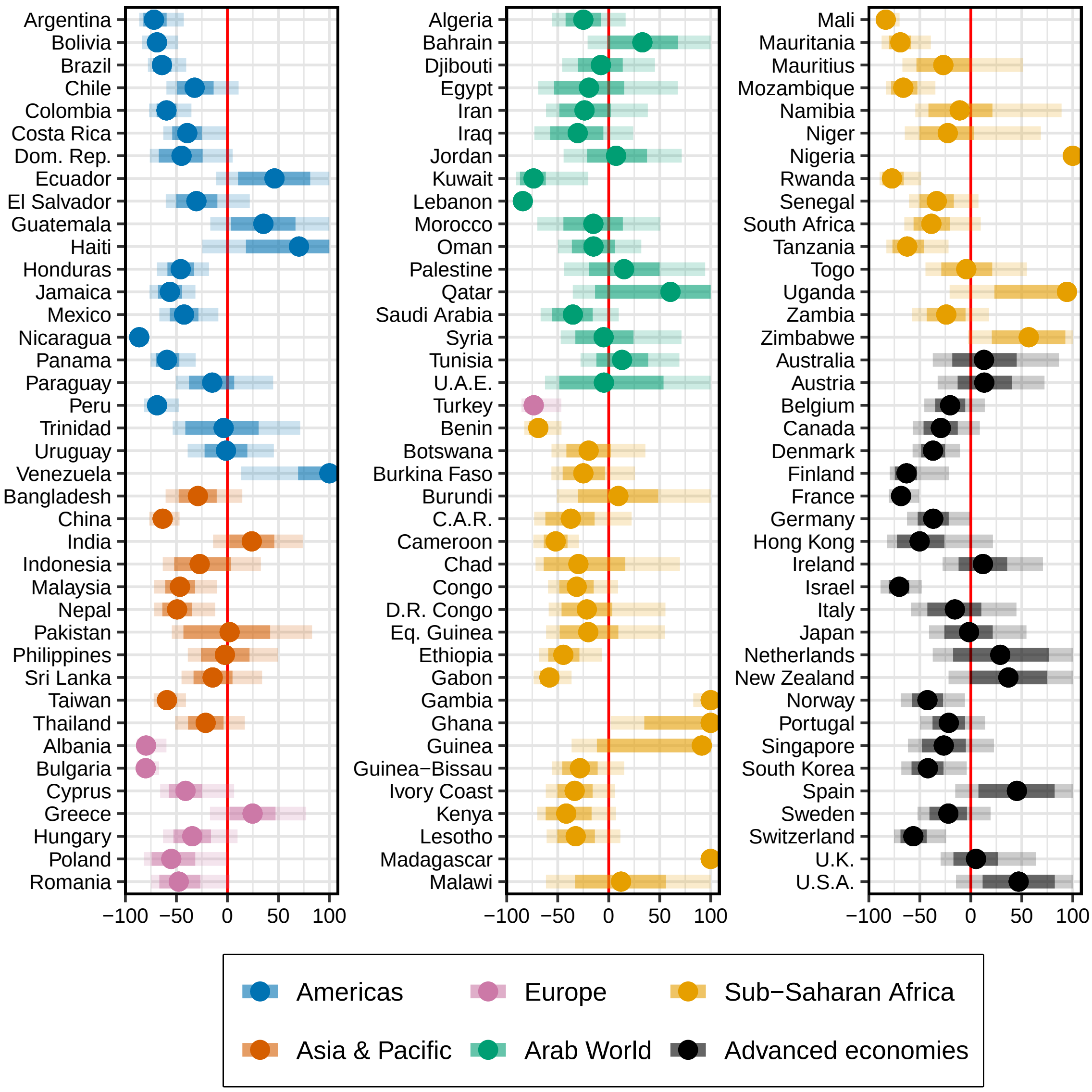


Figure B3. Change (%) in Gov.Spending Volatility, 1980-99 vs 2000-19

Notes: The figure reports the relative change (in percentage points) of government spending volatility from 1980-99 to 2000-19. For a given country, the dot represent the mean estimate, and the light (dark) bars represent the 95% (70%) confidence interval. The three statistics were computed using bootstrap with replacement and were truncated to -100% or 100% whenever they were outside these boundaries. Specifically, we repeated a three-step process $B = 5,000$ times for each country. First, we drew 20 growth rates from the period 1980-99 with replacement and did the same for the period 2000-19. Second, we estimated the government spending standard deviation for both periods using the data that we drew. Third, we took the relative change between the estimate of government spending volatility from 1980-99 to 2000-19. Repeating this process provided us with an estimate of the empirical distribution of the relative change in government spending volatility. We used the empirical distribution to compute the mean and the 70% and 95% confidence intervals.

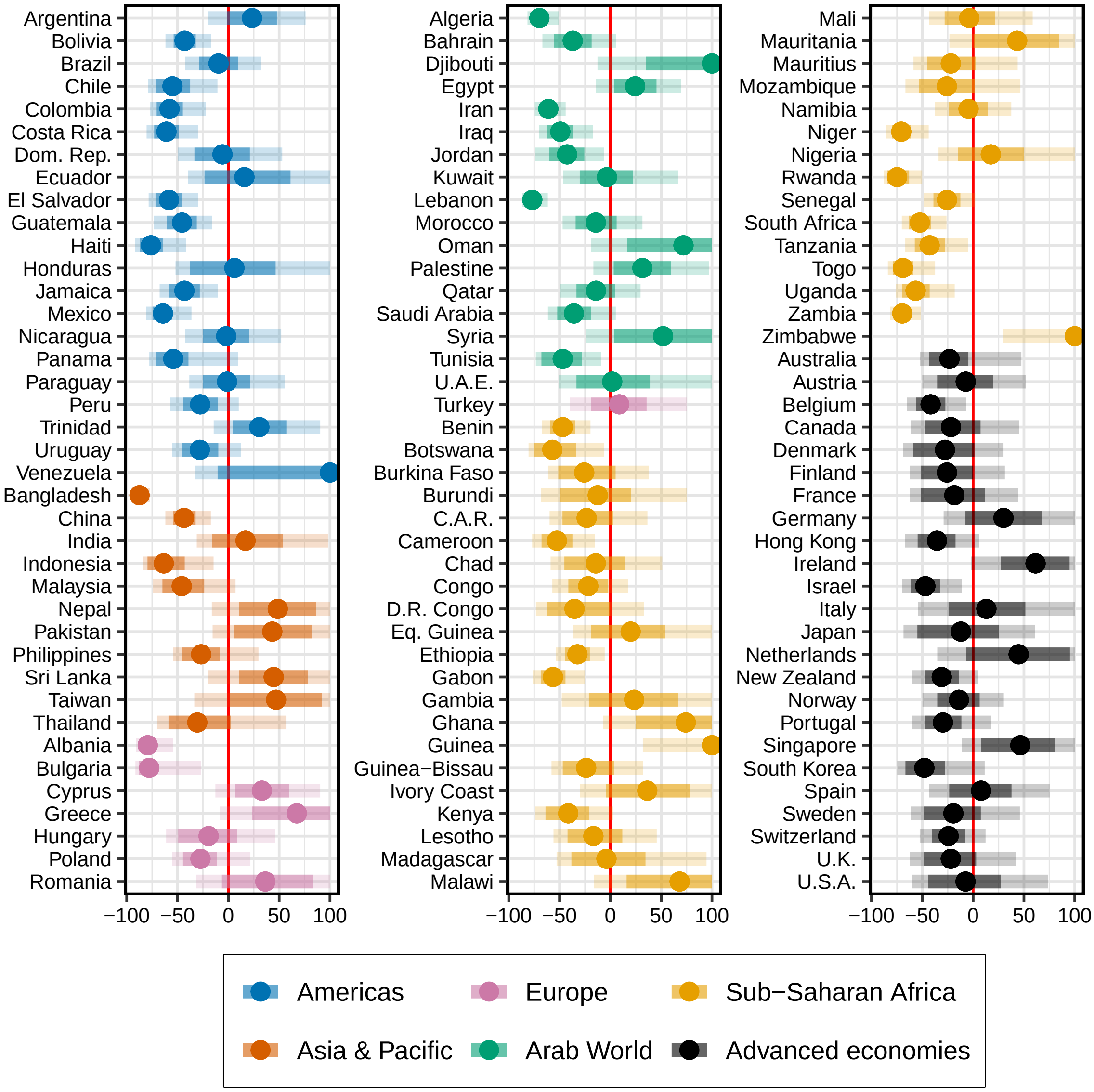


Figure B4. Change (%) in Investment Volatility, 1980-99 vs 2000-19

Notes: The figure reports the relative change (in percentage points) of investment volatility from 1980-99 to 2000-19. For a given country, the dot represent the mean estimate, and the light (dark) bars represent the 95% (70%) confidence interval. The three statistics were computed using bootstrap with replacement and were truncated to -100% or 100% whenever they were outside these boundaries. Specifically, we repeated a three-step process $B = 5,000$ times for each country. First, we drew 20 growth rates from the period 1980-99 with replacement and did the same for the period 2000-19. Second, we estimated the investment standard deviation for both periods using the data that we drew. Third, we took the relative change between the estimate of investment volatility from 1980-99 to 2000-19. Repeating this process provided us with an estimate of the empirical distribution of the relative change in investment volatility. We used the empirical distribution to compute the mean and the 70% and 95% confidence intervals.

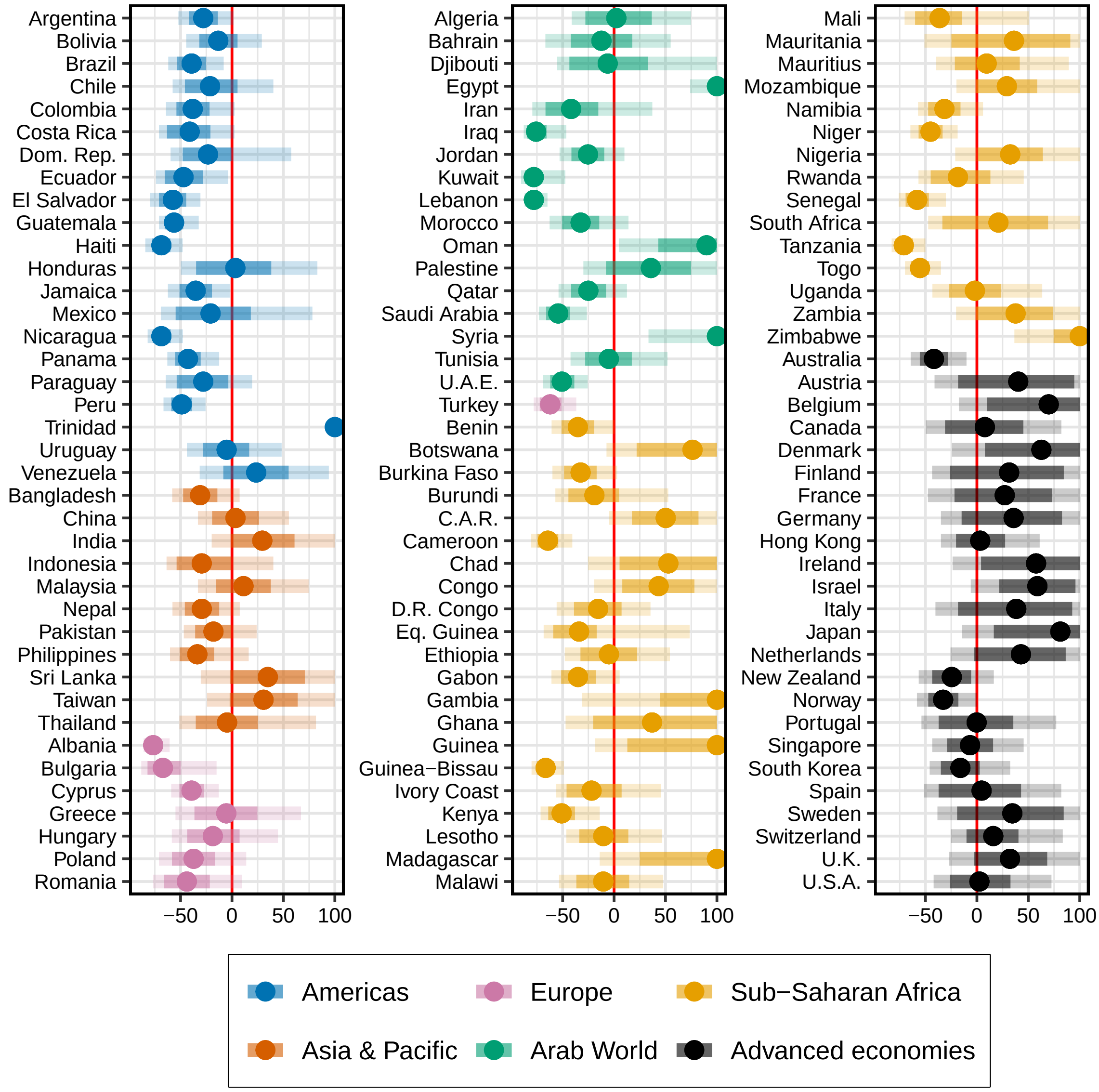


Figure B5. Change (%) in Exports Volatility, 1980-99 vs 2000-19

Notes: The figure reports the relative change (in percentage points) of exports volatility from 1980-99 to 2000-19. For a given country, the dot represent the mean estimate, and the light (dark) bars represent the 95% (70%) confidence interval. The three statistics were computed using bootstrap with replacement and were truncated to -100% or 100% whenever they were outside these boundaries. Specifically, we repeated a three-step process $B = 5,000$ times for each country. First, we drew 20 growth rates from the period 1980-99 with replacement and did the same for the period 2000-19. Second, we estimated the exports standard deviation for both periods using the data that we drew. Third, we took the relative change between the estimate of exports volatility from 1980-99 to 2000-19. Repeating this process provided us with an estimate of the empirical distribution of the relative change in exports volatility. We used the empirical distribution to compute the mean and the 70% and 95% confidence intervals.

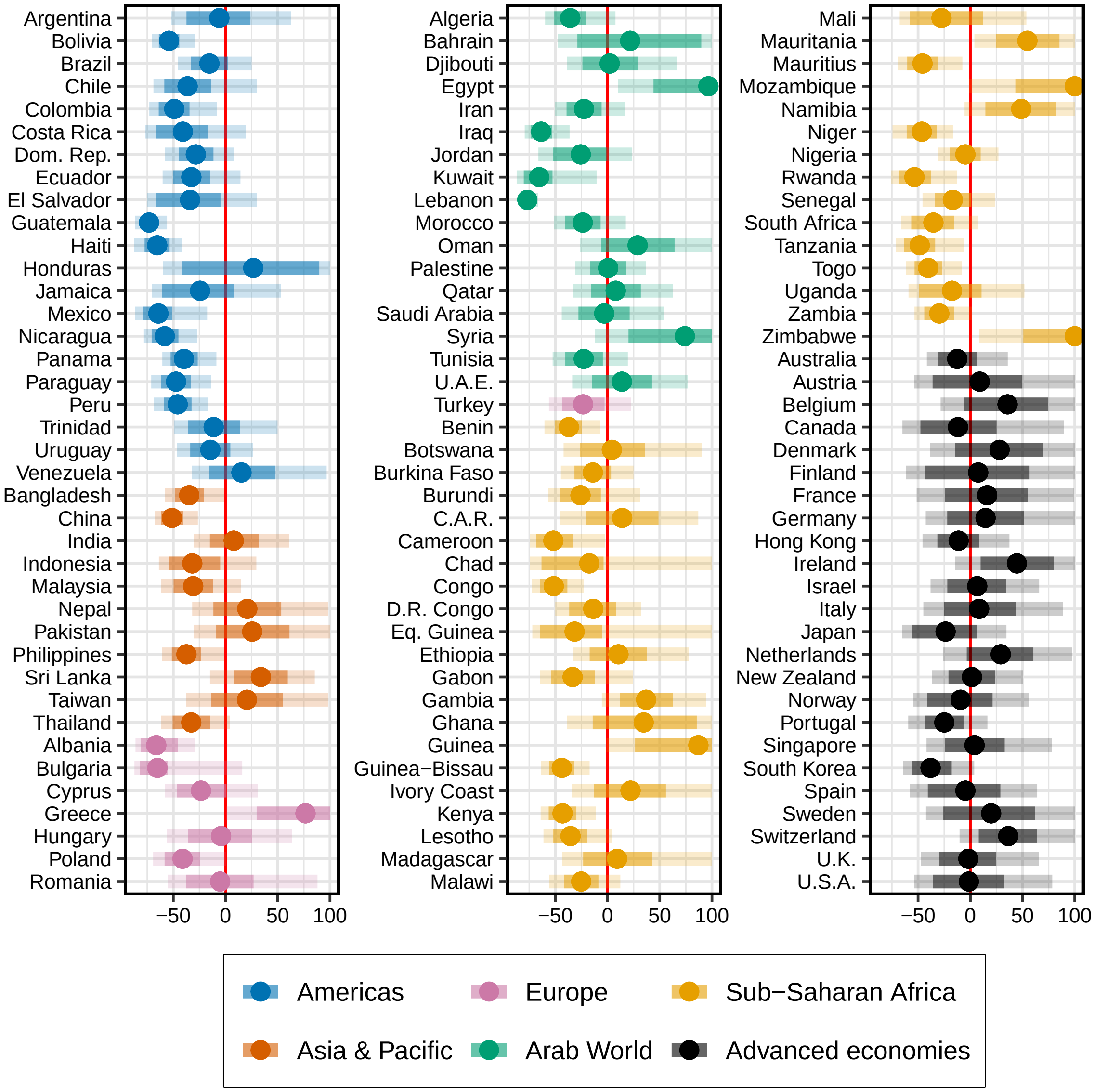


FIGURE B6. CHANGE (%) IN IMPORTS VOLATILITY, 1980-99 VS 2000-19

Notes: The figure reports the relative change (in percentage points) of imports volatility from 1980-99 to 2000-19. For a given country, the dot represent the mean estimate, and the light (dark) bars represent the 95% (70%) confidence interval. The three statistics were computed using bootstrap with replacement and were truncated to -100% or 100% whenever they were outside these boundaries. Specifically, we repeated a three-step process $B = 5,000$ times for each country. First, we drew 20 growth rates from the period 1980-99 with replacement and did the same for the period 2000-19. Second, we estimated the imports standard deviation for both periods using the data that we drew. Third, we took the relative change between the estimate of imports volatility from 1980-99 to 2000-19. Repeating this process provided us with an estimate of the empirical distribution of the relative change in imports volatility. We used the empirical distribution to compute the mean and the 70% and 95% confidence intervals.

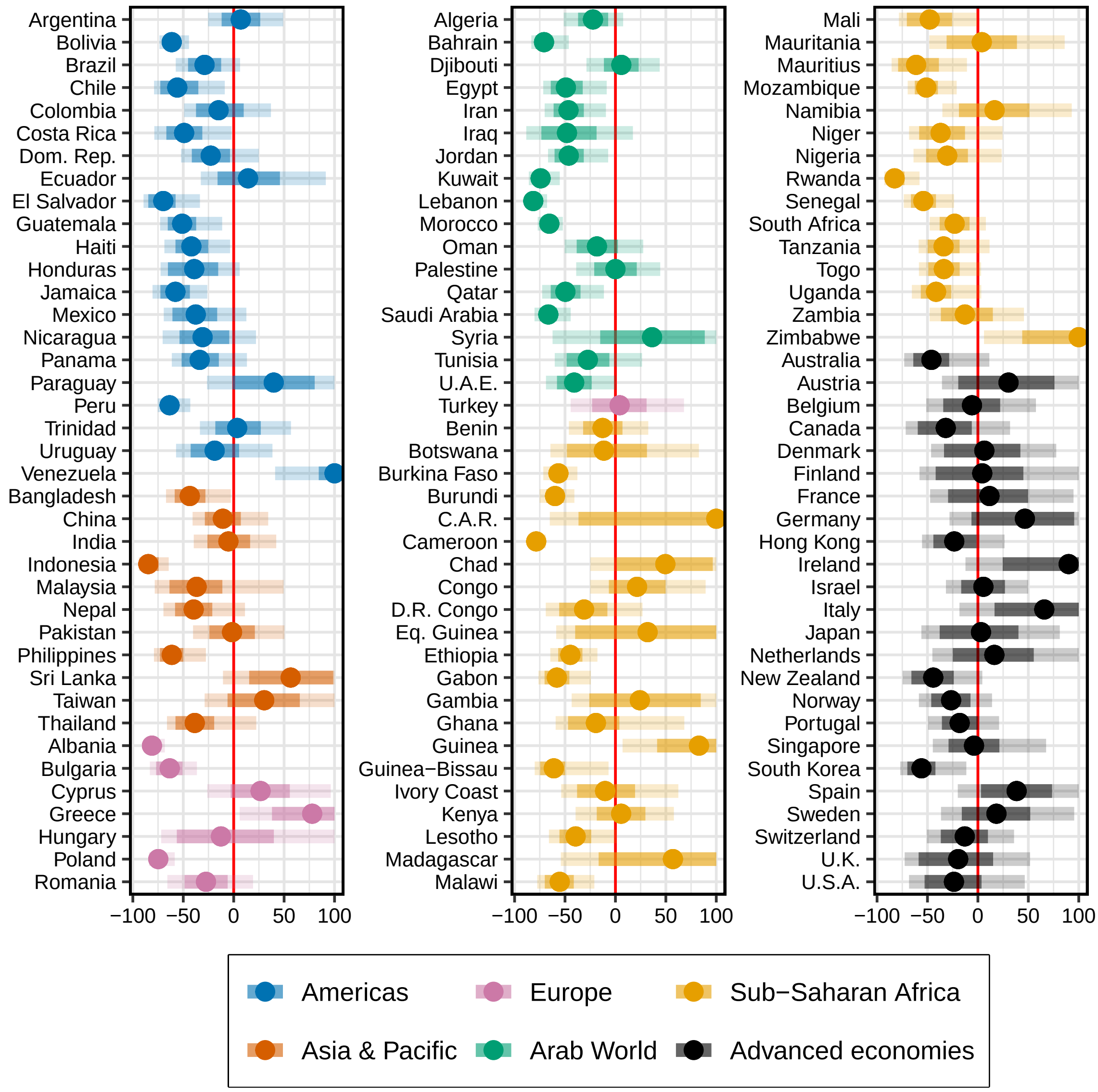


Figure B7. Change (%) in TFP Volatility, 1980-99 vs 2000-19

Notes: The figure reports the relative change (in percentage points) of TFP volatility from 1980-99 to 2000-19. For a given country, the dot represent the mean estimate, and the light (dark) bars represent the 95% (70%) confidence interval. The three statistics were computed using bootstrap with replacement and were truncated to -100% or 100% whenever they were outside these boundaries. Specifically, we repeated a three-step process $B = 5,000$ times for each country. First, we drew 20 growth rates from the period 1980-99 with replacement and did the same for the period 2000-19. Second, we estimated the TFP standard deviation for both periods using the data that we drew. Third, we took the relative change between the estimate of TFP volatility from 1980-99 to 2000-19. Repeating this process provided us with an estimate of the empirical distribution of the relative change in TFP volatility. We used the empirical distribution to compute the mean and the 70% and 95% confidence intervals.

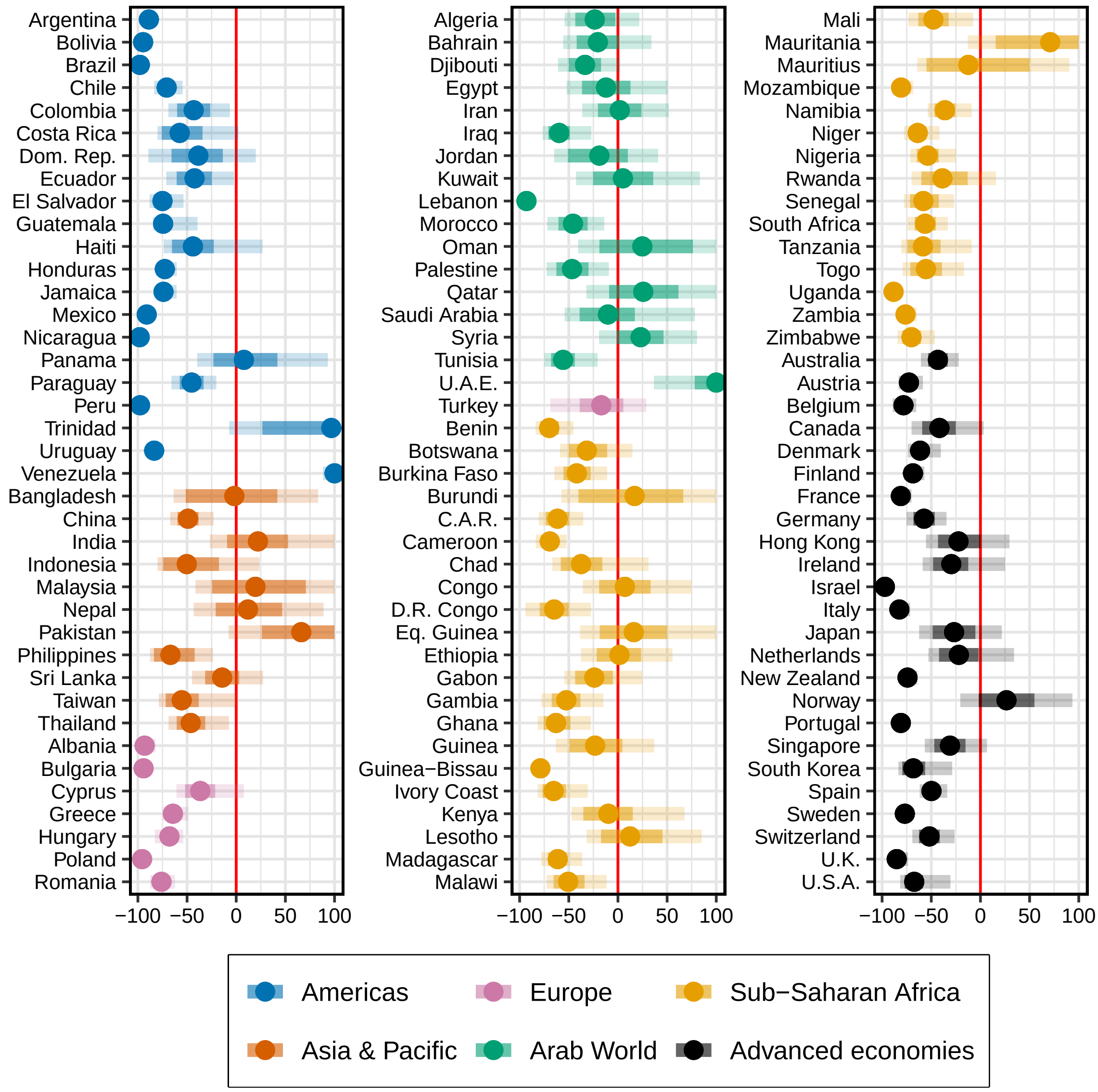


Figure B8. Change (%) in Average Inflation, 1980-99 vs 2000-19

Notes: The figure reports the relative change (in percentage points) of average inflation from 1980-99 to 2000-19. For a given country, the dot represent the mean estimate, and the light (dark) bars represent the 95% (70%) confidence interval. The three statistics were computed using bootstrap with replacement and were truncated to -100% or 100% whenever they were outside these boundaries. Specifically, we repeated a three-step process $B = 5,000$ times for each country. First, we drew 20 growth rates from the period 1980-99 with replacement and did the same for the period 2000-19. Second, we estimated average inflation for both periods using the data that we drew. Third, we took the relative change between the estimate of average inflation from 1980-99 to 2000-19. Repeating this process provided us with an estimate of the empirical distribution of the relative change in average inflation. We used the empirical distribution to compute the mean and the 70% and 95% confidence intervals.

B.2 More Results on the Moderation

B.2.1 Break Tests

In this section, we describe the formal break tests for changes in the volatility of output growth. We follow McConnell and Perez-Quiros (2000), who document facts for the Great Moderation in the U.S.

Specifically, we estimate an AR(1) on the quarterly growth rates of GDP in a variety of countries.

$$\Delta y_{i,t} = \mu + \phi \Delta y_{i,t-1} + \hat{\epsilon}_{i,t}$$

We then estimate break points in the standard deviation of the residuals $\hat{\epsilon}_{i,t}$ of the AR(1). Specifically, we estimate a break in the series $\sqrt{\pi/2}|\hat{\epsilon}_{i,t}|$, which is an unbiased estimator for the standard deviation if ε is normally distributed. The specification using absolute values is more robust to deviations from normality (Davidian & Carroll, 1987) and is therefore commonly used in the literature on the Great Moderation in advanced economies (Gadea et al., 2018; McConnell & Perez-Quiros, 2000).

We use the Bai and Perron (1998) sequential testing procedure that identifies structural breaks in linear models at unknown dates by testing the null hypothesis of m breaks against $m+1$ breaks, starting with $m = 0$. If m breaks are identified at years $T_1 < \cdots < T_m$, the period covering years T_{j-1} through T_j can be construed as the j-th regime ($j = 1, \cdots, m+1$, with T_0 and T_{m+1} being the initial and final year in the data).

We use the BP procedure on the linear model

$$\left| \sqrt{\frac{\pi}{2}} \cdot \hat{\epsilon}_t \right| = \sigma + u_t,$$

to identify structural breaks —if any— in the intercept σ, the standard deviation of the innovations in the output growth process.[19] We follow this procedure separately for each country, using all data available in our sample, to construct a panel on the latent GDP standard deviation σ across countries and over time. We implement these tests using the `mbreaks` package (Nguyen, Yamamoto, & Perron, 2023).

Figure B9 summarizes the distribution properties of the time series of latent GDP volatility in emerging and advanced economies via a dynamic box plot —originally named a schematic plot in Tukey (1977). Each box has two horizontal extremes that represent the 25% and 75% percentiles of the data from the corresponding year and region under study. Between these percentiles, the median is depicted as a bold horizontal line. The vertical line below (above) the 25% (75%) percentile extends to the maximum (minimum) between the minimum (maximum) of the distribution and the 25% (75%) percentile less (plus) 1.5 times the interquartile range.

[19] McConnell and Perez-Quiros (2000) use F-tests instead, which test for the presence of one structural break. On the other hand, the BP procedure has the advantage of being agnostic about the number of breaks in the data. Since our sample spans a period of 70 years for several countries, we consider it more appropriate to consider the possibility of more than one break.

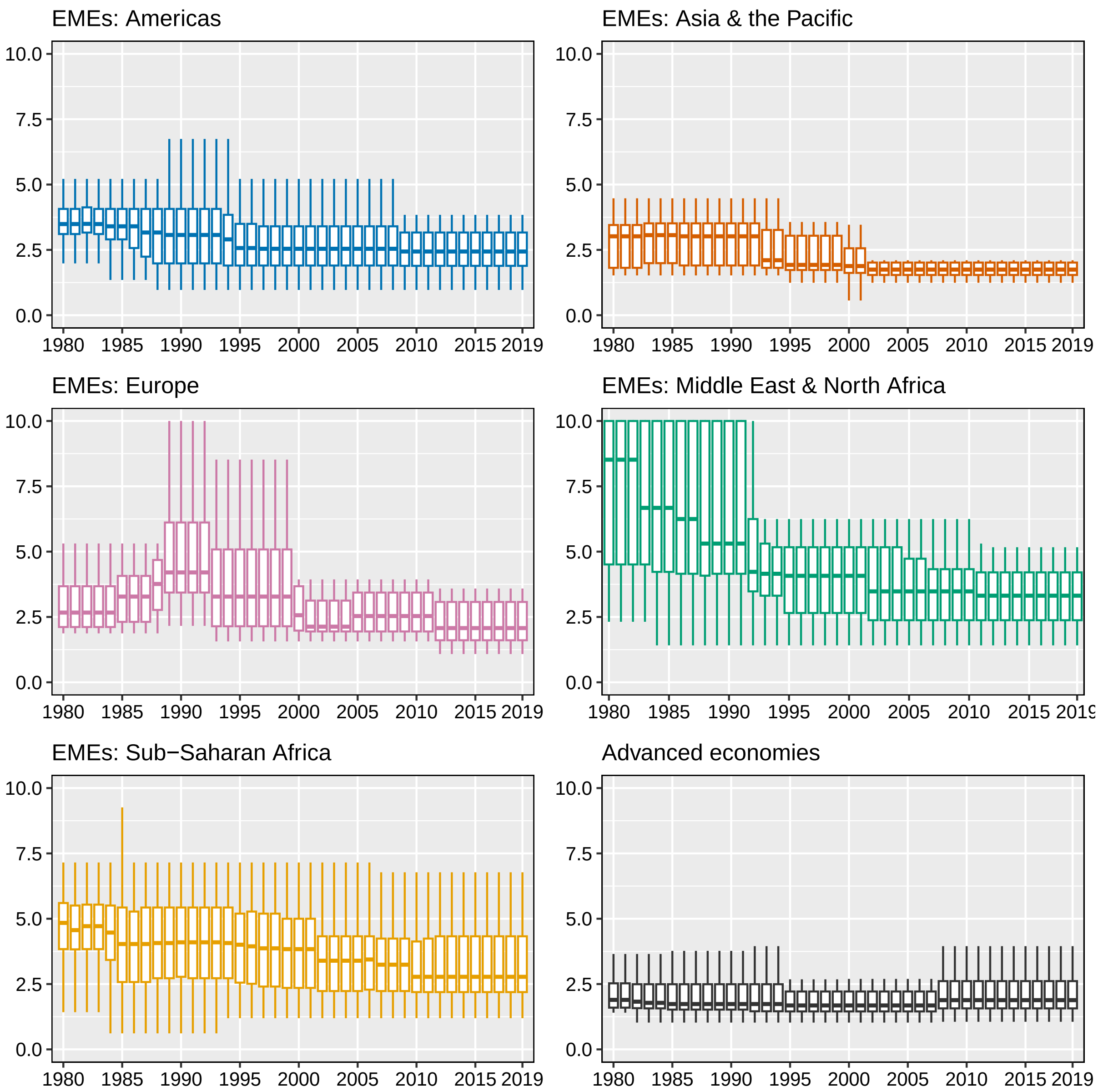
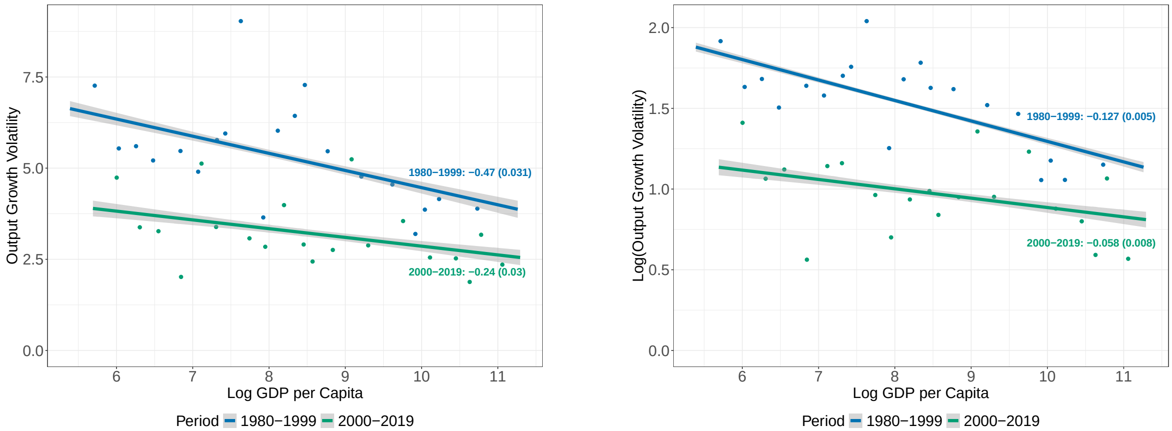


Figure B9. GDP Volatility Regimes, 1980-2019

Notes: The figure reports six panels with the dynamic box plots of the distribution of GDP standard deviation in six regions. The values of the GDP standard deviation were inferred by applying the Bai and Perron (1998, 2003) procedure to the residuals estimated from an AR(1) process on the first differences in log-GDP (see main text for the details). For each panel, there is a (white) box for each year in the period 1980-2019. Each of these boxes has two horizontal extremes representing the 25% and 75% percentiles of GDP standard deviation across the countries located in the region represented by the panel. The median is depicted as a bold horizontal line between the 25% and 75% percentiles. The vertical line below (above) the 25% (75%) percentile extends to the maximum (minimum) between the minimum (maximum) of the distribution and the 25% (75%) percentile less (plus) 1.5 times the interquartile range, where the interquartile range is defined as the difference between the 75% and 25% percentiles.

One key finding emerges from Figure B9: the most noticeable changes in the distribution of emerging markets GDP volatility occurred before the year 2000. The panels



(a) Volatility–Develop. Relation

(b) Log Volatility–Develop. Relation

Figure B10. Volatility-Development Gradient

Notes: This figure shows binscatter plots using cross-country regressions of volatility on real GDP per capita for the periods 1980-99 and 2000-19. In panel (a), volatility is measured as the standard deviation of output growth. In panel (b), volatility is measured as the log of this standard deviation. The numbers in both panels indicate the coefficient β in regression B1 together with standard errors.

roughly show that the median, 25% and 75% percentile, and extreme values of the distribution of emerging markets GDP volatility shrunk mainly during the years covered by the period 1980-99. In four of the five regions, the behavior of the aforementioned statistics is close to strictly decreasing, and in the remaining region (Europe), the figure reveals that the higher level of GDP volatility in the 1980-99 period, in contrast to the 2000-19 period, is explained by structural increases that started to happen at the end of the 1980s but that were reversed by the end of the 1990s.

The panels in Figure B9 reveal another piece of information that aids in describing the time series dynamics that led to the EMGM. After the year 2000, GDP volatility stabilized in Asia & the Pacific; decreased in the Americas, the Arab World, and Sub-Saharan Africa (although more slowly than in the period 1980-99); and remained below the 1980-99 levels in Europe. On the other hand, the lower-right panel of Figure B9 shows that the distribution of GDP volatility remained close to constant in advanced economies. Hence, not only were there marked reductions in GDP volatility during the 1980s and 1990s, but the moderation was not reversed in the last two decades and, in some cases, became more pronounced.

B.2.2 The Volatility-Development Gradient

Another way of viewing the emerging market great moderation we document is as a decline in the gradient between volatility and development (Koren & Tenreyro, 2007). Figure B10 shows this explicitly. Both panels present binscatter plots using cross-country regressions showing the relationship between volatility and development for the periods 1980-99 and

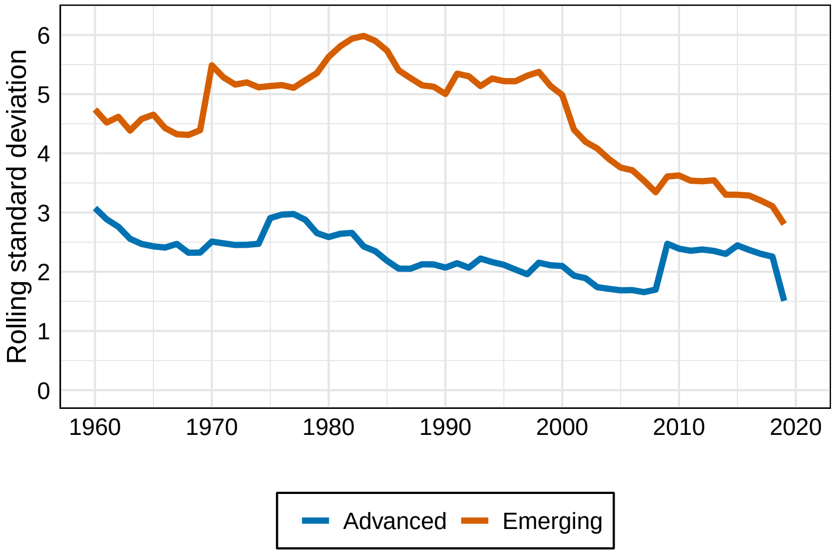


FIGURE B11. OUTPUT VOLATILITY: ADVANCED VS. EMERGING SINCE 1980

Notes: The plot shows the average backward 10-years rolling standard deviation of output growth for emerging markets (solid orange line) and advanced markets (dashed blue line). The rolling standard deviation is computed separately for each country, we show the unweighted averages across emerging and advanced.

2000-19 of the form

$$\text{Volatility}_i = \alpha + \beta \log(\text{Real GDP per Capita})_i + \varepsilon_i. \tag{B1}$$

Here, real GDP per capita refers to the average GDP per capita over the period and the volatility is measured as the standard deviation of output growth (resp. the log of this standard deviation in panel (b)).

The coefficient β gives the relationship between volatility and development and is displayed together with the fitted lines. In both specifications, this coefficient drops by 50% over the two time periods, so the volatility-development gradient has considerably flattened over time. In other words, the Emerging Market Great Moderation is not just a function of increased development, but in fact the relationship between development and volatility has changed over time.

B.2.3 A Long-Run View on Volatility

We now present additional results on the moderation that go further back in time. The drawback is that for some economies, our data only starts later in the 1960s or 1970s, leading to an unbalanced sample at that point. First, we extend the evidence on the development of output volatility in Figure 1 back to 1960. Region-specific results are in Table B2.

In line with the trend suggested by Figure B11, we find that most of the reduction in volatility in emerging economies starts during the second period of our sample, 1980-99. Before this period, the standard deviation of output growth in emerging economies remains relatively constant and moves from 5.46 to 5.32. This masks some heterogeneity, as there are already some declines in volatility in Asia before. However, these declines are smaller than what we observe after the 1980-99 period.

In contrast, for advanced economies, much of the decline in volatility occurs between the two periods 1960-79 and 1980-99. Output volatility drops by around 27%, from around 2.7 to 2.1 percent, over this time period, but remains relatively constant afterwards. This also allows us to compare the magnitude of the Great Moderation in advanced economies to emerging markets. In relative terms, the Emerging Market Great Moderation is larger than advanced economy moderation (40% vs 27% in levels). In absolute terms, the Emerging Market Great Moderation is around three times as large as the moderation in advanced economies, because emerging markets start from a higher baseline level of volatility.

Table B2: GDP Volatility: 1960-1979, 1980-99, 2000-19

Region	1960-1979	1980-1999	2000-2019
Emerging economies	5.46	5.32	3.43
	(0.23)	(0.23)	(0.19)
Americas	3.67	3.98	3.06
	(0.22)	(0.26)	(0.24)
Asia & Pacific	3.78	2.79	1.72
	(0.33)	(0.38)	(0.15)
Europe	3.87	4.93	2.99
	(0.45)	(0.69)	(0.35)
Arab World	9.66	9.10	4.49
	(1.00)	(0.90)	(0.40)
Sub-Saharan Africa	5.97	5.17	3.78
	(0.25)	(0.29)	(0.24)
Advanced economies	2.69	2.12	1.97
	(0.21)	(0.13)	(0.34)

Notes: This table reports the average output volatility for the periods 1980-99 and 2000-19, together with the difference in volatility in levels and in logs. Standard errors in parenthesis are computed via a bootstrap procedure with 5000 iterations.

B.3 Robustness of the Moderation

B.3.1 Robustness: Business Cycle Properties

In this section, we report the robustness of the main changes in business cycle facts in emerging markets. We test the robustness of our facts in three ways.

First, we vary the definition of business cycles, using two other standard approaches in the literature. While our baseline analysis computes business cycle properties directly from growth rates, Table B3 computes volatility using HP-Filtered data and Table B4 reports volatility using the Hamilton filter. Our results are robust to these detrending procedures. In particular, we find an important reduction in output volatility, which drops by around 50% both in the HP-filtered and Hamilton-filtered data. Other core properties of emerging market business cycles, such as the excess volatility of consumption, remain intact. Next, we use a specification in which we drop extreme observations, defined as those in which GDP changes by more than 15% in a given year. We drop those years and report business cycle statistics in Table B5. Finally, we use a different dataset, the World Bank's World Development Indicators, in Table B6. The results are consistent and similar; the differences mostly come from the fact the World Development Indicators cover a somewhat shorter sample.

Next, we vary the definition of an emerging market. In our baseline analysis, we use the S&P emerging market classification, as in Aguiar and Gopinath (2007). In an extension, we consider two alternative country classifications. First, we use the World Bank's country classification, which consists of four categories (low, lower-middle, upper-middle, and high-income economies) and is based on gross national income per capita.[20] Table B7 summarizes results using the World Bank country classification, classifying high-income countries as advanced. The breakdown into categories allows us to shed further light on business cycles along the path of development in Tables B8 and B9, where we plot business cycles for all four country groups. This again shows that the moderation we document is not concentrated among more advanced emerging economies but rather applies across emerging economies. Volatility is not necessarily stable along the path of development, and, in fact, *upper-middle* income countries have slightly more volatile business cycles than *lower-middle* income countries, though in both country groups the business cycle has moderated considerably. Other business cycle moments that distinguish emerging from advanced economies, such as the excess volatility of consumption, continue to persist across time periods. This also continues to hold when we use the country classification of Uribe and Schmitt-Grohé (2017) (Table B10) or the exact same countries as in Aguiar and Gopinath (2007) (Table B11).

Finally, the fact that the World Bank's classification goes back to 1987 allows us to compute business cycle moments for a moving sample, in which the country classification changes over time. We do so in Table B6.

[20] See here for further details.

Table B3: Business Cycles: 1980-99 vs 2000-19, Hodrick-Prescott Filter

Statistic	Period	Emerging Markets						
		Mean	Median	S.D.	p5	p25	p75	p95
$\sigma(y)$	1980-1999	3.46	2.76	3.13	1.07	1.85	3.73	7.49
	2000-2019	1.98	1.55	1.57	0.67	1.04	2.16	5.54
$\sigma(c)/\sigma(y)$	1980-1999	1.69	1.37	1.04	0.72	1.08	2.01	3.52
	2000-2019	1.70	1.26	1.34	0.63	0.90	2.07	4.51
$\sigma(i)/\sigma(y)$	1980-1999	4.91	4.40	2.50	1.83	3.10	5.79	9.80
	2000-2019	5.64	4.58	3.32	1.96	3.63	6.96	11.66
$\sigma(NX/Y)$	1980-1999	6.75	4.45	7.02	1.60	2.72	8.27	20.38
	2000-2019	6.16	4.26	5.00	1.53	2.82	8.72	14.66
$\rho(NX/Y, y)$	1980-1999	-0.11	-0.13	0.34	-0.66	-0.31	0.08	0.47
	2000-2019	-0.11	-0.07	0.29	-0.57	-0.27	0.07	0.29
$\rho(c, y)$	1980-1999	0.60	0.65	0.26	0.15	0.45	0.78	0.93
	2000-2019	0.51	0.53	0.34	-0.11	0.27	0.83	0.94
$\rho(i, y)$	1980-1999	0.51	0.58	0.36	-0.24	0.31	0.78	0.93
	2000-2019	0.47	0.53	0.35	-0.16	0.24	0.79	0.91
Statistic	Period	Advanced Economies						
		Mean	Median	S.D.	p5	p25	p75	p95
$\sigma(y)$	1980-1999	1.38	1.23	0.52	0.83	1.01	1.54	2.44
	2000-2019	1.29	1.18	0.57	0.80	0.98	1.43	2.14
$\sigma(c)/\sigma(y)$	1980-1999	1.08	0.95	0.42	0.65	0.79	1.23	1.58
	2000-2019	0.83	0.74	0.38	0.38	0.57	1.02	1.64
$\sigma(i)/\sigma(y)$	1980-1999	4.16	4.14	0.89	2.76	3.63	4.63	5.52
	2000-2019	3.77	3.72	1.07	2.55	3.06	4.22	5.88
$\sigma(NX/Y)$	1980-1999	2.08	1.47	1.44	0.77	1.13	2.67	5.24
	2000-2019	2.58	1.95	1.68	0.90	1.19	3.44	6.08
$\rho(NX/Y, y)$	1980-1999	-0.31	-0.33	0.16	-0.55	-0.44	-0.21	-0.08
	2000-2019	-0.05	-0.03	0.22	-0.37	-0.29	0.15	0.23
$\rho(c, y)$	1980-1999	0.73	0.77	0.18	0.35	0.66	0.88	0.91
	2000-2019	0.75	0.80	0.16	0.53	0.64	0.86	0.93
$\rho(i, y)$	1980-1999	0.80	0.84	0.16	0.44	0.76	0.92	0.94
	2000-2019	0.79	0.88	0.19	0.51	0.69	0.92	0.96

Notes: The table reports business cycle moments for emerging and advanced economies. Variables refer to deviations from a HP-filtered trend. The table reports the mean, median, standard deviation, 5th, 25th, 75th, and 95th percentiles of the statistics across the countries in each category. The table reports moments for the periods 1980-1999 and 2000-2019.

Table B4: Business Cycles: 1980-99 vs 2000-19, Hamilton Filter

Statistic	Period	Emerging Markets						
		Mean	Median	S.D.	p5	p25	p75	p95
$\sigma(y)$	1980-1999	8.18	6.67	6.39	2.90	4.90	9.00	20.26
	2000-2019	5.26	3.99	3.84	2.02	2.86	6.10	13.60
$\sigma(c)/\sigma(y)$	1980-1999	1.48	1.27	0.79	0.67	1.05	1.79	2.74
	2000-2019	1.48	1.27	0.74	0.64	0.96	1.81	3.05
$\sigma(i)/\sigma(y)$	1980-1999	4.19	3.78	2.18	1.73	2.83	4.72	8.63
	2000-2019	4.42	3.77	2.06	2.00	2.96	5.46	8.50
$\sigma(NX/Y)$	1980-1999	6.80	4.58	7.00	1.60	2.73	8.62	20.18
	2000-2019	6.22	4.42	5.00	1.54	2.84	8.78	14.63
$\rho(NX/Y, y)$	1980-1999	-0.07	-0.07	0.34	-0.58	-0.33	0.20	0.50
	2000-2019	-0.07	-0.07	0.35	-0.68	-0.30	0.18	0.48
$\rho(c, y)$	1980-1999	0.59	0.63	0.30	0.03	0.48	0.80	0.93
	2000-2019	0.57	0.62	0.30	0.02	0.38	0.83	0.95
$\rho(i, y)$	1980-1999	0.56	0.63	0.33	-0.19	0.40	0.81	0.94
	2000-2019	0.51	0.56	0.33	-0.02	0.24	0.79	0.93
Statistic	Period	Advanced Economies						
		Mean	Median	S.D.	p5	p25	p75	p95
$\sigma(y)$	1980-1999	3.55	3.10	1.20	2.13	2.82	4.13	5.68
	2000-2019	3.16	2.88	1.54	1.87	2.31	3.40	4.84
$\sigma(c)/\sigma(y)$	1980-1999	1.03	0.98	0.25	0.80	0.89	1.12	1.46
	2000-2019	0.87	0.86	0.38	0.50	0.59	1.07	1.26
$\sigma(i)/\sigma(y)$	1980-1999	3.80	3.73	0.87	2.68	3.24	4.22	5.49
	2000-2019	3.49	3.22	1.39	2.11	2.76	3.83	5.64
$\sigma(NX/Y)$	1980-1999	2.08	1.47	1.44	0.77	1.13	2.67	5.24
	2000-2019	2.58	1.95	1.68	0.90	1.19	3.44	6.08
$\rho(NX/Y, y)$	1980-1999	0.00	0.03	0.35	-0.54	-0.24	0.23	0.47
	2000-2019	0.05	0.03	0.27	-0.46	-0.07	0.29	0.42
$\rho(c, y)$	1980-1999	0.78	0.80	0.13	0.57	0.70	0.88	0.93
	2000-2019	0.73	0.73	0.18	0.46	0.65	0.86	0.95
$\rho(i, y)$	1980-1999	0.84	0.88	0.11	0.60	0.78	0.92	0.95
	2000-2019	0.79	0.83	0.16	0.49	0.69	0.91	0.95

Notes: The table reports business cycle moments for emerging and advanced economies. Variables refer to deviations from a Hamilton-filtered trend. The table reports the mean, median, standard deviation, 5th, 25th, 75th, and 95th percentiles of the statistics across the countries in each category. The table reports moments for the periods 1980-1999 and 2000-2019.

Table B5: Business Cycles: 1980-99 vs 2000-19, Dropping Outliers

Statistic	Period	Emerging Markets						
		Mean	Median	S.D.	p5	p25	p75	p95
$\sigma(y)$	1980-1999	4.25	4.38	1.45	1.95	3.23	5.26	6.82
	2000-2019	3.03	2.71	1.50	1.22	1.93	3.80	5.98
$\sigma(c)/\sigma(y)$	1980-1999	1.77	1.44	1.05	0.89	1.10	2.07	3.45
	2000-2019	1.64	1.25	1.21	0.64	0.99	1.93	3.43
$\sigma(i)/\sigma(y)$	1980-1999	4.94	4.42	2.16	2.30	3.35	6.62	9.11
	2000-2019	5.42	4.56	2.88	2.32	3.63	6.45	11.13
$\sigma(NX/Y)$	1980-1999	1.18	1.03	0.59	0.58	0.84	1.44	2.08
	2000-2019	0.79	0.64	0.57	0.20	0.43	1.10	1.51
$\rho(NX/Y, y)$	1980-1999	-0.12	-0.13	0.34	-0.69	-0.33	0.09	0.45
	2000-2019	-0.15	-0.12	0.35	-0.74	-0.43	0.12	0.34
$\rho(c, y)$	1980-1999	0.54	0.61	0.31	0.01	0.43	0.76	0.94
	2000-2019	0.54	0.53	0.29	0.09	0.33	0.83	0.93
$\rho(i, y)$	1980-1999	0.51	0.54	0.31	-0.16	0.41	0.76	0.89
	2000-2019	0.50	0.54	0.32	-0.03	0.25	0.78	0.89

Statistic	Period	Advanced Economies						
		Mean	Median	S.D.	p5	p25	p75	p95
$\sigma(y)$	1980-1999	2.21	1.95	0.88	1.21	1.66	2.53	4.07
	2000-2019	2.01	1.92	0.75	1.23	1.48	2.19	3.48
$\sigma(c)/\sigma(y)$	1980-1999	1.08	1.00	0.34	0.76	0.86	1.28	1.53
	2000-2019	0.85	0.81	0.33	0.42	0.57	1.03	1.27
$\sigma(i)/\sigma(y)$	1980-1999	4.06	3.98	0.91	2.58	3.58	4.73	5.59
	2000-2019	3.69	3.63	0.93	2.57	3.08	4.21	5.34
$\sigma(NX/Y)$	1980-1999	0.39	0.35	0.18	0.14	0.26	0.51	0.67
	2000-2019	0.23	0.21	0.13	0.07	0.15	0.29	0.50
$\rho(NX/Y, y)$	1980-1999	-0.42	-0.45	0.21	-0.74	-0.53	-0.28	-0.09
	2000-2019	-0.05	-0.04	0.41	-0.61	-0.39	0.24	0.64
$\rho(c, y)$	1980-1999	0.75	0.80	0.17	0.37	0.67	0.87	0.90
	2000-2019	0.72	0.77	0.18	0.33	0.68	0.84	0.92
$\rho(i, y)$	1980-1999	0.79	0.84	0.14	0.51	0.74	0.89	0.95
	2000-2019	0.75	0.80	0.21	0.38	0.66	0.91	0.94

Notes: The table reports business cycle moments for emerging and advanced economies, dropping years in which GDP changes by more than 15%. Variables are first-difference filtered, as in the baselinevanalysis. The table reports the mean, median, standard deviation, 5th, 25th,v75th, and 95th percentiles of the statistics across the countries in eachvcategory. The table reports statistics for the periods 1980-1999 and 2000-2019.

Table B6: Business Cycles: 1980-99 vs 2000-19, WDI Data

Statistic	Period	Emerging Markets						
		Mean	Median	S.D.	p5	p25	p75	p95
$\sigma(y)$	1980-1999	4.49	3.77	2.80	1.99	2.63	5.30	8.95
	2000-2019	2.60	2.36	1.43	1.04	1.68	3.02	5.63
$\sigma(c)/\sigma(y)$	1980-1999	1.62	1.41	0.90	0.72	1.06	1.93	3.19
	2000-2019	1.37	1.12	0.75	0.74	0.94	1.65	2.86
$\sigma(i)/\sigma(y)$	1980-1999	5.04	4.43	2.52	2.37	3.30	6.18	8.40
	2000-2019	5.96	5.47	3.37	3.31	4.02	6.74	9.77
$\sigma(NX/Y)$	1980-1999	0.06	0.04	0.05	0.01	0.03	0.07	0.17
	2000-2019	0.06	0.04	0.09	0.01	0.03	0.06	0.16
$\rho(NX/Y, y)$	1980-1999	-0.15	-0.17	0.33	-0.63	-0.43	0.09	0.45
	2000-2019	-0.06	-0.01	0.30	-0.54	-0.26	0.10	0.47
$\rho(c, y)$	1980-1999	0.58	0.63	0.32	0.03	0.45	0.81	0.98
	2000-2019	0.56	0.61	0.27	0.09	0.34	0.81	0.89
$\rho(i, y)$	1980-1999	0.52	0.54	0.35	-0.17	0.35	0.80	0.91
	2000-2019	0.51	0.61	0.36	-0.21	0.32	0.81	0.91
Statistic	**Period**	**Advanced Economies**						
		Mean	Median	S.D.	p5	p25	p75	p95
$\sigma(y)$	1980-1999	2.04	1.87	0.75	1.21	1.63	2.20	3.18
	2000-2019	2.03	1.91	0.94	1.31	1.52	2.11	3.00
$\sigma(c)/\sigma(y)$	1980-1999	1.13	1.08	0.36	0.77	0.93	1.31	1.54
	2000-2019	0.79	0.74	0.27	0.41	0.58	0.96	1.19
$\sigma(i)/\sigma(y)$	1980-1999	4.22	3.98	0.86	2.95	3.65	4.73	5.68
	2000-2019	3.55	3.29	0.76	2.57	3.11	3.90	4.76
$\sigma(NX/Y)$	1980-1999	0.02	0.01	0.01	0.01	0.01	0.02	0.06
	2000-2019	0.02	0.02	0.02	0.01	0.01	0.03	0.06
$\rho(NX/Y, y)$	1980-1999	0.06	0.14	0.32	-0.42	-0.17	0.28	0.46
	2000-2019	0.05	0.06	0.27	-0.38	-0.11	0.28	0.33
$\rho(c, y)$	1980-1999	0.77	0.80	0.14	0.59	0.69	0.88	0.90
	2000-2019	0.73	0.77	0.17	0.44	0.65	0.85	0.93
$\rho(i, y)$	1980-1999	0.79	0.84	0.14	0.50	0.76	0.89	0.95
	2000-2019	0.77	0.83	0.21	0.45	0.72	0.91	0.94

Notes: The table reports business cycle moments for emerging and advanced economies using first-difference filtered variables. Data is from the World Bank's World Development Indicators. The table reports the mean, median, standard deviation, 5th, 25th, 75th, and 95th percentiles of the statistics across the countries in each category, using our baseline classification. The table reports moments for the periods 1980-1999 and 2000-2019, moments are unweighted averages across countries.

Table B7: Business Cycles: 1980-99 vs 2000-19, World-Bank Classification

Statistic	Period	Emerging Markets						
		Mean	Median	S.D.	p5	p25	p75	p95
$\sigma(y)$	1980-1999	3.96	2.53	3.85	1.22	1.82	4.97	9.35
	2000-2019	2.67	2.14	1.37	1.29	1.63	3.32	5.51
$\sigma(c)/\sigma(y)$	1980-1999	1.16	1.10	0.40	0.72	0.87	1.34	2.13
	2000-2019	1.13	1.00	0.73	0.47	0.68	1.27	3.19
$\sigma(i)/\sigma(y)$	1980-1999	3.81	3.80	1.36	1.64	3.32	4.37	5.72
	2000-2019	4.01	3.54	1.65	2.57	2.99	4.41	6.45
$\sigma(NX/Y)$	1980-1999	0.05	0.02	0.08	0.01	0.01	0.05	0.13
	2000-2019	0.04	0.03	0.04	0.01	0.02	0.06	0.12
$\rho(NX/Y, y)$	1980-1999	0.05	0.12	0.35	-0.57	-0.18	0.30	0.53
	2000-2019	0.06	0.05	0.28	-0.36	-0.13	0.29	0.47
$\rho(c, y)$	1980-1999	0.63	0.69	0.31	-0.04	0.57	0.86	0.94
	2000-2019	0.65	0.75	0.26	0.14	0.52	0.84	0.93
$\rho(i, y)$	1980-1999	0.68	0.77	0.27	0.20	0.56	0.86	0.94
	2000-2019	0.68	0.79	0.27	0.10	0.60	0.86	0.94

Statistic	Period	Advanced Economies						
		Mean	Median	S.D.	p5	p25	p75	p95
$\sigma(y)$	1980-1999	5.47	4.30	4.66	1.91	3.23	5.84	12.28
	2000-2019	3.48	2.46	2.96	1.13	1.87	3.85	11.15
$\sigma(c)/\sigma(y)$	1980-1999	1.58	1.40	0.75	0.77	1.08	1.79	3.15
	2000-2019	1.50	1.19	0.85	0.57	0.97	1.88	3.03
$\sigma(i)/\sigma(y)$	1980-1999	4.76	4.41	2.17	2.08	3.10	6.29	9.06
	2000-2019	5.11	4.37	2.63	1.78	3.48	5.97	10.38
$\sigma(NX/Y)$	1980-1999	0.06	0.04	0.06	0.02	0.03	0.08	0.20
	2000-2019	0.06	0.04	0.05	0.01	0.03	0.08	0.14
$\rho(NX/Y, y)$	1980-1999	-0.08	-0.10	0.32	-0.54	-0.34	0.15	0.41
	2000-2019	-0.08	-0.09	0.35	-0.60	-0.36	0.13	0.50
$\rho(c, y)$	1980-1999	0.61	0.65	0.26	0.17	0.49	0.79	0.93
	2000-2019	0.55	0.54	0.28	0.14	0.35	0.82	0.93
$\rho(i, y)$	1980-1999	0.52	0.56	0.33	-0.23	0.41	0.77	0.90
	2000-2019	0.48	0.54	0.31	-0.03	0.26	0.74	0.89

Notes: The table reports business cycle moments for emerging and advanced economies using first-difference filtered variables. The table reports the mean, median, standard deviation, 5th, 25th, 75th, and 95th percentiles of the statistics across the countries in each category, using the classification of the World Bank. The table reports moments for the periods 1980-1999 and 2000-2019.

Table B8: Business Cycles: 1980-99 vs 2000-19, High-Income and Upper-Middle Income Countries

Statistic	Period	High-Income Countries						
		Mean	Median	S.D.	p5	p25	p75	p95
$\sigma(y)$	1980-1999	3.96	2.53	3.85	1.22	1.82	4.97	9.35
	2000-2019	2.67	2.14	1.37	1.29	1.63	3.32	5.51
$\sigma(c)/\sigma(y)$	1980-1999	1.16	1.10	0.40	0.72	0.87	1.34	2.13
	2000-2019	1.13	1.00	0.73	0.47	0.68	1.27	3.19
$\sigma(i)/\sigma(y)$	1980-1999	3.81	3.80	1.36	1.64	3.32	4.37	5.72
	2000-2019	4.01	3.54	1.65	2.57	2.99	4.41	6.45
$\sigma(NX/Y)$	1980-1999	0.05	0.02	0.08	0.01	0.01	0.05	0.13
	2000-2019	0.04	0.03	0.04	0.01	0.02	0.06	0.12
$\rho(NX/Y, y)$	1980-1999	0.05	0.12	0.35	-0.57	-0.18	0.30	0.53
	2000-2019	0.06	0.05	0.28	-0.36	-0.13	0.29	0.47
$\rho(c, y)$	1980-1999	0.63	0.69	0.31	-0.04	0.57	0.86	0.94
	2000-2019	0.65	0.75	0.26	0.14	0.52	0.84	0.93
$\rho(i, y)$	1980-1999	0.68	0.77	0.27	0.20	0.56	0.86	0.94
	2000-2019	0.68	0.79	0.27	0.10	0.60	0.86	0.94
Statistic	Period	Upper-Middle-Income Countries						
		Mean	Median	S.D.	p5	p25	p75	p95
$\sigma(y)$	1980-1999	5.98	4.11	5.97	2.42	3.34	5.82	14.46
	2000-2019	3.55	2.38	3.46	1.43	1.92	3.16	12.69
$\sigma(c)/\sigma(y)$	1980-1999	1.43	1.23	0.67	0.90	1.09	1.56	1.95
	2000-2019	1.23	1.11	0.44	0.78	0.97	1.40	2.14
$\sigma(i)/\sigma(y)$	1980-1999	4.54	4.39	1.87	2.64	3.25	5.06	7.21
	2000-2019	4.33	4.10	1.76	2.39	3.32	4.60	7.41
$\sigma(NX/Y)$	1980-1999	0.06	0.05	0.05	0.02	0.03	0.08	0.17
	2000-2019	0.05	0.04	0.03	0.01	0.03	0.05	0.11
$\rho(NX/Y, y)$	1980-1999	-0.19	-0.21	0.28	-0.58	-0.42	0.04	0.28
	2000-2019	-0.04	-0.05	0.38	-0.61	-0.32	0.14	0.49
$\rho(c, y)$	1980-1999	0.65	0.66	0.24	0.29	0.46	0.85	0.94
	2000-2019	0.63	0.75	0.31	-0.01	0.47	0.86	0.93
$\rho(i, y)$	1980-1999	0.67	0.76	0.29	0.23	0.58	0.84	0.94
	2000-2019	0.67	0.72	0.25	0.21	0.54	0.84	0.94

Notes: The table reports business cycle moments for high and middle income economies using first-difference filtered variables. Classification of high and upper-middle income economies follows the World Bank. The table reports the mean, median, standard deviation, 5th, 25th, 75th, and 95th percentiles of the statistics across the countries in each category. The table reports moments for the periods 1980-1999 and 2000-2019.

Table B9: Business Cycles: 1980-99 vs 2000-19, Lower-Middle-Income and Low Income Countries

Statistic	Period	Lower-Middle Income Countries						
		Mean	Median	S.D.	p5	p25	p75	p95
$\sigma(y)$	1980-1999	4.70	4.02	4.06	1.60	2.57	4.85	9.11
	2000-2019	2.97	2.03	2.54	0.92	1.57	3.41	7.24
$\sigma(c)/\sigma(y)$	1980-1999	1.68	1.56	0.82	0.77	1.03	2.17	3.05
	2000-2019	1.53	1.15	0.99	0.54	0.92	1.98	3.69
$\sigma(i)/\sigma(y)$	1980-1999	4.55	4.37	2.23	1.77	2.70	5.14	9.15
	2000-2019	5.42	5.32	2.80	1.66	3.71	6.89	10.40
$\sigma(NX/Y)$	1980-1999	0.07	0.04	0.07	0.01	0.03	0.10	0.21
	2000-2019	0.06	0.04	0.05	0.02	0.02	0.08	0.16
$\rho(NX/Y, y)$	1980-1999	-0.03	0.00	0.31	-0.45	-0.33	0.20	0.42
	2000-2019	-0.11	-0.11	0.36	-0.60	-0.41	0.14	0.52
$\rho(c, y)$	1980-1999	0.57	0.64	0.31	-0.02	0.48	0.78	0.86
	2000-2019	0.51	0.51	0.29	0.13	0.33	0.69	0.92
$\rho(i, y)$	1980-1999	0.45	0.50	0.31	-0.22	0.39	0.60	0.87
	2000-2019	0.45	0.44	0.25	0.07	0.26	0.68	0.79
Statistic	**Period**	**Low-Income Countries**						
		Mean	Median	S.D.	p5	p25	p75	p95
$\sigma(y)$	1980-1999	6.03	5.39	3.51	3.20	3.90	6.89	9.74
	2000-2019	4.21	3.42	2.88	1.92	2.36	4.39	11.07
$\sigma(c)/\sigma(y)$	1980-1999	1.62	1.43	0.76	0.76	1.18	1.70	3.15
	2000-2019	1.80	1.80	0.92	0.76	1.06	2.28	3.25
$\sigma(i)/\sigma(y)$	1980-1999	5.38	5.58	2.43	2.22	3.19	7.34	8.76
	2000-2019	5.64	4.60	3.17	2.27	3.84	6.88	11.80
$\sigma(NX/Y)$	1980-1999	0.06	0.04	0.05	0.02	0.03	0.07	0.14
	2000-2019	0.08	0.06	0.06	0.02	0.04	0.09	0.16
$\rho(NX/Y, y)$	1980-1999	0.00	0.00	0.34	-0.49	-0.19	0.20	0.60
	2000-2019	-0.08	-0.08	0.31	-0.52	-0.26	0.06	0.46
$\rho(c, y)$	1980-1999	0.62	0.65	0.17	0.29	0.55	0.74	0.83
	2000-2019	0.53	0.51	0.21	0.30	0.36	0.62	0.89
$\rho(i, y)$	1980-1999	0.43	0.46	0.34	-0.22	0.35	0.66	0.80
	2000-2019	0.27	0.36	0.32	-0.24	0.04	0.53	0.67

Notes: The table reports business cycle moments for high and middle income economies using first-difference filtered variables. Classification of lower-middle and low income economies follows the World Bank. The table reports the mean, median, standard deviation, 5th, 25th, 75th, and 95th percentiles of the statistics across the countries in each category. The table reports moments for the periods 1980-1999 and 2000-2019.

Table B10: Business Cycles: 1980-99 vs 2000-19, Uribe and Schmitt-Grohé (2017) Classification

Statistic	Period	Emerging Markets						
		Mean	Median	S.D.	p5	p25	p75	p95
$\sigma(\Delta y)$	1980-1999	6.99	5.45	6.74	1.91	3.42	7.68	14.76
	2000-2019	4.07	3.04	3.55	1.35	2.23	4.51	10.22
$\sigma(c)/\sigma(y)$	1980-1999	1.52	1.32	0.71	0.75	1.06	1.75	2.99
	2000-2019	1.49	1.22	0.84	0.57	0.97	1.79	3.22
$\sigma(i)/\sigma(y)$	1980-1999	4.51	4.27	2.12	1.75	3.05	5.45	8.74
	2000-2019	4.94	4.24	2.54	2.06	3.16	5.75	10.38
$\sigma(NX/Y)$	1980-1999	0.07	0.04	0.07	0.02	0.03	0.08	0.20
	2000-2019	0.06	0.04	0.05	0.02	0.03	0.09	0.14
$\rho(NX/Y, y)$	1980-1999	-0.06	-0.09	0.33	-0.55	-0.33	0.16	0.49
	2000-2019	-0.06	-0.08	0.34	-0.60	-0.26	0.15	0.50
$\rho(c, y)$	1980-1999	0.59	0.64	0.28	0.02	0.48	0.78	0.94
	2000-2019	0.57	0.58	0.29	0.11	0.35	0.85	0.94
$\rho(i, y)$	1980-1999	0.53	0.57	0.32	-0.23	0.41	0.77	0.92
	2000-2019	0.51	0.54	0.31	-0.02	0.26	0.78	0.89
Statistic	Period	Advanced Economies						
		Mean	Median	S.D.	p5	p25	p75	p95
$\sigma(y)$	1980-1999	2.09	1.87	0.84	1.21	1.57	2.19	3.76
	2000-2019	2.10	1.78	1.11	1.19	1.47	2.22	3.78
$\sigma(c)/\sigma(y)$	1980-1999	1.03	0.94	0.28	0.73	0.85	1.25	1.46
	2000-2019	0.76	0.70	0.34	0.41	0.56	0.90	1.22
$\sigma(i)/\sigma(y)$	1980-1999	4.03	3.80	0.96	2.55	3.55	4.55	5.72
	2000-2019	3.67	3.57	0.95	2.53	3.21	4.04	5.47
$\sigma(NX/Y)$	1980-1999	0.02	0.01	0.02	0.01	0.01	0.02	0.05
	2000-2019	0.02	0.02	0.02	0.01	0.01	0.03	0.06
$\rho(NX/Y, y)$	1980-1999	0.12	0.20	0.31	-0.24	-0.16	0.29	0.49
	2000-2019	0.10	0.15	0.23	-0.29	-0.03	0.29	0.32
$\rho(c, y)$	1980-1999	0.75	0.80	0.17	0.33	0.69	0.87	0.89
	2000-2019	0.68	0.75	0.19	0.31	0.54	0.82	0.87
$\rho(i, y)$	1980-1999	0.79	0.84	0.14	0.50	0.76	0.88	0.93
	2000-2019	0.75	0.80	0.21	0.46	0.67	0.90	0.94

Notes: The table reports business cycle moments for emerging and advanced economies using first-difference filtered variables. The table reports the mean, median, standard deviation, 5th, 25th, 75th, and 95th percentiles of the statistics across the countries in each category, using the classification of Uribe and Schmitt-Grohé (2017). The table reports moments for the periods 1980-1999 and 2000-2019.

Table B11: Business Cycles: 1980-99 vs 2000-19, Aguiar and Gopinath (2007) Classification

Statistic	Period	Emerging Markets						
		Mean	Median	S.D.	p5	p25	p75	p95
$\sigma(y)$	1980-1999	4.19	4.13	1.25	2.36	3.86	4.48	6.13
	2000-2019	2.75	2.36	1.27	1.76	2.11	2.65	5.12
$\sigma(c)/\sigma(y)$	1980-1999	1.31	1.20	0.47	0.76	1.09	1.52	2.06
	2000-2019	1.06	1.07	0.16	0.82	0.99	1.14	1.25
$\sigma(i)/\sigma(y)$	1980-1999	3.89	4.33	0.79	2.89	3.16	4.46	4.80
	2000-2019	4.24	4.10	1.54	2.62	3.17	4.88	6.70
$\sigma(NX/Y)$	1980-1999	0.03	0.03	0.02	0.02	0.02	0.04	0.06
	2000-2019	0.03	0.03	0.01	0.02	0.02	0.03	0.05
$\rho(NX/Y, y)$	1980-1999	-0.34	-0.40	0.16	-0.57	-0.41	-0.23	-0.10
	2000-2019	-0.09	0.03	0.33	-0.65	-0.22	0.11	0.26
$\rho(c, y)$	1980-1999	0.77	0.83	0.15	0.55	0.65	0.88	0.93
	2000-2019	0.83	0.84	0.11	0.66	0.79	0.89	0.95
$\rho(i, y)$	1980-1999	0.84	0.89	0.12	0.62	0.81	0.94	0.94
	2000-2019	0.76	0.78	0.21	0.43	0.69	0.90	0.96
Statistic	Period	Advanced Economies						
		Mean	Median	S.D.	p5	p25	p75	p95
$\sigma(y)$	1980-1999	1.95	1.77	0.51	1.37	1.68	2.29	2.74
	2000-2019	1.78	1.62	0.56	1.12	1.42	2.09	2.66
$\sigma(c)/\sigma(y)$	1980-1999	1.05	1.00	0.30	0.65	0.84	1.32	1.42
	2000-2019	0.86	0.74	0.41	0.45	0.56	1.13	1.43
$\sigma(i)/\sigma(y)$	1980-1999	4.43	4.23	0.76	3.62	3.92	4.72	5.83
	2000-2019	3.97	3.82	1.03	2.57	3.28	4.54	5.63
$\sigma(NX/Y)$	1980-1999	0.02	0.02	0.01	0.01	0.01	0.02	0.04
	2000-2019	0.03	0.03	0.02	0.01	0.01	0.03	0.05
$\rho(NX/Y, y)$	1980-1999	0.14	0.20	0.20	-0.19	0.01	0.28	0.38
	2000-2019	0.09	0.13	0.18	-0.17	-0.04	0.26	0.30
$\rho(c, y)$	1980-1999	0.71	0.73	0.20	0.32	0.63	0.88	0.92
	2000-2019	0.74	0.77	0.18	0.44	0.75	0.84	0.94
$\rho(i, y)$	1980-1999	0.77	0.83	0.16	0.49	0.71	0.90	0.95
	2000-2019	0.75	0.79	0.24	0.38	0.70	0.91	0.94

Notes: The table reports business cycle moments for emerging and advanced economies using first-difference filtered variables. The table reports the mean, median, standard deviation, 5th, 25th, 75th, and 95th percentiles of the statistics across the countries in each category, using the classification of Aguiar and Gopinath (2007). The table reports moments for the periods 1980-1999 and 2000-2019.

Table B12: Business Cycles: 1980-99 vs 2000-19, World-Bank Classification (Moving)

Statistic	Period	Emerging Markets						
		Mean	Median	S.D.	p5	p25	p75	p95
$\sigma(y)$	1980-1999	5.42	4.59	4.35	1.94	3.36	5.83	10.40
	2000-2019	3.42	2.52	2.79	1.17	1.91	3.78	10.48
$\sigma(c)/\sigma(y)$	1980-1999	1.54	1.35	0.72	0.78	1.07	1.77	3.07
	2000-2019	1.51	1.23	0.85	0.61	0.97	1.87	3.17
$\sigma(i)/\sigma(y)$	1980-1999	4.61	4.33	2.13	1.90	3.07	5.70	8.84
	2000-2019	5.11	4.43	2.60	1.91	3.32	6.02	10.44
$\sigma(NX/Y)$	1980-1999	0.06	0.04	0.06	0.02	0.03	0.09	0.18
	2000-2019	0.06	0.04	0.05	0.01	0.03	0.09	0.14
$\rho(NX/Y, y)$	1980-1999	-0.08	-0.09	0.32	-0.56	-0.34	0.14	0.43
	2000-2019	-0.07	-0.08	0.35	-0.60	-0.32	0.14	0.49
$\rho(c, y)$	1980-1999	0.61	0.65	0.27	0.16	0.50	0.78	0.94
	2000-2019	0.55	0.55	0.29	0.10	0.33	0.84	0.94
$\rho(i, y)$	1980-1999	0.54	0.58	0.32	-0.20	0.42	0.78	0.91
	2000-2019	0.50	0.54	0.31	-0.03	0.26	0.77	0.88
Statistic	Period	Advanced Economies						
		Mean	Median	S.D.	p5	p25	p75	p95
$\sigma(y)$	1980-1999	3.37	2.00	4.43	1.21	1.68	2.91	8.68
	2000-2019	2.54	2.03	1.46	1.25	1.54	2.94	5.67
$\sigma(c)/\sigma(y)$	1980-1999	1.07	0.97	0.35	0.67	0.84	1.32	1.52
	2000-2019	0.95	0.81	0.58	0.43	0.57	1.11	1.72
$\sigma(i)/\sigma(y)$	1980-1999	3.81	3.84	1.20	1.52	3.50	4.35	5.52
	2000-2019	3.58	3.46	0.89	2.57	2.90	3.94	5.25
$\sigma(NX/Y)$	1980-1999	0.04	0.02	0.09	0.01	0.01	0.05	0.08
	2000-2019	0.03	0.03	0.03	0.01	0.01	0.04	0.09
$\rho(NX/Y, y)$	1980-1999	0.14	0.20	0.33	-0.35	-0.17	0.32	0.54
	2000-2019	0.08	0.09	0.25	-0.32	-0.07	0.29	0.43
$\rho(c, y)$	1980-1999	0.64	0.76	0.30	-0.02	0.58	0.87	0.90
	2000-2019	0.70	0.76	0.19	0.35	0.54	0.84	0.93
$\rho(i, y)$	1980-1999	0.69	0.80	0.29	0.22	0.56	0.87	0.94
	2000-2019	0.71	0.80	0.25	0.16	0.60	0.90	0.94

Notes: The table reports business cycle moments for emerging and advanced economies using first-difference filtered variables. The table reports the mean, median, standard deviation, 5th, 25th, 75th, and 95th percentiles of the statistics across the countries in each category, using the classification of the World Bank. Classification of countries changes over time following the World Bank country classification. The table reports moments for the periods 1980-1999 and 2000-2019.

B.3.2 The Moderation in Quarterly Data

We first reproduce the decline in output volatility using quarterly data. Data is available for eighteen more developed emerging markets historically (see Table A1).

Moderation in GDP. Figure B12 shows the decline in output volatility in emerging markets, as documented in Figure 1 using quarterly data. There is a strong decline in business cycle volatility in quarterly data as well. In numbers, the rolling standard deviation declines from roughly 2% to only around 1% at the end of our sample. Before the 1990s, volatility in emerging markets was relatively stable and fluctuated only mildly, with a small dip in the 1970s. There is a brief rise in volatility around the financial crisis in emerging markets, but volatility continues to fall afterward.

In advanced economies, volatility is around 1 for most of the early part of the sample and then declines to slightly over 0.5 at the end of the sample. The decline before the financial crisis reflects the Great Moderation, as documented in McConnell and Perez-Quiros (2000), which continues to persist after the financial crisis (Gadea et al., 2018). The rise in volatility during the financial crisis in emerging and advanced economies is comparable in size.

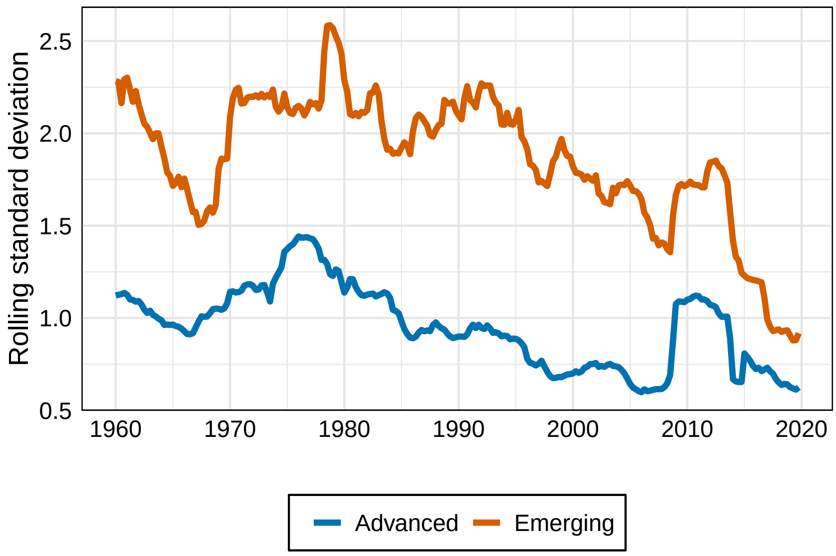


FIGURE B12. Output Volatility in Quarterly Data: Advanced versus Emerging

Notes: This figure shows the rolling standard deviation of quarterly output growth in emerging and advanced economies, computed over a 10-year backward looking window. The standard deviation is computed separately for each country, the figure shows the unweighted average across advanced and emerging. Details on the quarterly data and the sample of emerging and advanced economies are in section A.2.

Business Cycle Properties in Quarterly Data. Table B13 reports the business cycle statistics for emerging economies using quarterly data. As with our baseline results, we confirm a moderation; output volatility in the median emerging economy decreased from

Table B13: Business Cycles: 1980-99 vs 2000-19, Quarterly Data

Statistic	Period	Emerging Markets						
		Mean	Median	S.D.	p5	p25	p75	p95
$\sigma(y)$	1980-1999	2.01	1.86	0.64	1.30	1.60	2.28	3.06
	2000-2019	1.53	1.21	0.81	0.59	0.96	2.15	2.79
$\sigma(c)/\sigma(y)$	1980-1999	1.38	1.25	0.67	0.69	0.93	1.67	2.49
	2000-2019	1.10	1.09	0.32	0.64	0.93	1.34	1.54
$\sigma(i)/\sigma(y)$	1980-1999	5.18	3.86	3.20	2.41	3.09	5.48	11.24
	2000-2019	4.80	3.53	4.34	1.17	2.85	5.41	11.31
$\sigma(NX/Y)$	1980-1999	0.04	0.03	0.03	0.02	0.03	0.04	0.10
	2000-2019	0.06	0.04	0.06	0.02	0.03	0.06	0.18
$\rho(NX/Y, y)$	1980-1999	-0.12	-0.18	0.19	-0.33	-0.27	0.05	0.17
	2000-2019	0.12	0.14	0.17	-0.18	0.11	0.24	0.28
$\rho(c, y)$	1980-1999	0.59	0.61	0.21	0.18	0.51	0.72	0.84
	2000-2019	0.59	0.63	0.23	0.18	0.53	0.73	0.81
$\rho(i, y)$	1980-1999	0.55	0.57	0.23	0.16	0.45	0.69	0.87
	2000-2019	0.49	0.54	0.26	0.05	0.39	0.67	0.80

Notes: The table reports business cycle moments for emerging markets using quarterly data. The sample of countries is detailed in Table A1. Variables refer to first-difference filtered series. The table reports the mean, median, standard deviation, and the 5th, 25th, 75th, and 95th percentiles of the statistics across the countries in each category. The table reports moments for the periods 1980-1999 and 2000-2019.

around 2% to 1.2%, which is aligned with the 40% decline in output volatility that we find using annual data.

Regarding the volatility of other macroeconomic aggregates, we observe —for consumption and investment— a decrease in volatility similar to the one we observe for output, as can be inferred from the figures for σ_c/σ_y and σ_i/σ_y. In contrast to our baseline results, emerging markets seem to have improved at smoothing consumption (σ_c/σ_y decreased) and their trade balance looks less countercyclical ($\rho(NX/Y, y)$ increased). This difference in results stems from a selection problem in quarterly data. Fourteen out of the eighteen countries for which quarterly national accounts are available are located in the two regions (the Americas and Asia and the Pacific) that, in annual data, show changes in business cycle moments similar to the ones we find here for quarterly data.

C Appendix to section 4

C.1 Additional Tables for the Baseline Model

C.1.1 Prior Distribution of Parameters

Table C1 reports the prior distributions that we used in the estimation procedure of the baseline model that we discuss in section 4.1 of the main article.

Table C1: Prior Distributions

	Prior	Mean	S.D.	Q 2.5%	Q 97.5%
Autocorrelations:					
$\rho_{R,z}$, $\gamma_{R,z}$, $\delta_{W,z}$, $\rho_{R,g}$, $\gamma_{R,g}$, $\delta_{W,g}$	$\mathcal{U}(-0.995, 0.995)$	0.0	0.33	-0.95	0.95
Standard deviations (%):					
$\sigma^z_{i,p}$, $\sigma^z_{R,p}$, $\sigma^z_{W,p}$, $\sigma^\nu_{W,p}$,	$\mathcal{N}^+(0,4)$	1.6	1.2	0.06	4.50
Coefficients linking $\sigma^g_{i,p}$ to $\sigma^z_{i,p}$:					
$\theta^{(1)}_{R,p}$, $\theta^{(2)}_{R,p}$	$\mathcal{N}^+(0,4)$	1.6	1.2	0.06	4.50
Growth (%) and sensitivity parameters:					
μ_i	$\mathcal{N}(2,3)$	2.0	3.0	-3.85	7.85
ψ_i, ζ_i, ϕ_i	$\mathcal{N}^+(0,4)$	1.6	1.2	0.06	4.50

Notes: $\mathcal{U}([a,b])$ denotes a uniform distribution on the interval $[a,b]$; $\mathcal{N}(\alpha,\beta)$ denotes a normal distribution with mean α and variance β; and $\mathcal{N}^+(\alpha,\beta)$ corresponds to a $\mathcal{N}(\alpha,\beta)$ distribution truncated at zero. b) The indices i, R, and p correspond to country, region and period indices.

C.1.2 Business Cycle Regressions under Alternative Data Treatments

In Section 4.2, we show that there is a positive (and statistically significant) relationship between consumption smoothing, σ_c/σ_y, and the share of output variance explained by the trend component. Similarly, we underscore that there is a negative relationship between the SVETC and the cyclicality of the trade balance. Both results were obtained with data on the outcome variables and the SVETC that were previously winsorized, by region, at the 5% and 95% quantiles. In what follows, we show that our results hold with alternative data treatments.

Specifically, in Table C2 we present the results for our business cycle regressions (explained in Section 4.2) using raw data (Panel A) and winsorized data, by period, with the 5% and 95% quantiles as the winsorization thresholds (Panel B). The figures in the table confirm that the results presented in the article hold.

Table C2: TESTING THE CYCLE IS THE TREND HYPOTHESIS, ROBUSTNESS

	Consumption smoothing $y_{i,p} \equiv \log(\sigma_c/\sigma_y)_{i,p}$			Net exports cyclicality $y_{i,p} \equiv \text{corr}_{i,p}(NX/Y, \Delta y)$		
	Simple OLS (1)	Simple OLS + FE (2)	Macro controls (3)	Simple OLS (1)	Simple OLS + FE (2)	Macro controls (3)
Panel A. Results with raw data						
SVETC$_{i,p}$	0.923***	0.643*	0.697*	-0.137	-0.318	-0.248
	(0.279)	(0.332)	(0.363)	(0.227)	(0.253)	(0.272)
Region FE	✕	✓	✓	✕	✓	✓
Period FE	✕	✓	✓	✕	✓	✓
R-squared	0.039	0.196	0.198	0.002	0.090	0.100
Observations	232	232	232	232	232	232
Panel B. Results with winsorized data by period						
SVETC$_{i,p}$	0.836***	0.608*	0.651*	-0.037	-0.237	-0.164
	(0.292)	(0.363)	(0.380)	(0.231)	(0.264)	(0.276)
Region FE	✕	✓	✓	✕	✓	✓
Period FE	✕	✓	✓	✕	✓	✓
R-squared	0.033	0.201	0.203	0.000	0.094	0.106
Observations	232	232	232	232	232	232

Notes: This table reports the regression coefficients of regressing the level of consumption smoothing (σ_c/σ_y) and the correlation between the net-exports-to-output ratio and output growth ($\text{corr}(NX/Y, \Delta y)$) on the share of variance explained by the trend component (SVETC). Robust standard errors are shown in parentheses. *** and ** indicate significance at the 1% and 5% levels, respectively. The x-marks (✕) and check-marks (✓) stand for *no* and *yes*, respectively.

C.2 Alternative Model for Emerging Market Business Cycles

We now present a model in which the volatility of trend and cycle shocks can change from one year to the next; that is, our model has *full* stochastic volatility. The model is in the spirit of our baseline model, but due to the increased complexity, we have to abstract away from the origin of the shocks, so there is no explicit identification of domestic, regional, and global shocks. Despite this limitation, our model can still identify the share of variance explained by the trend component and the parameters that determine the long-run risks.

Model. As in the baseline model, GDP $Y_{i,t}$ of country i in region $R \equiv R(i)$ is composed of a trend and a cycle:

$$Y_{i,t} = \underbrace{\Gamma_{i,t-1} \exp\left(g_{i,t}\right)}_{\equiv \text{Trend } \Gamma_{i,t}} \cdot \underbrace{\exp\left(z_{i,t}\right)}_{\equiv \text{Cycle } Z_{i,t}}, \tag{C2}$$

but we do not take a stance on the origin of the shocks that impact on the trend and cycle. Instead, we model processes g and z simply as

$$g_{i,t} = (1-\rho_{R,g})\mu_{i,p} + \rho_{R,g} \cdot g_{i,t-1} + \sigma^g_{i,t}\eta^g_{i,t}, \tag{C3}$$

$$z_{i,t} = \rho_{R,z} \cdot z_{i,t-1} + \sigma^z_{i,t}\eta^z_{i,t}, \tag{C4}$$

where we still assume that the average long-run growth rate of a country, $\mu_{i,p}$, may differ by period, but allow the volatility of shocks to g and z, denoted by $\sigma^g_{i,t}$ and $\sigma^z_{i,t}$, to fluctuate year-to-year. As before, $\eta^g_{i,t}$ and $\eta^z_{i,t}$ represent standardized normal shocks.

To specify the functional form of stochastic volatility, we draw from Schorfheide et al. (2018) and define

$$\log \sigma^z_{i,t} = \log \sigma^z_i + \gamma_R \cdot \left(\log \sigma^z_{i,t-1} - \log \sigma^z_i\right) + \omega_z \eta^\sigma_{i,t}, \tag{C5}$$

$$\sigma_{i,t} = \Lambda_{R,p}\sigma^z_{i,t}, \tag{C6}$$

where γ_R represents the persistence of the volatility of z-processes in region R and $\Lambda_{R,p}$ is a scaling factor for countries in region R that varies only across the periods under study (pre-1980, 1980-99, and 2000-19). Both γ_R and $\Lambda_{R,p}$, are parameters that are pooled regionally.

Bear in mind that although with this model we cannot identify the geographic origin of the shocks directly, we gain two features: i) we are able to measure a second source of long-run risk, the persistence of volatility; and ii) our estimates of the share of variance explained by the trend component will be more precise due to the pooling assumption. An additional aspect to keep in mind is that despite not modeling the geographic sources of the shocks, one could identify g and z and use a dynamic factor model on them to identify whether these are driven by domestic, regional, or global variation.

Estimation. As we did with our baseline model, we allow for measurement error and write the observation equation

$$\Delta y^{obs}_{i,t} = \Delta y_{i,t} + \nu_{i,t} \tag{C7}$$

where, as in the baseline model, the measurement error $\nu_{i,t}$ follows a mean-zero normal distribution with standard deviation $\phi_i \sigma^\nu_{W,p}$, with $\sigma^\nu_{W,p}$ being a period-varying constant common across all countries in the world and ϕ_i regulating its influence on country i.

To estimate the model, we use weakly informative priors that are quite disperse. For the persistence parameters $\rho_{R,g}$, $\rho_{R,z}$, and γ_R we assume as priors uniform distributions on $[-0.995, 0.995]$. For the $\mu_{i,p}$ we use the same prior as before, that is, a $\mathcal{N}(2,3)$ distribution. For ω_z, we assume a $\mathcal{N}(0, 0.35)$ distribution to allow, with non-negligible probability, for scenarios in which volatility is scaled by a factor of 2 from one year to the next. For

σ_i^z, representing the long-run volatility if volatility shocks ($\eta_{i,t}^{\sigma}$) are muted, we assume a log-$\mathcal{N}(0,1)$ distribution to permit for scenarios in which the cycle absorbs most of the variation —such a prior implies that there is more than 5% probability of the cycle explaining all variation in economies with GDP volatility of 5%.

In contrast to our baseline model, where we estimated it jointly for all countries in our sample, we now estimate the model separately for each of the six regions/groups considered in our study. This is done to exploit the panel as much as possible. Again, we use Hoffman and Gelman (2014)'s Hamiltonian Monte Carlo (HMC) with No U-Turn Sampler (NUTS).

C.2.1 Empirical Results: Volatility at Yearly Frequency

In line with our findings on GDP period volatility, we identify a fall in volatility at the regional level. Figure C13 shows average GDP volatility across each of the regions defined for this study. The dark (light) shaded areas show the 70% (95%) confidence interval. All in all, GDP volatility has decreased in emerging economies.

For the Americas, we observe that at the start of the sample, GDP volatility was at its highest levels (around 4%), which coincides with the regional sovereign default crisis that hit many American economies. After the first few years of the 1980s, volatility started to decrease and continued doing so gradually up until recent times when the Great Financial Crisis hit, a period that increased average volatility in the Americas for the period 2008-2010, but that rapidly returned to average levels of around 2%. Therefore, this gradual decrease in volatility coincides with the gradual improvement in the institutions of American economies, as well as their shift towards becoming economies focused on services —tourism has been one policy highly pursued across Latin America; representing nowadays a higher share of GDP than agricultural activities in some cases like Costa Rica or the Caribbean islands.

The decrease in volatility in the Arab World is remarkable. Eyeballing their volatility time series in Figure C13, we can see that volatility averaged around 8% during the 1980s, coinciding with many political and warfare episodes that likely spanned economic instability (Appendix C.2.4 presents evidence of the effect of political crises on volatility). After the first half of the 1990s, average GDP volatility stabilized around 3% for most years. Moreover, despite the political turmoil across the region sparked by the Arab Spring at the start of the 2010s, volatility —at the regional level— remained quite stable.

In line with our finding that Asia and the Pacific is the least volatile emerging market region when measuring volatility with the rolling standard deviation, we also find that this holds with the stochastic volatility model. In particular, our model shows a decreasing trend in volatility starting in the mid 1980s (from around 3% in 1985 to about 1.5% in 2019). We identify two episodes of enlarged volatility. The first correspond to the time of the Asian Financial Crisis that started in July 1997, and the second coincides with the Great Financial Crisis, which likely followed from the shrinkage that aggregate demand

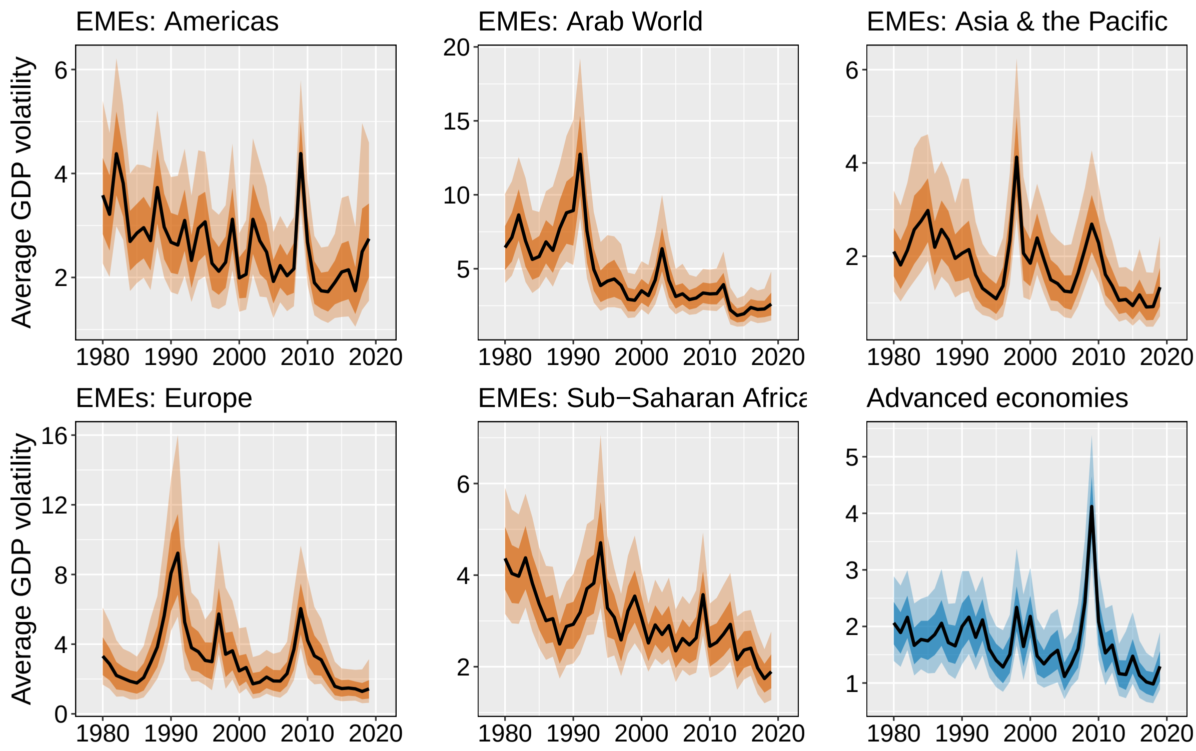


FIGURE C13. GDP VOLATILITY, 1980-2019

Notes: The figure reports the average yearly GDP volatility (black line), as estimated from our stochastic volatility model. The dark (light) shaded areas represent the 70% (95%) credibility intervals.

experienced in advanced economies, where much of the Asian exports are sold. Other than these episodes and the 1980s experience, GDP volatility levels in Asia and the Pacific are closer to those observed for advanced economies.

Turning to Europe, it becomes clear that during the pre-2000 period there were two episodes that exacerbated volatility. The first episode coincides with the fall of the Iron Curtain, that is, the period in which the Soviet Union disintegrated and the new European emerging markets started a structural transformation towards a regime that looked more like their neighboring economies in Western Europe. A few years later, around 1996, although volatility had been decreasing steadily since 1991, volatility increased again, which coincides with the surge of financial crises such as the Bulgarian financial crisis that resulted in a currency crisis and the need for public debt renegotiation. With regards to the post-2000 period, as with most emerging market regions, there was a volatility an increase in volatility around the Great Financial Crisis. Nonetheless, for European emerging markets, such an increase was much more exacerbated than for other regions.

In the case of Sub-Saharan Africa, there is a trend towards a decrease in volatility since the 1980s (going from around 4% in 1980 to around 2% in 2019). This moderation mirrors the findings of Krantz (2023). It is worth noting that the downward sloping trend was interrupted by a spike in volatility in the first half of the 1990s, which coincides with the surge in civil wars in the region during that period.

Finally, for advanced economies we do not observe a lot of variation in average GDP volatility. For the pre-2000 period, it fluctuated around 2%, while it seems that in the post-2000 period —and ignoring for a moment the Global Financial Crisis— volatility was closer to 1.5%. Nonetheless, the Global Financial Crisis increased volatility temporarily to around 4%. Bearing this in mind, our high-frequency estimates of volatility suggest that advanced economies are as well still going through a moderation process, one that has been hidden by the events at the end of the 2000s.

C.2.2 Empirical Results: Is the Cycle the Trend?

Taking first log-differences in (C2) we obtain

$$\Delta y_{i,t} = \Delta z_{i,t} + g_{i,t}.$$

Assuming $\sigma^g_{i,t}$ and $\sigma^z_{i,t}$ are at their long-run values, we can iterate the previous identity forward ad infinitum and take the variance to approximate the share of variance explained by the trend component (SVETC) as[21]

$$SVETC_{i,t} = \frac{\dfrac{(\sigma^g_i)^2}{1-\rho_g^2}}{\dfrac{(\sigma^g_i)^2}{1-\rho_g^2} + 2\dfrac{(\sigma^z_i)^2}{1+\rho_z}} = \frac{\dfrac{\Lambda^2_{R,p}}{1-\rho_g^2}}{\dfrac{\Lambda^2_{R,p}}{1-\rho_g^2} + \dfrac{2}{1+\rho_z}},$$

where the second equality follows from assumption (C6). Hence, this model shares with the baseline model the property of a constant SVETC across the periods studied.

Table C3 shows our estimates of the SVETC. Specifically, it shows the median and the 5% and 95% quantiles of its posterior distribution for each economic group consider in our study and for $p \in \{1980\text{-}99, 2000\text{-}19\}$. As with our baseline model, we observe that the SVETC remained quite unchanged in emerging markets at around 60%, while in advanced economies the SVETC went from 58.5% in 1980-99 to 34% in 2000-19. These estimates, like the ones from the baseline model, support the view that emerging markets are more exposed to trend shocks, consistent with Aguiar and Gopinath (2007)'s *cycle is the trend* hypothesis.

Although the results on the SVETC are qualitatively the same when comparing the results from the baseline model against those from the stochastic volatility model, there are differences in terms of magnitude. The baseline model estimated an SVETC of around 80% for emerging markets in both periods, while the stochastic volatility model positions such quantity at around 60% in both periods. Furthermore, in advanced economies, the baseline model estimates the SVETC to be around 80% for 1980-99 and around 60% for 2000-19. Why does this happen? Intuitively, without full stochastic volatility —as in the baseline model— the estimation procedure has to decide on whether to attribute

[21] The underlying assumption for the approximation that we present is that the variance of fluctuations in volatility is close to zero. The approximation converges to equality when there is no stochastic volatility.

Table C3: SHARE OF VARIANCE EXPLAINED BY THE TREND COMPONENT

	1980-99			2000-19			Change		
	Median	5%	95%	Median	5%	95%	Median	5%	95%
Emerging economies	66.4	59.1	72.0	61.3	56.3	66.4	-4.9	-12.2	3.0
Americas	77.2	67.6	83.4	59.4	49.7	68.7	-17.1	-28.5	-5.2
Arab World	64.2	46.6	77.5	73.9	64.3	82.4	9.5	-7.3	29.3
Asia and the Pacific	57.6	36.1	74.6	49.8	30.8	69.8	-7.1	-32.7	19.4
Europe	67.7	34.3	83.5	68.5	52.1	80.9	1.1	-23.0	35.2
S.S. Africa	65.0	51.9	73.8	59.1	50.2	66.8	-5.9	-18.6	8.1
Advanced economies	58.5	45.2	69.3	34.0	22.4	46.1	-24.3	-38.8	-7.9

Notes: This table reports the median and the 5% and 95% quantiles of the posterior distribution of the share of variance explained by the trend component (SVETC) for the periods 1980-99 (columns 2-4) and 2000-19 (columns 5-7). Additionally, it reports the same statistics for the posterior distribution of the changes in the SVETC (columns 8-10).

more variance to cycle or trend shocks to be able to match the episodes of high GDP fluctuations. Once stochastic volatility is considered, another degree of freedom is added, so the model gains more flexibility in terms of matching the distribution of the data. This likely leads to different estimates of the same quantity of interest. Hence, in a sense, the stochastic volatility model can be seen as producing more precise estimates of the SVETC.

C.2.3 Empirical Results: Long-Run Risks in Output

The literature on long-run risks discusses two of these risks: one from the persistence of the trend, the other from the persistence of volatility. The baseline model is mute about the latter, but the stochastic volatility model is not. Table C4 reports the median and the 5% and 95% quantiles for the persistence of trend shocks (ρ_g) and the persistence of volatility shocks (γ).

Consistent with our baseline results, we identify a non-negligible role for the persistence of trend shocks. The median estimate for emerging markets ($\rho_g = 0.70$) implies a half-life of a shock equal to 1.94 years. For advanced economies, the implied half-life corresponds to 1.5 years. These half-life figures are slightly larger than the ones that we found for the regional trend shock in the baseline model, and they correspond to less than 30% of the half-life implies by international shocks in the baseline model. Why does this happen? Our heuristic response to this issue is that, as implied by the baseline model, in emerging economies the international factors explained less than 20% of GDP growth variation while domestic factors explained between 60% and 70% of such variation. Hence, the stochastic volatility model inherits a g-process that has statistical properties closer to those of the domestic factor in the baseline model. For advanced economies, one may as well use the same argument since global factors explained around a third of GDP growth

Table C4: Long-Run Risks in the Stochastic Volatility Model

	g-shocks persistence (ρ_g)			SV shocks persistence (γ)		
	Median	5%	95%	Median	5%	95%
Emerging economies	0.70	0.66	0.73	0.37	0.31	0.43
Americas	0.68	0.61	0.75	0.11	-0.05	0.28
Arab World	0.65	0.60	0.71	0.48	0.33	0.63
Asia and the Pacific	0.81	0.70	0.89	0.54	0.41	0.65
Europe	0.61	0.50	0.74	0.66	0.52	0.77
S.S. Africa	0.71	0.63	0.77	0.37	0.26	0.46
Advanced economies	0.63	0.56	0.70	0.14	-0.03	0.29

Notes: This table reports the median and the 5% and 95% quantiles of the posterior distribution of the persistence parameters of trend shocks (ρ_g) and volatility shocks (γ).

variation even in the most recent times.

Turning to the long-run risk stemming from the persistence of volatility shocks, we do not find GDP volatility shocks to be as persistent as those found by researchers in the case of consumption growth, which are closer to unity (Nakamura et al., 2017; Schorfheide et al., 2018). Despite this difference, we do find that GDP volatility shocks show an important degree of persistence in emerging markets, but for advanced economies, this does not seem to be the case.

C.2.4 Empirical Results: Volatility Response to Crises

Selected episodes of spikes in volatility. In Section 3.4, we documented that, for emerging economies, crises (both financial and political) were at least three times as frequent during the period 1980-99 as they were during 2000-19. This observation, given the Emerging Market Great Moderation, suggests that the intuitive notion that crises spark economic growth instability may, in fact, be shaping the levels of volatility in emerging economies.

Figure C14 illustrates our measure of stochastic volatility for nine countries over seven-year periods, with the central year being the year when a crisis started. Panels A, B, and C focus on cases of financial (banking and/or currency) crises, sovereign debt crises, and political (in-site wars and/or coups) crises, respectively. Overall, the figure shows a marked increase in volatility around the start of crises (see the note in the figure for a quick historical note on each crisis episode).

Two cases worth mentioning in detail are those of Mexico and Haiti, due to their polar nature in terms of how foreign intervention can help a return towards stability. For Mexico, volatility hiked up from 2.5% in 1994 to 9% in 1995 and went down to its

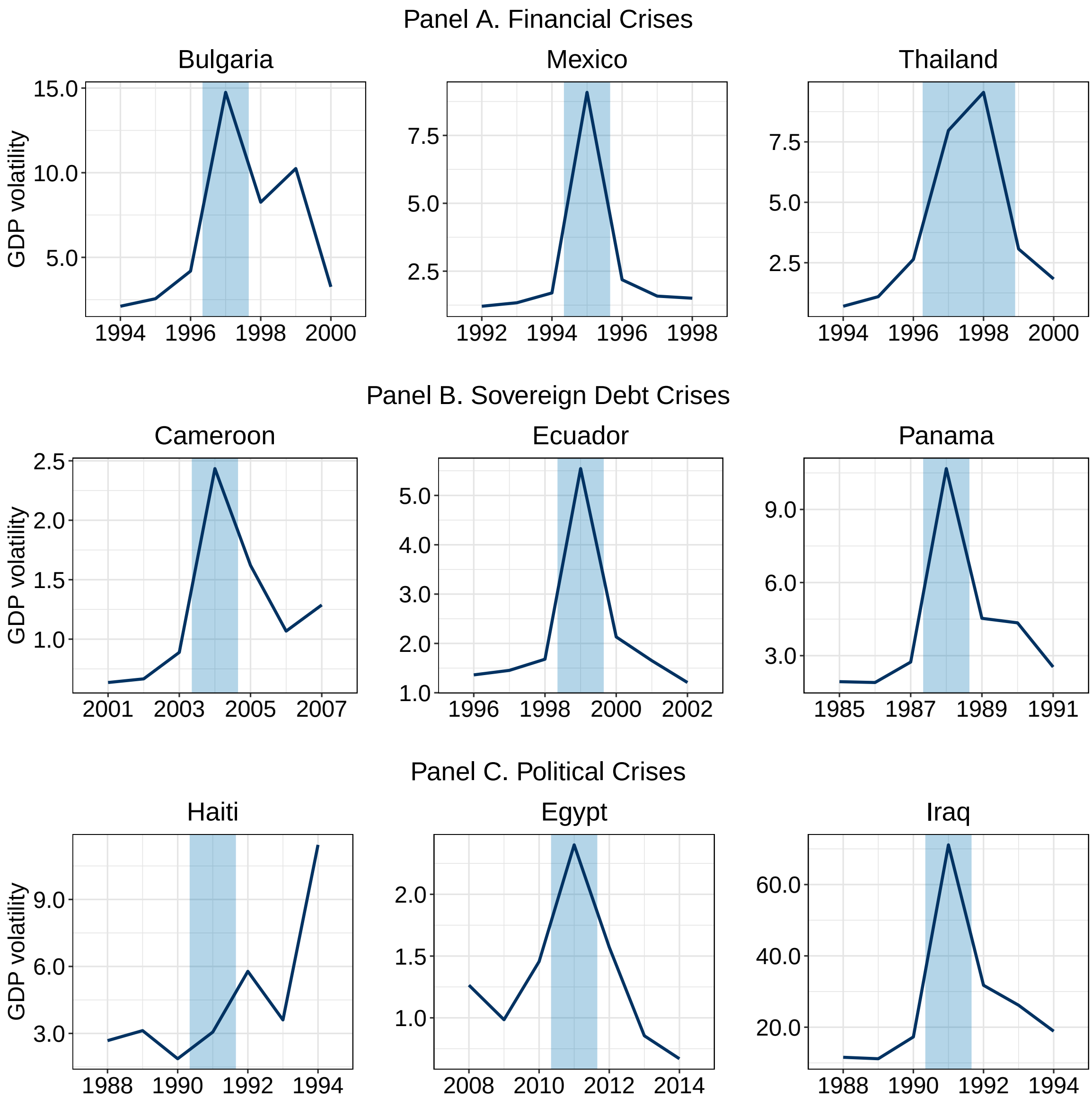


Figure C14. Volatility by Type of Crisis

Notes: This figure shows the volatility for the years $t-3, ..., t, ...t+3$ for a selected sample (t corresponds to the start of a crisis). For Bulgaria, a banking and currency crisis was exacerbated in December 1996. For Mexico and Thailand, in December 1994 and July 1997 —respectively— currency crises unfolded, respectively. In the case of Cameroon, Ecuador, and Panama, these countries defaulted on their debts in 2004, 1999, and 1988, respectively. Haiti experienced a coup in 1991, followed by US embargoes until 1995. Egypt had the Arab Spring in 2011, leading to the resignation of its dictator who had been in power for 29 years. Iraq started the Gulf War in 1991.

previous levels the year after. This coincides with the peso crisis that started at the end of December 1994 when the Mexican central bank did not have enough reserves to hold the peg on the dollar that they have had for more than 20 years; thus resulting in a more than 100% devaluation of the peso. Stability was quickly achieved largely through collaboration with the Clinton administration that helped Mexico to get a bail-out. On the other hand, Haiti held presidential elections in January 1991 and eight months later their president elected got stripped from power by the Haitian Armed Forces. The U.S. president at the time, George H.W. Bush, imposed a trade embargo on Haiti around the end of 1991 which further sparked economic instability, and in mid-1994 the United Nations banned petroleum sales to Haiti, resulting in a deeper level of economic instability.[22]

The effect of crises on volatility. To assess the dynamic response of volatility to crises of different types, we employ the local projection approach of Jordà (2005). Specifically, we estimate the regression equations

$$(\textit{GDP volatility})_{i,t+k} = \beta_k \cdot \textit{Crisis}_{i,t} + \gamma' X_{i,t-1} + u_{i,t}, \quad k = 0, 1, ..., 10 \tag{C8}$$

where $\textit{Crisis}_{i,t}$ is the treatment variable, taking a value equal to 1 if there is a crisis in year t. For the sake of completeness, we present our estimates for three categories of crises: financial crises (merging currency and banking crises, which tend to coincide), sovereign default crises, and political crises (merging coups and in-site wars). The coefficients β_k capture the response of GDP volatility to a crisis k periods after it started. The macroeconomic conditions the year prior to the start of the crisis are potentially an important confounder of the dynamic effects β_k that we are trying to identify. To control for these confounders, we include time $t-1$ GDP volatility, GDP growth, inflation, and the democracy index as part of the vector of correlates $X_{i,t-1}$. [23] We also include in $X_{i,t-1}$ a dummy indicating whether a crisis of the type studied was happening at $t-1$, as well as a common global intercept.

The parameters β_k ($k = 0, 1, ..., 10$) serve as the inputs for the construction of the impulse-response function of GDP volatility to crises. Figure C15 displays the estimates in three panels. On average, crises of the three types studied tend to increase volatility in the year they occur as well as in the following two years. For financial and political crises, this is true with a 70% confidence interval, and the same is almost as true for sovereign debt crises, except that in the year a sovereign debt crisis starts, volatility does not increase immediately.

[22]For details on the Haitian crisis, see `https://history.state.gov/milestones/1993-2000/haiti`.

[23]Jordà (2023) recommends always including the lagged response variable when using local projection in levels instead of long-differences, which makes both approaches equivalent.

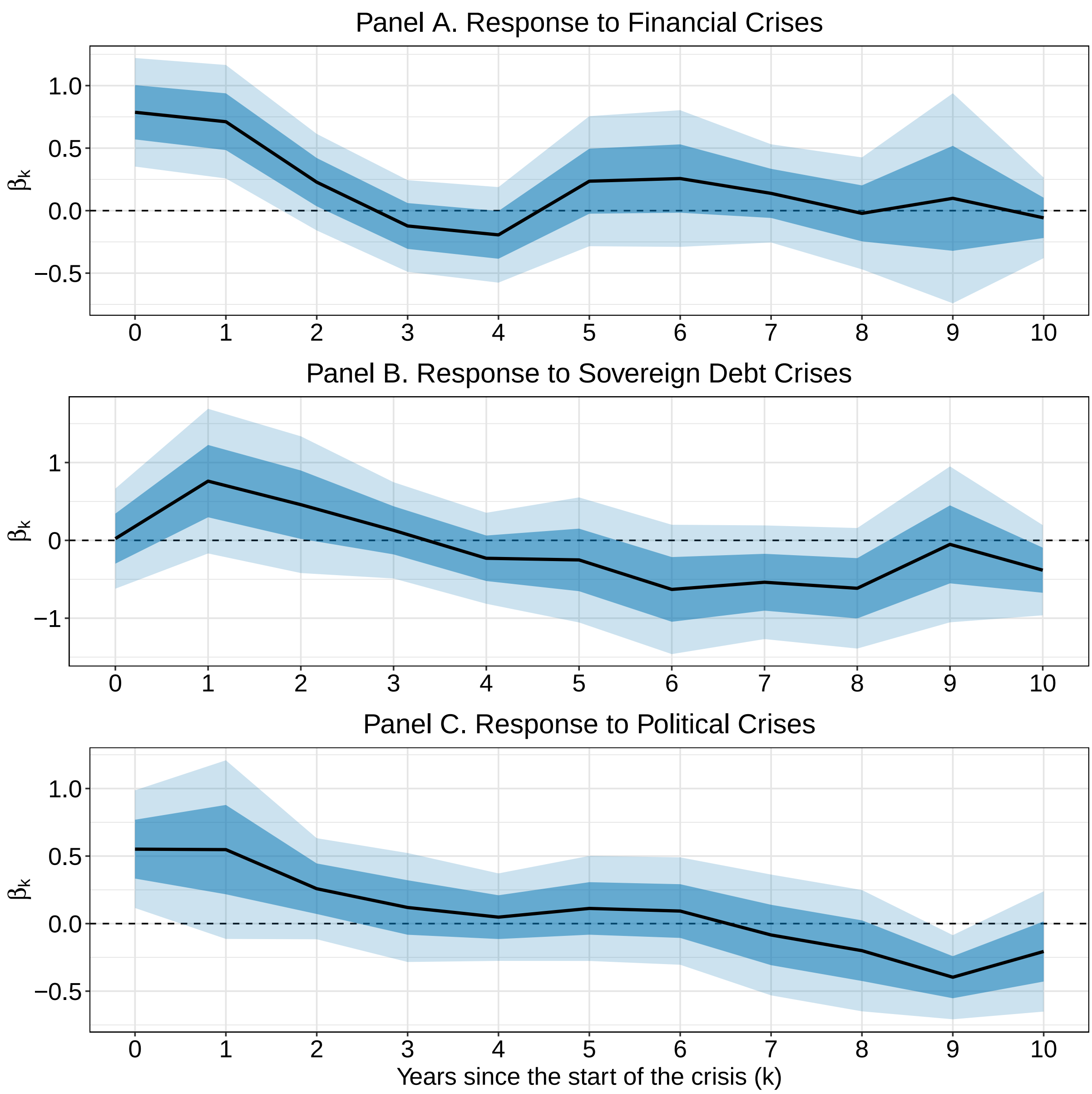


FIGURE C15. VOLATILITY RESPONSE TO CRISES

Notes: This figure illustrates the impulse-response functions of volatility to banking and currency crises (Panel A), sovereign debt crises (Panel B), and coups and wars inside territory (Panel C). The solid black line represent β_k, while the dark (light) blue shaded areas correspond to the 70% (95%) confidence intervals.

D Appendix to section 5

In this section, we give details on the model we use to compute the welfare costs of fluctuations in emerging markets. We first outline the model and its calibration, then we present additional results on the welfare cost of business cycles.

D.1 Emerging market business cycle model

We employ the standard emerging market business cycle model, as put forth by Aguiar and Gopinath (2006, 2007). We model an endowment economy, which borrows from abroad. To simplify the model as much as possible, there is no possibility of default. The model is a standard open-economy model with permanent and transitory income shocks.

Model Environment. Output Y_t is composed of a transitory component z_t and a trend Γ_t,

$$Y_t = e^{z_t}\Gamma_t.$$

The processes for the transitory component and the trend are given by

$$\begin{aligned} z_t &= \rho_z z_{t-1} + \varepsilon_t^z, \\ \Gamma_t &= e^{g_t}\Gamma_{t-1}, \\ g_t &= \mu_g + \rho_g g_{t-1} + \varepsilon_t^g. \end{aligned}$$

All innovations are distributed $\varepsilon_t^z \sim$ i.i.d. $\mathcal{N}(0, \sigma_z^2), \varepsilon_t^g \sim$ i.i.d. $\mathcal{N}(0, \sigma_g^2)$. The parameter μ_g corresponds to the long run growth rate of the economy. The variance of the standard deviation of the permanent and transitory shocks, as well as their autocorrelation is taken from our empirical estimation.

Figure D16 illustrates the impact of permanent and transitory shocks on the growth path. We illustrate permanent shocks in blue and transitory shocks in orange. While a permanent shocks pushes the economy on a fully different growth path, transitory shocks are recovered eventually.

Household Problem. The representative agent's utility function is modeled using a standard CRRA utility function.

$$U = \mathbb{E}\sum_{t=0}^{\infty}\beta^s\left(\frac{C_t^{1-\gamma}}{1-\gamma}\right)$$

There is a one-period bond available for borrowing and lending. The interest rate reacts to the level of outstanding debt following (Schmitt-Grohe & Uribe, 2003), i.e.

$$\frac{1}{q_t} = 1 + r_t = 1 + r^* + \psi(\exp(\frac{B_{t+1}}{\Gamma_t} - b) - 1),$$

where b is the steady-state level of debt. Then, the household budget constraint becomes

$$Y_t = C_t + e^{g_t}q_t b_{t+1} - b_t$$

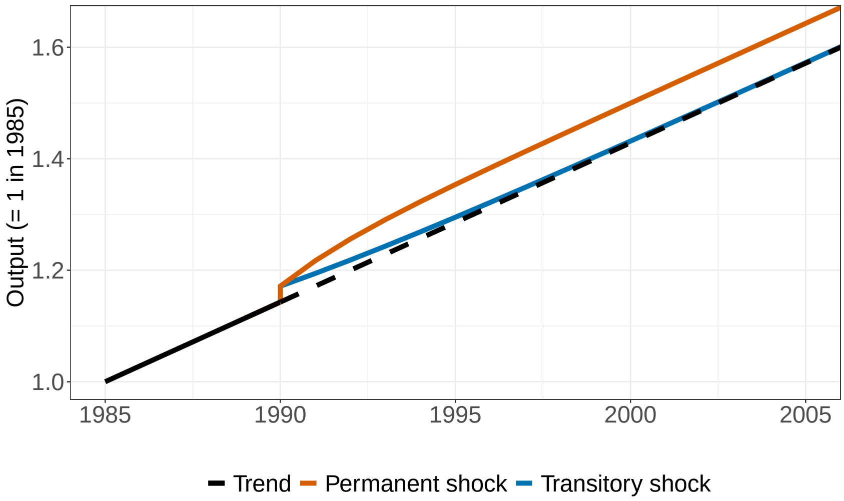


FIGURE D16. The impact of permanent and transitory shocks on the growth path

Notes: This figure illustrates the impact of transitory and permanent shocks on the growth path of an economy. We use an illustrative calibration in which the economy growth at an annual rate of 2% and is hit by a positive shock (permanent or transitory) with a size of 2% in 1990. The autocorrelation for permanent and transitory shocks is set to $\rho_g = 0.6$ and $\rho_z = 0.8$, following our empirical model.

Calibration. We calibrate the model to annual frequency. The calibration follows standard values in the literature and is summarized in table D1. We take a number of parameters directly from Aguiar and Gopinath (2007), namely the weight of tie steady state risk aversion, the elasticity of interest rates to debt, the discount factor (which we annualize). For the other parameters, we instead use the parameter values from García-Cicco et al. (2010), who also calibrate their model to annual rather than quarterly data.

For the parameters governing the shock process, we take a different approach than the emerging market business cycle literature, which the estimates the properties of the shocks to match the data moments. In contrast, we take the persistence and volatility of shocks directly from our empirical model in section 4, which only targets the volatility and structure of output fluctuations.

Param.	Value	Description	Source
β	0.922	Discount factor	García-Cicco et al. (2010)
b	0.100	Steady state normalized debt	García-Cicco et al. (2010)
ψ	0.001	Elasticity of interest rates	Aguiar and Gopinath (2007)
σ	2.000	Risk aversion	Aguiar and Gopinath (2007)
μ_g	0.023	Steady State Growth	Own Estimation
ρ_z	0.800	Persistence transitory shocks	Own Estimation
ρ_g	0.600	Persistence permanent shocks	Own Estimation

Table D1: Calibrated Parameters of the Economic Model

Notes: This table summarizes the parameter calibration for the endowment economy.

D.2 Model Fit

Table D2 compares the fit of our model to the data. We show the fit of the model to the data for the case of Mexico, a prominent country analyzed in many studies on emerging market business cycles. We calibrate the volatility of the permanent and transitory shocks following our empirical model, that is σ_g is set to 3.56 in 1980-1999 and 2.32 for the final period; σ_z is set to 1.9 in the early period and 1.17 in the later period. The model fits the data relatively well in the key dimensions we study in this paper. In particular, the estimated decline in the volatility of permanent and transitory shocks maps well into the observed decline in output volatility. Concretely, output volatility declines by around 57% in the model and by around 69% in the data. In levels, the output volatility in the estimated model is slightly higher than in the data.[24] Moreover, the model is able to match the excess volatility of consumption in emerging markets. This is because although we estimate a decline in the size of permanent shocks, these shocks remain large so that there remains an important persistent component in outcome. Because the model finds that permanent shocks dominate throughout for the case of Mexico, the volatility of consumption relative to output remains hih throughout, the same holds for the trade balance, which remains strongly countercyclical.

	1980-1999		2000-2019	
Moment	**Data**	**Model**	**Data**	**Model**
$\sigma(y)$	4.00	4.72	2.36	3.04
$\sigma(c)/\sigma(y)$	1.13	1.51	1.06	1.53
$\sigma(\Delta y)$	5.54	5.03	3.45	3.21
$\rho(y, nx/y)$	-0.63	-0.25	0.20	-0.26
$\rho(y, c)$	0.86	0.79	0.90	0.79

Table D2: Model Fit: Mexico

Notes: This table compares the empirical moments of the Mexican business cycle to model simulations. Model simulations are computed for 10000000 periods using the model of Aguiar and Gopinath (2007) and the calibration presented in table D1. The standard deviations of the permanent shocks and transitory shocks are recovered using our estimation as outlined in section 4. Business cycle moments are computed for first-difference filtered quantities, both in the model and data.

D.3 Welfare Gains under Alternative Parametrizations

In section 5, we compute the welfare gains from the great moderation in emerging markets. In order to compute welfare costs of business cycles, we assume a CRRA utility function as well as an endowment process with an average annual growth rate of $\mu = 3\%$. We

[24]This is because we estimate the model to maximize the fit over all emerging markets, not for one individual country.

compute the welfare gains from a decline in the volatility of the endowment process under a higher growth rate of $\mu = 8\%$ and plot it in figure D17. Table D3 provides the underlying numbers.

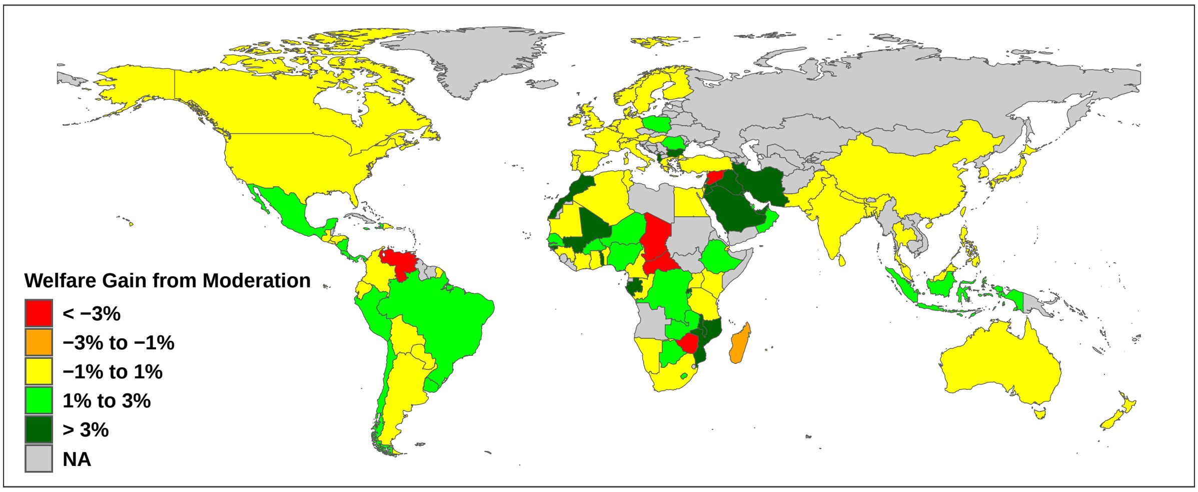


FIGURE D17. WELFARE GAINS UNDER HIGHER STEADY STATE GROWTH

Notes: This map plots the implied welfare gains from moving from the 1980-99 volatility regimes to the 2000-19 volatility regime under a higher average growth rate of $\mu = 8\%$.

Table D3: Welfare Gains from Moderation of Business Cycles

Country	Welfare Gains	Welfare Gains ($\mu = 8\%$)	Country	Welfare Gains	Welfare Gains ($\mu = 8\%$)
Albania	23.74	11.53	Kenya	0.01	0.01
Algeria	0.80	0.58	Kuwait	206.61	90.99
Argentina	-1.01	-0.50	Lebanon	197.86	87.54
Australia	0.08	0.16	Lesotho	2.64	1.46
Austria	0.00	0.02	Madagascar	-2.23	-1.17
Bahrain	16.48	8.18	Malawi	6.91	3.54
Bangladesh	-0.17	0.04	Malaysia	1.32	0.94
Belgium	0.02	0.07	Mali	8.71	4.25
Benin	1.78	1.00	Mauritania	0.83	0.43
Bolivia	0.75	0.64	Mauritius	1.02	0.74
Botswana	2.38	1.21	Mexico	2.27	1.26
Brazil	1.95	1.10	Morocco	14.15	7.02
Bulgaria	10.78	5.43	Mozambique	7.61	4.04
Burkina Faso	2.35	1.42	Namibia	-0.12	-0.07
Burundi	3.54	1.99	Nepal	0.70	0.60
Cameroon	1.41	0.98	Netherlands	0.00	0.03
Canada	0.13	0.18	New Zealand	0.18	0.24
C.A.R	-16.47	-7.81	Nicaragua	2.03	1.11
Chad	-7.32	-3.57	Niger	4.81	2.46
Chile	4.34	2.39	Nigeria	2.33	1.28
China	0.28	0.39	Norway	0.01	0.07
Hong Kong	0.69	0.53	Oman	4.67	2.39
Colombia	0.61	0.46	Pakistan	-0.04	0.09
Congo	-0.06	-0.03	Panama	2.70	1.48
Costa Rica	1.77	1.09	Paraguay	-1.35	-0.73
Cyprus	1.27	0.73	Peru	5.64	2.99
D.R. of the Congo	4.00	2.21	Philippines	0.92	0.76
Denmark	0.03	0.07	Poland	4.86	2.70
Djibouti	0.82	0.43	Portugal	0.08	0.13
Dominican Republic	1.47	0.82	Qatar	6.03	2.82
Ecuador	0.69	0.43	South Korea	1.02	0.77
Egypt	1.27	0.87	Romania	2.59	1.35
El Salvador	1.00	0.73	Rwanda	39.57	18.53

Ethiopia	5.88	2.98	Saudi Arabia	33.27	15.43
Finland	0.16	0.16	Senegal	4.01	2.26
France	0.00	0.03	Singapore	0.57	0.43
Gabon	7.48	3.79	South Africa	0.56	0.43
Gambia	-0.01	-0.01	Spain	0.00	0.02
Germany	0.00	0.00	Sri Lanka	0.01	-0.03
Ghana	0.78	0.49	State of Palestine	17.38	7.90
Greece	-0.40	-0.25	Sweden	0.02	0.03
Guatemala	0.54	0.49	Switzerland	0.01	0.06
Guinea	-0.47	-0.33	Syria	-7.49	-3.39
Guinea-Bissau	8.07	4.15	Taiwan	0.02	0.02
Haiti	3.33	1.79	Thailand	1.14	0.83
Honduras	1.01	0.66	Togo	6.27	3.15
Hungary	1.35	0.77	Trinidad and Tobago	0.21	0.11
India	0.00	0.12	Tunisia	0.98	0.62
Indonesia	2.38	1.67	Turkey	1.74	0.88
Iran	23.92	11.04	Tanzania	0.24	0.25
Iraq	259.76	112.61	Uganda	1.12	0.73
Ireland	0.10	0.09	United Arab Emirates	28.93	13.52
Israel	0.12	0.15	United Kingdom	0.03	0.08
Italy	0.00	0.00	United States	0.06	0.13
Ivory Coast	0.86	0.45	Uruguay	2.38	1.29
Jamaica	1.94	1.23	Venezuela	-16.63	-7.84
Japan	0.01	0.03	Zambia	2.15	1.32
Jordan	9.19	4.74	Zimbabwe	-18.01	-8.50

Notes: This table shows the welfare gains from a reduction in volatility of business cycles for each country. Welfare Gains are calculated under two scenarios: The baseline scenario ($\mu = 3\%$) and a high growth scenario ($\mu = 8\%$).