The Emerging Market Great Moderation*

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Abstract

We document a Great Moderation in emerging markets, a dramatic fall in aggregate macroeconomic volatility by about 40%, without changes in other distinctive characteristics of emerging market business cycles. Using a novel methodology, we link the moderation to canonical emerging market business cycle theories. Consistent with those theories, the contribution of fluctuations in the growth trend is substantial, and has not diminished. The moderation resulted in important welfare gains in emerging economies and stems from a reduction in country-specific volatility, which can be linked to shifts in monetary policy.

JEL Classification: E32, F41

Keywords: Emerging Markets, Business Cycles, Volatility, Welfare

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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 aimed at understanding the sources of fluctuations in emerging economies, starting with the seminal work of Aguiar and Gopinath (2007). In this paper, we reassess these findings and document an *Emerging Market Great Moderation*, a dramatic fall in the volatility of business cycles in emerging markets with no changes in other distinctive characteristics of emerging market business cycles. We connect the 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 (unweighted) average of the standard deviations of real annual output growth, calculated separately for 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 has been falling sharply since 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 the 1980s. This implies large changes in the macroeconomic environment of these countries.

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. Of the 92 economies in our baseline sample, 71 have seen a decline in volatility since 1980, and only very few see increases in volatility. The moderation holds across macroeconomic aggregates, and we document a significant decline in the volatility of all

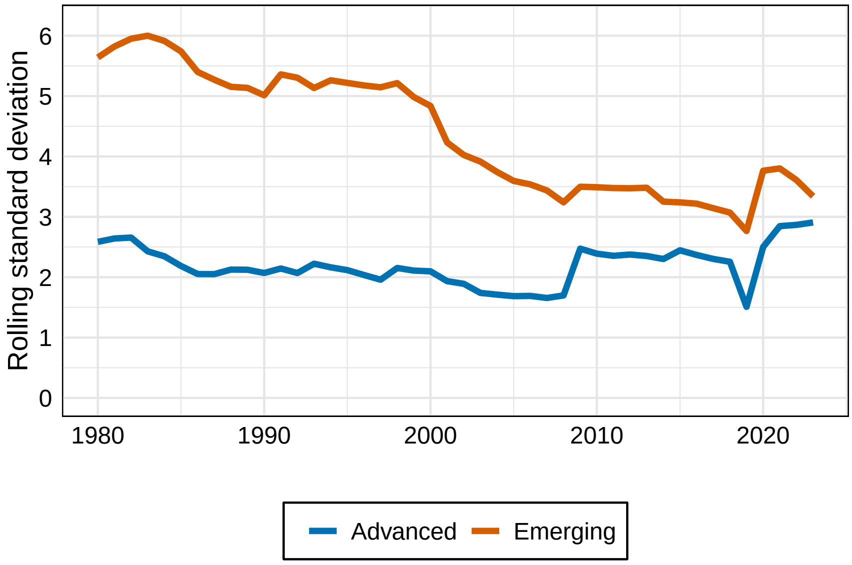

Figure 1. Rolling Standard Deviation of GDP Growth, 1980-Present

Notes: The plot shows the average backward 10-years rolling standard deviation of output growth for 92 emerging markets (orange) and 24 advanced markets (blue). 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. Figure B1 adds the median and the interquartile range across emerging and advanced.

aggregate demand components of GDP: consumption, 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.

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 continues to be 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 de-trending procedures to construct business cycle fluctuations, as well as various classifications of advanced and emerging economies. Additionally, 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 why business cycles in these countries are so volatile and differ strongly from those in advanced economies. We introduce new methods to this literature to shed light on why consumption smoothing and the cyclicality of the trade balance remained unchanged despite the moderation in macroeconomic volatility. Specifically, drawing from models that incorporate shocks to permanent income to explain the properties of emerging business cycles (Aguiar and Gopinath, 2006, 2007), we show that the unchanged levels of consumption smoothing and trade balance cyclicality can be reconciled with a decline in macroeconomic volatility if the share of income variance explained by shocks to permanent income has remained constant. 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, so that it overreacts relative to income.

The hypothesis that emerging markets differ in their business cycle properties due to large shocks to permanent income is at the core of business cycle and sovereign debt models of emerging economies; but has been subject to substantial controversy (García-Cicco et al., 2010; Guntin et al., 2023; Hong, 2023). To test this theory, 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 and 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, in the sense that is specified by these models. 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.

We estimate the model using over 60 years of data for the emerging and advanced economies in our sample. Our model successfully captures salient features of emerging market growth trajectories and recovers well-known events, such as the 2008 financial crisis and the persistent output losses associated with it, as well as other crises in emerging markets (Cerra and Saxena, 2008; Hall, 2015). 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 shifts in the permanent component of output growth. When allowing for stochastic volatility, we find that the volatility level of both permanent and transitory shocks has declined roughly in the same proportion over the past years, so the share of permanent shocks 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 persist. Comparing emerging and advanced, we find that in the recent period, the share of permanent shocks is indeed larger in emerging than in advanced, but this does not hold historically. In the cross-section, we show that countries with a larger contribution of permanent shocks also display higher volatility of consumption relative to output.

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 not 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 fluctuations, more than twenty times the 0.05% identified by Lucas (2003).

For every country, we compute the implied welfare gains of moving from the 1980-99 income process to the 2000-19 process, which usually features substantially lower volatility. The resulting welfare gains are large, more than 10% of consumption for the countries with the biggest improvements, and 1% for the median economy. 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 many 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.

We study what factors led to the decline in macroeconomic volatility in emerging markets. In an extension of the baseline model, we allow for regional and global shocks, and use the estimates from this model to narrow down the source of the moderation. The moderation is mostly explained by a decline in volatility in country-specific and regional shocks. In contrast, global shocks have contributed more to volatility in both emerging and advanced, (consistent with the literature on the Global Financial Cycle, Miranda-Agrippino and Rey, 2020). Motivated by this finding, we present evidence suggesting that the improvement of monetary and political institutions was key for emerging economies to increase their macroeconomic stability.

Related literature. This paper contributes to several strands of the literature. We first contribute to the literature on emerging market business cycles (Neumeyer and Perri, 2005; Aguiar and Gopinath, 2007; Koren and Tenreyro, 2007; García-Cicco et al., 2010; Chang and Fernández, 2013; Drechsel and Tenreyro, 2018; Guntin et al., 2023; Hong, 2023). 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 and Gopinath, 2006; Aguiar et al., 2016; Gordon and Guerron-Quintana, 2018), but their importance has been questioned (Neumeyer and Perri, 2005; García-Cicco et al., 2010; Hong, 2023; Germaschewski et al., 2024; Miyamoto and Nguyen, 2017). 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 Kim and Nelson (1999); McConnell and Perez-Quiros (2000); Stock and Watson (2005); Gadea et al. (2018)). 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 1978-95, respectively. Relative to these papers, we cover a larger sample of countries and connect the moderation to the emerging market business cycle literature.

Finally, we connect the literature on business cycle volatility with the literature on the long-run properties of output fluctuations (Campbell and Mankiw, 1987; Clark, 1987; Cochrane, 1988; Barro and Ursúa, 2008; Cerra and Saxena, 2008; Cerra et al., 2023; Jordà et al., 2024) which is mostly focused 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 component and its contribution to the moderation. The persistent component of business cycles is large outside of advanced economies, although we also find evidence in favor of persistence in advanced-economy business cycles. The large persistence of fluctuations in the business cycles of emerging markets informs asset pricing models seeking to explain equity returns in emerging markets using long-run risks (David et al., 2024).

Layout. The article is organized as follows. Section 2 discusses the data we use. Section 3 documents the Emerging Market Great Moderation, i.e., the decline in macroeconomic volatility alongside the persistent distinctive features of emerging market business cycles. Section 4 proposes an explanation to the Emerging Market Great Moderation that draws from canonical business cycle theories, and introduces a novel methodology to test it. Section 5 shows evidence in favor of the explanation we propose to the phenomenon that we study in this paper. Section 6 presents the welfare gains from the moderation, we discuss underlying drivers in Section 7. Finally, Section 8 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 et al., 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 2019, after which we supplement them with output growth from World Bank's World Development Indicators. We do this only for figures 1 and B1, in order to avoid the Covid Pandemic in our remaining results, which may induce anomalous dynamics, in particular when considering the comovement with consumption.[1]

To complement our baseline analyses, we use quarterly data from Monnet and Puy (2019) as well as other country-specific sources, which provide quarterly data on GDP and other macroeconomic indicators collected from the IMF's archives in a number of emerging markets. An overview of the data sources and the precise variables is in Appendix A.1.

Sample. We classify the world into advanced and emerging economies.[2] 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 and 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. In recent years, these countries cover more than 90% of the world's population; around 80% of the world's population live in the emerging economies in our studies. For some analyses, we further group countries by region, the regional grouping follows the United Nations and is given in Appendix A.

We start from the full list of countries and exclude two sets of countries from our sample before differentiating advanced and emerging. First, we restrict our sample to countries with a population of more than 1 million 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 many countries in that region. These two conditions result in a sample of 116 countries that represent 90.3% of the world population in 2019.

Measurement of Economic Fluctuations. We measure business cycle fluctuations using growth rates.[3] 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

[1]Hence, the other results in the paper rely on the Penn World Tables unless explicitly noted.

[2]Throughout, we use the words *emerging market* and *emerging economy* interchangeably.

[3]Concretely, we first take logarithms of variables (GDP,...) and then compute first differences.

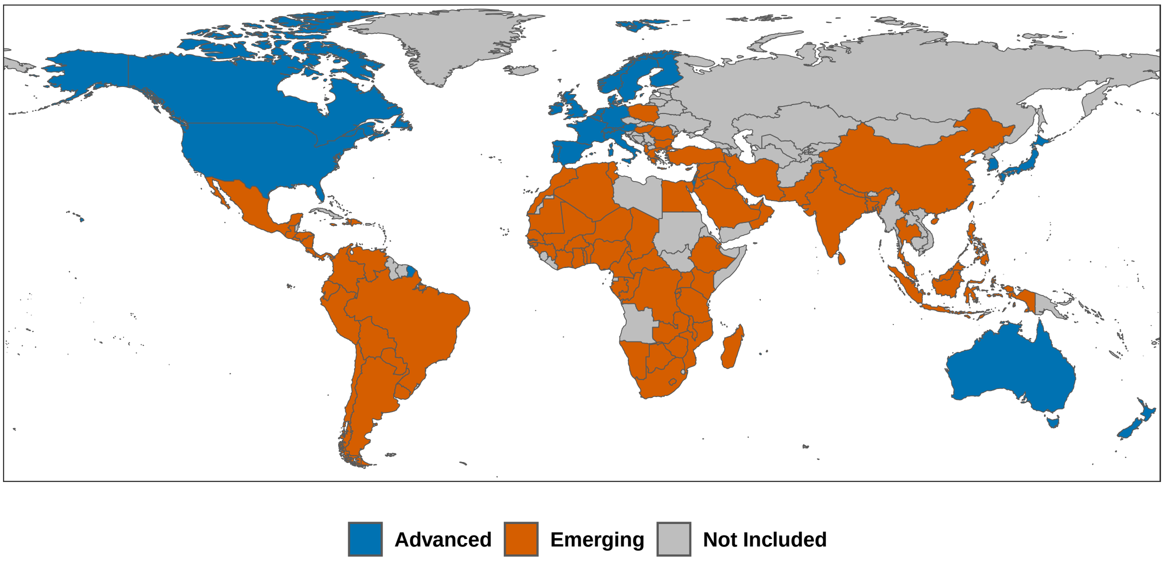

FIGURE 2. COUNTRIES COVERED IN THE SAMPLE

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.

using an econometric technique such as the Hodrick-Prescott (HP) filter (Aguiar and Gopinath, 2007) or other filters. In practice, these approaches produce similar results, as we show in Appendix B.3.1. We prefer using first differences, which use the full variation in the data and map directly into our empirical model in section 4. Throughout the text, we use the term volatility to refer to the standard deviation.

3 What Has Changed since the Early 1980's?

3.1 Moderation in Output Volatility

In Figure 1 in the introduction, we have shown that output growth volatility in emerging markets has fallen sharply over 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 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 5.5% in the 1980-99 period and 3.5% during the 2000-19 period. This implies a fall in volatility of around 40% over this horizon. This decline is not driven by economies in specific regions, volatility declines throughout emerging economies. Even for the Americas, where output volatility fell the least, there is still a 25% reduction.

Table 1. Output Volatility: 1980-1999 vs 2000-2019

Region	1980-1999	2000-2019	Difference	Percent Change
Emerging economies	5.50	3.50	2.01	-45.4
	(0.23)	(0.19)	(0.30)	(7.3)
Americas	4.16	3.20	0.96	-26.2
	(0.26)	(0.25)	(0.36)	(10.7)
Asia & Pacific	2.96	1.79	1.17	-50.4
	(0.39)	(0.14)	(0.41)	(16.5)
Europe	5.17	3.13	2.04	-50.3
	(0.69)	(0.36)	(0.78)	(19.1)
Arab World	9.61	4.71	4.90	-71.3
	(0.90)	(0.40)	(0.98)	(13.5)
Sub-Saharan Africa	5.18	3.70	1.48	-33.7
	(0.30)	(0.24)	(0.38)	(9.1)
Advanced economies	2.21	2.08	0.14	-6.4
	(0.14)	(0.34)	(0.37)	(18.8)

Notes: This table reports the average output volatility for the periods 1980-1999 and 2000-2019, together with the difference in volatility in levels and percent terms. The average corresponds to an unweighted average across countries in that region. To compute standard errors, we sample 20 years of growth rates in each economy with replacement and compute the unweighted average across the countries in that region. Standard errors correspond to the standard deviation of $B = 5000$ bootstrap samples.

On the other hand, in advanced economies, output volatility fell by less than 10%. We report distribution of volatility within emerging markets in Table 2. Volatility has declined across countries. 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. This shows that the moderation is not driven by a few countries only, it is broad based and holds across emerging economies.

Figure 3 illustrates that the moderation is also clearly visible at the country level. It shows the mean and the 70% and 95% symmetric confidence intervals for the change in output volatility for all countries in our sample computed with data from 1980-99 to 2000-19. We observe that for the vast majority of emerging countries, output volatility is declining. More precisely, output volatility was lower for the period 2000-19 than for the two-decade period that preceded it in 71 out of the 92 emerging economies, i.e in more than 75%. The confidence bars reveal that the reduction in output volatility is statistically significant for 60 (38) emerging economies at the 70% (95%) confidence level. Hence, at the 70% (95%) 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) emerging economies saw a

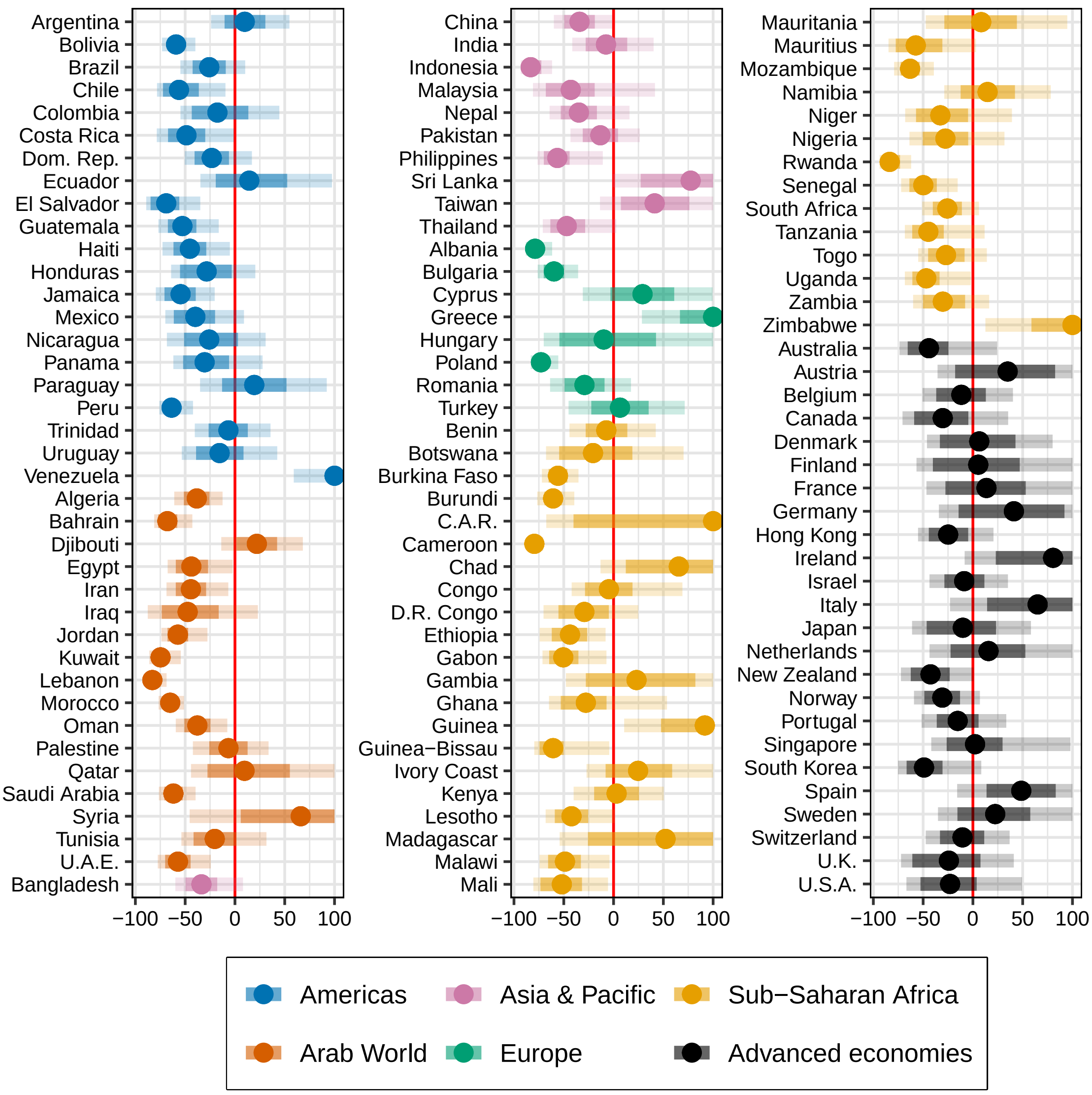

FIGURE 3. CHANGE (%) IN OUTPUT VOLATILITY, 1980-99 VS 2000-19

Notes: This figure reports the relative change (in percentage points) of output volatility from 1980-99 to 2000-19. For a given country, the dot represents the mean estimate, and the light (dark) bars represent the 95% (70%) bootstrapped confidence interval. Bootstrapped confidence bands and mean estimates are truncated at 100%. To construct standard errors, we sample 20 growth rates from the two periods with replacement and then compute the percent change in the standard deviation across both samples. We report the quantiles of the empirical distribution across 5000 iterations.

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 and Watson, 2005). We find that volatility has since remained low despite the Global Financial Crisis in 2008, consistent with Gadea et al. (2018). For 12 out of 24 advanced economies, volatility has fallen from 1980-99 up to 2000-19, but the decline is generally small and statistically insignificant. This means that volatility in advanced economies has been relatively stable in recent years, as suggested by Figure 1.

Finally, we compare volatility in advanced and emerging economies directly. The decline in volatility in emerging markets is far more widespread than the changes in volatility in advanced economies. In most advanced economies, volatility is relatively unchanged at around 2%. For the average advanced economy, volatility stands at 3.5% in the most recent period, but the median emerging economy (2.7%) is only slightly more volatile than many advanced economies. Extending our sample to the present and including the Covid pandemic shows that emerging economies are moving even closer to advanced economies in recent years (Figure B1).

We summarize these observations as follows:

Fact 1. Moderation in output volatility across emerging markets. *Output volatility has fallen since the 1980s 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 Aggregates

Have other macroeconomic aggregates experienced a moderation similar to that observed for output? The panels in Table 2 show the volatility of components of output (consumption, government expenditure, investment, exports, and imports) and production fundamentals (capital and Solow residual) across countries. As before, we compute the standard deviation of each variable for each country and time period, and then show the distribution across emerging countries. The moderation we have documented for output holds across all other aggregates. In all cases, volatility drops significantly, both for the average emerging market, at the median and the tails of the distribution.

Fact 2. Macroeconomic extent of the decline in volatility. *The moderation in emerging markets encompasses: 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).*

Across macroeconomic aggregates, one way to rank the extent of moderation across variables is the following. The volatility of the capital stock, which across countries decreased by around 15%, decreased the least. On the other hand, the volatility of most other aggregates decreased by around 30%, with output volatility (and the solow residual) falling the strongest. As in the case of output volatility, which we analyzed in section 3.1, the observed shift downward in the distribution also holds across regions and countries, indicating a consistent fall in macroeconomic volatility (see Appendix B.1 for details). Therefore, the moderation observed in emerging markets extends beyond output volatility.

Table 2. Volatility of Aggregates: 1980-99 vs 2000-2019

Statistic	Period	Mean	Median	p5	p25	p75	p95
GDP	1980-1999	5.50	4.62	1.95	3.31	5.86	10.25
	2000-2019	3.50	2.71	1.22	1.93	3.89	9.52
Consumption	1980-1999	7.70	6.61	2.52	4.65	9.51	15.01
	2000-2019	5.41	3.67	1.16	2.42	6.18	14.53
Gov. Spending	1980-1999	10.72	7.86	3.11	5.29	12.91	29.19
	2000-2019	7.37	4.93	1.82	3.29	9.70	17.65
Investment	1980-1999	21.87	18.01	2.09	2.61	3.23	3.87
	2000-2019	15.82	12.66	1.55	2.20	2.89	3.50
Exports	1980-1999	14.77	11.71	5.72	8.55	16.71	34.54
	2000-2019	10.98	7.99	4.12	6.42	13.69	22.66
Imports	1980-1999	16.10	14.80	6.97	10.79	17.78	30.06
	2000-2019	11.69	10.10	5.52	7.95	13.60	22.45
Capital	1980-1999	2.11	1.90	0.83	1.34	2.71	3.60
	2000-2019	1.82	1.39	0.60	1.02	2.27	4.30
Solow residual	1980-1999	5.36	4.35	1.85	3.20	5.69	10.58
	2000-2019	3.36	2.64	1.13	1.86	3.92	8.73

Notes: This table shows the volatility of different macroeconomic aggregates across emerging markets. For each variable, we report the mean, median, and percentiles within the group of emerging markets. Volatility is measured as the standard deviation in each country-period.

The decline in the volatility of exports and imports further indicates that moderation is not simply an artifact of improvements in statistical measurement because these aggregates are constructed from customs data, which tend to be easier to measure. The fact that consumption volatility did not decline more than output volatility is consistent with canonical models of emerging market business cycles, which we discuss below.

3.3 Business Cycles: Emerging vs. Advanced Economies

By how much are the gaps between emerging and advanced economy business cycles closing? It is tempting to interpret the moderation as a natural consequence of 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 market business cycles have not yet converged.[4] We focus on two moments that have been argued to distinguish emerging and advanced economies (Aguiar and Gopinath, 2007; Uribe and Schmitt-Grohé, 2017):

i) *Excess Consumption Volatility:*

[4]We also show below that the moderation is stronger what the cross-sectional relationship between volatility and development would suggest.

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.

These properties of emerging economies are at odds with standard open economy business cycles models. Table 3 shows these moments across emerging and advanced economies for the two periods we consider. The facts documented in the prior literature 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 1.6 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.[5] Second, the cyclicality of the trade balance has remained relatively constant in both emerging and advanced economies. In emerging markets, it is slightly negative, around -0.06, while in advanced economies it is slightly positive at around 0.07.

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 consumption-output volatility shifted downward throughout the distribution. This means that across the board, advanced economies exhibit more consumption smoothing. The results on the cyclicality of the trade balance are slightly more mixed, however still round 70% of advanced economies display a procyclical trade balance.

The same did not happen in emerging economies. While the ratio of consumption to output volatility fell by around 7 percentage points for emerging markets (in contrast to nearly 25 percentage points in advanced economies), consumption remains more volatile than income in emerging. While individual countries are exceptions to this pattern, around 75% of emerging economies still see excessively volatile consumption. The cyclicality of the trade balance is virtually identical across periods. In total, the distance between advanced and emerging economies has grown in the sense of the textbook facts (3) that distinguish the two. The increase in the gap is driven by advanced economies aligning more with the properties of standard open economy models.

[5] The fact that output is as volatile as consumption in advanced economies before 2000 is consistent with other studies focusing on historical annual data (Jordà et al., 2017).

Table 3. Business Cycles: 1980-99 vs 2000-19

Statistic	Period	Emerging Markets						
		Mean	Median	S.D.	p5	p25	p75	p95
$\sigma(y)$	1980-1999	5.50	4.62	4.54	1.95	3.31	5.86	10.25
	2000-2019	3.50	2.71	2.67	1.22	1.93	3.89	9.52
$\sigma(c)/\sigma(y)$	1980-1999	1.60	1.34	0.92	0.75	1.07	1.80	3.16
	2000-2019	1.53	1.23	0.86	0.65	0.97	1.87	3.24
$\rho(nx/y, y)$	1980-1999	-0.06	-0.09	0.33	-0.55	-0.32	0.17	0.49
	2000-2019	-0.07	-0.09	0.35	-0.60	-0.34	0.14	0.50
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	2.08	1.92	0.99	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	0.84	0.76	0.34	0.42	0.57	1.03	1.27
$\rho(nx/y, y)$	1980-1999	0.07	0.13	0.31	-0.37	-0.17	0.26	0.46
	2000-2019	0.06	0.09	0.27	-0.42	-0.07	0.29	0.35

Notes: The table reports business cycle moments for emerging and advanced economies. Variables are 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. The table reports moments for the periods 1980-1999 and 2000-2019.

3.4 Additional Facts and Robustness

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 tackle this question in Appendix B.2.1, using the structural break testing procedure developed by Bai and Perron (1998). 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, and model output growth as an AR(1) process. Then, we test for structural breaks in the standard deviation of the innovations. Applying this procedure across countries 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 a few years before 2000. 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, the moderation has not reversed in the last two decades and, in some cases, has become more pronounced. Moreover, this shows that the resilience that emerging markets have shown in the Covid pandemic and monetary tightening in advanced economies in recent years (Hardy et al., 2024) is not particular to the last years, but has been widespread in emerging markets since at least 2000.

The Gradient of Volatility and Development. Another way of viewing the Emerging Market Great Moderation we document 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 volatility on income per capita, as in Koren and Tenreyro (2007). The regression coefficient, that is, the volatility-development gradient, has considerably flattened over time. Quantitatively, the gradient between volatility and development has halved over time, so that volatility difference between rich and poor countries are much smaller today. In turn, there is a large decline in the intercept of the regression, 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 what would be predicted by economic growth.

A Long View on Volatility. In this article, we focus on 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 B1 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 relative terms, 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 large, because initial volatility is much higher in emerging markets.

The Frequency of Crises. We provide a first descriptive analysis of other changes that emerging economies have undergone in the past decades in Appendix B.2.4. The frequency of crises has decreased considerably, usually by even more than 50%. We adopt a broad notion of a crisis and study both economic and political crises. The incidence of financial crises (banking, currency, and sovereign debt) has fallen, these crises occur in less than 1% of years in recent decades, while their frequency was greater than 4% in the previous period. Not only has financial turmoil subsided greatly, political crises have also experienced a similar decline. We also study the frequency of wars, intra-state conflicts and coups and find that their frequency has also declined by more than 50%.

Robustness. Appendix B.3 demonstrates that the change in business cycle properties we identify is robust to alternative data treatments. There are three key inputs into our results: the measurement of the business cycle, a classification of countries into advanced and emerging and the underlying economic data. We vary each 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 estimated model 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 other moments we consider. We also show that our results are not driven by outliers in Table B5, which drops all growth rates larger than 15%. The moderation is not just driven by crises, but also by a decline in regular year-to-year volatility

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 use the World Bank's classification (Table B6), which also allows us to distinguish further between *middle-income* and *low-income* countries (Tables B7 and B8). 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). 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 B9).

Third, we check the robustness of our main measure of economic activity, that is, real GDP from the Penn World tables. GDP is inherently hard to measure and may be subject to numerous measurement difficulties which may spuriously lead to a moderation as measurement becomes more accurate.[6] In robustness checks, we use different measures of economic activity. In particular, we use GDP adjusted for informality from Elgin et al. (2021), credit growth from Müller and Verner (2024) and imports and exports of goods from Tradhist (Fouquin and Hugot, 2016). Informality-adjusted GDP corrects for the fact that recessions may be mismeasured as activity shifts to the informal sector. The advantage of credit and trade data is that they are constructed directly from balance sheets and customs data, which tend to be easier to measure. All measures show a large decline in volatility, in emerging economies, as we show in Figures B7 and B10, where we also discuss the data further in detail.

Finally, we employ quarterly data in Table B11. This reduces our sample of emerging markets to 18 countries, as quarterly data only become available after 2000 in most emerg-

[6]It is important to note that many emerging economies have a long statistical tradition – for instance, many Latin American countries have been building national accounts since the second world war in a harmonized fashion, supported by the UN's ECLAC (see for instance the annual publications in the 'Statistical Yearbook for Latin America' since the 1970's).

ing economies.[7] 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. The moderation holds in quarterly as well as annual data.

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? The seminal account of Aguiar and Gopinath (2007) attributes these properties to the structure of the shocks emerging markets are exposed to. In particular, they argue that emerging markets are exposed to shocks to the growth trend. However, this conclusion has been controversial, and other papers have emphasized different sources of fluctuations in emerging markets. In section 4.1 we explain the intuition at the core of this theory. Section 4.2 then explains our empirical approach to test for the presence of permanent shocks in emerging markets.

4.1 A Test to Emerging Market Business Cycle Theories

Seminal models of emerging market business cycles attribute, to varying degrees, excess consumption volatility to the presence of shocks to the trend of output. This tradition started with Aguiar and Gopinath (2007), and although other researchers (García-Cicco et al., 2010; Drechsel and Tenreyro, 2018) disagree about the quantitative importance of such shocks, they agree that an increase in the share of output variance explained by the trend component should result in a higher consumption-output volatility ratio.

Traditional emerging market business cycle models would be consistent with the developments of that we document if the share of variance explained by trend shocks has not changed much in emerging markets but has decreased in advanced. We formalize this statement analytically in a stylized model à la Aguiar and Gopinath (2006).

The model consists of a representative agent that obtains utility consumption, and engages in intertemporal consumption smoothing using a risk-free bond. The agent maximizes expected utility

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t u(C_t) \tag{1}$$

subject to the period constraint

$$C_t = Y_t + \exp(r)B_t - B_{t+1}, \tag{2}$$

where $u(C_t)$ is the t-period utility function based on consumption C_t; β is the discount factor; Y_t is an endowment process, r is the risk-free rate, and B_t is the debt level in period $t-1$. For the sake of simplicity, we assume that $\beta \cdot \exp(r) = 1$.

[7] We source quarterly data from Monnet and Puy (2019) and add data from national statistical offices when available; see Table A1 for the sample.

Following Aguiar and Gopinath (2006), the endowment process is described by

$$Y_t = \exp(z_t) \cdot \mathcal{T}_t, \tag{3}$$

$$\mathcal{T}_t = \mathcal{T}_{t-1} \cdot \exp(\mu + g_t), \tag{4}$$

to capture the notion that output is composed of cyclical fluctuations z_t and a trend component $\mathcal{T}_t$ growing at a mean rate μ but subject to fluctuations g_t.[8] Both types of fluctuations, g_t and z_t, are assumed to follow an AR(1) process:

$$g_t = \rho_g \cdot g_{t-1} + \sigma^g \cdot \eta_t^g, \qquad |\rho_g| < 1, \tag{5}$$

$$z_t = \rho_z \cdot z_{t-1} + \sigma^z \cdot \eta_t^z, \qquad |\rho_z| < 1, \tag{6}$$

where ρ_g and ρ_z are persistence parameters, and σ^g and σ^z are the scaling constants of the unit-variance structural innovations η_t^g and η_t^z. Figure E11 graphically shows the effect of permanent (g) and transitory (z) shocks on output Y. Permanent shocks correspond to a shift to a growth path to a higher level, while transitory shocks result in the economy reverting back to its initial path.

Model blocks (1)-(6) capture a key mechanism of models like those developed by Aguiar and Gopinath (2007) and García-Cicco et al. (2010): The trend is subject to shocks that have a permanent effect on output, which implies that —all else equal— consumption should react stronger in an economy in which permanent shocks are more important because households perceive shocks as moving permanent income. Consistent with Aguiar and Gopinath (2007) and Boz et al. (2011) we define the share of permanent shocks in overall output fluctuations, which we term the g-share, as:

$$g\text{-share}_t \equiv \frac{\text{var}(g_t)}{\text{var}(\Delta y_t)} = \frac{1}{1-\rho_g^2} \Bigg/ \left[\frac{1}{1-\rho_g^2} + 2 \cdot \frac{(\sigma^z/\sigma^g)^2}{1+\rho_z} \right]. \tag{7}$$

Below we show analytically that the properties of emerging market business cycles identified above are tightly connected to the share of permanent shocks in output fluctuations (i.e. the g-share defined above).

Proposition 1. *Fix $\rho_z > 0$ and $\rho_g > 0$. If the convergence condition*[9]

$$\mu + \frac{var(\Delta y_t)}{2} < r \tag{8}$$

is satisfied, then under linear approximations

[8]The type of process we assume can be traced back to Harvey and Todd (1983) and Watson (1986). Here, we follow the sovereign debt literature in assuming a process for the endowment to obtain analytical solutions. The emerging market business cycle literature often assumes this process for productivity, leading to similar dynamics (Aguiar and Gopinath, 2007).

[9]The Convergence condition (8) is very similar to the convergence condition $\mu < r$ used in models with a deterministic trend. The main difference is that our setting considers a stochastic trend, so a risk adjustment term appears naturally and generalizes the case $\sigma^g = \sigma^z = 0$.

1. *Consumption smoothing,* $\sqrt{\sigma(\Delta c_t)/\sigma(\Delta y_t)}$*, is increasing in the g-share.*

2. *Trade balance cyclicality,* $cor(\Delta y_t, (NX/Y)_t)$*, is decreasing in the g-share.*

Proof. A detailed *step-by-step* proof can be found in Appendix C.1. □

The intuition for the result stated in Proposition 1 comes from the permanent income hypothesis. With a trend shock, permanent income moves. Consumption adjusts with permanent income and moves more than current income, which only adjusts more slowly. Faced with a positive trend shock, the country runs a trade deficit in the initial years to finance the increased consumption, leading to a countercyclical trade balance.

Through the lens of Proposition 1, with constant autocorrelation parameters, the decrease in output volatility at the same time that other properties of emerging market business cycles remain unchanged would be consistent with a drop in the volatility of permanent and transitory shocks, while at the same time the share of variance explained by permanent shocks remains constant. Similarly, we should find a fall in the g-share in advanced economies to explain the observed improvement in consumption smoothing. Importantly, the statement of Proposition 1 is conditional on the other structural parameters, including the autocorrelation and overall variance of the shocks.

Therefore, the patterns documented in Section 3 together with Proposition 1 offer an opportunity to test one of the mechanisms that have been discussed the most in the business cycle literature to understand emerging market business cycles. One challenge remains: the identification of the g-share. In the next section we explain our approach to identify this quantity.

4.2 Empirical Approach

We now specify an econometric model to identify the share of output variance explained by the trend component, g-share, and describe our estimation procedure. The model is the empirical counterpart of the theoretical model described above in terms of the endowment process. Our approach builds on Nakamura et al. (2017) and Schorfheide et al. (2018), who estimate the variance of permanent and transitory shocks to consumption growth to test the long-run risk model.

Model. Output $Y_{i,t}$ of country i in region $R \equiv R(i)$ is composed of a trend $\mathcal{T}_{i,t}$ and a cycle $Z_{i,t}$ given by

$$Y_{i,t} = \mathcal{T}_{i,t} \cdot \mathcal{Z}_{i,t}, \tag{9}$$

$$\mathcal{T}_{i,t} \equiv \mathcal{T}_{i,t-1} \exp\left(\mu_{p(t)} + g_{i,t}\right)$$

$$\mathcal{Z}_{i,t} \equiv \exp(z_{i,t}) \tag{10}$$

This specification encompasses innovations $g_{i,t}$ and $z_{i,t}$, for which we impose the autoregressive structure

$$g_{i,t} = \rho_{R,g} \cdot g_{i,t-1} + \sigma^g_{i,p}\eta^g_{i,t}, \tag{11}$$

$$z_{i,t} = \rho_{R,z} \cdot z_{i,t-1} + \sigma^z_{i,p} \eta^z_{i,t}. \tag{12}$$

Our specification allows the volatility of innovations to vary by period, consistent with the shift in volatility documented above. 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 deterministic growth rate μ and the standard deviations of shocks σ^g_i and σ^z_i vary over time.[10] The $\eta^g_{i,t}$ are unit variance shocks that we call trend (or permanent) shocks. Similarly, the $\eta^z_{i,t}$ are transitory shocks with unit variance. Finally, the autocorrelation of innovations is captured by the parameters $\rho_{R,g}$ and $\rho_{R,z}$ from the interval $(-1, 1)$.

Measurement equation. From equations (9)-(12), the growth rate of output implied by the model is described by

$$\Delta y_{i,t} = g_{i,t} + \Delta z_{i,t}. \tag{13}$$

We allow this theoretical object to differ from the observed growth rates, $\Delta y^{obs}_{i,t}$, by introducing independent and normally distributed random errors $\nu_{i,t}$. Hence, the observation equation is

$$\Delta y^{obs}_{i,t} = \Delta y_{i,t} + \nu_{i,t}, \tag{14}$$

where $\nu_{i,t}$ is mean zero and has a period-varying standard deviation $\sigma^\nu_{R,p}$ common across all countries in region $R \equiv R(i)$. The error terms $\nu_{i,t}$ are especially important in the context of emerging economies, where measurement error may be particularly relevant. They may also help to capture sources of fully-transitory variation that are not captured by the structural assumptions of our model. Given the second reason, we call the $\nu_{i,t}$'s simply as error terms instead of measurement error as some authors do.

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

$$\sigma^g_{i,p} = \theta^{(1)}_{R,p} + \theta^{(2)}_{R,p} \cdot \sigma^z_{i,p}, \quad \theta_{1,p}, \theta_{2,p} \geq 0, \tag{15}$$

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 autocorrelation at the country-specific level and the standard deviation of the two types of domestic innovation. Importantly, we test the sensitivity of our results to these assumptions below. The first pooling assumption has been used in other branches of the literature on macroeconomic volatility (Nakamura et al., 2013, 2017), where the persistence of shocks is assumed to be the same across countries.[11] We impose the second assumption for our

[10] In Appendix C, we allow for year-to-year stochastic volatility and show that the results in section 5 are unchanged after introducing a richer model with full stochastic volatility.

[11] An alternative is to fix the persistence of shocks ex-ante (Naoussi and Tripier, 2013), we show that this strategy leads to similar results below.

specific setting having in mind the belief that the level of trend shock volatility must be positively related to that of transitory shocks volatility.

Estimation. The model we specify is very close to state-space models that have been estimated using the Kalman filter (e.g., the model by Boz et al. (2011)). Nonetheless, we depart from this estimation because it is not designed to handle the case in which the state variables are subject to innovations with time-varying volatility, as in our case. We use Hamiltonian Monte Carlo (HMC) to estimate our model parameters (Gelman et al., 2013; Betancourt, 2017), implemented using using Stan (Carpenter et al., 2017).[12] This estimation technique extends MCMC approaches that have been used in prior work in economics, e.g., the Gibbs sampler and Metropolis algorithm used by Nakamura et al. (2017) and Schorfheide et al. (2018) in the long-run risks literature.

To estimate the posterior distribution of the parameters, we assume weakly informative priors on the parameters. Table C1 in Appendix C.2 summarizes the distributional properties of the parameters' priors. For autocorrelations parameters ρ_g and ρ_z, we use uniform priors covering the interval $[-0.995, 0.995]$. For the standard deviations of z-shocks $\sigma^z_{i,p}$ we use a half-normal distribution with scale parameter equal to 2, and for the loading parameters $\theta^{(1)}_{R,p}$ and $\theta^{(2)}_{R,p}$ we use half-normal distributions with scale parameter equal to 1. These priors implicitly impose a prior distribution on $\sigma^g_{i,p}$ with a unit mean and a standard deviation of 0.8; hence, our priors on the volatility parameters align with the tradition in macroeconomics of assuming a minor role for trend shocks in business cycle fluctuations. For trend growth, absent trend shocks, we assume a normal prior with a mean and standard deviation of 3% and 2%, respectively. Finally, for the standard deviation of the error terms $\nu_{i,t}$ we use a truncated normal distribution centered at 0.5 with scale parameter equal to 0.5.

For each group R out of the six groups under analysis—advanced economies and the five geographic-based groups of emerging economies—we estimate the posterior distribution of the model parameters using one-hundred thousand posterior draws from an MCMC chain, discarding the first ninety-five thousand draws. We chose the number of posterior updates and draws to guarantee us that the retained samples contain at least as much information as 400 i.i.d. draws, as implied by the *effective sample size* of the parameter estimates.[13]

[12] Specifically, we use HMC with a no-U-turn sampler (NUTS) (Hoffman and Gelman, 2014); a Markov Chain Monte Carlo (MCMC) estimation technique designed to overcome the well-known random-walk behavior and sensitivity to correlated parameters problems of other MCMC techniques that are popular amongst practitioners tackling problems with a large number of parameters. For a detailed description of this method, see Betancourt (2017).

[13] The *effective sample size* (ESS) measures how many i.i.d. draws the —likely autocorrelated— posterior samples are effectively equivalent to; thus, with a large enough ESS the posterior distribution of each parameter is well identified. As a rule of thumb, Vehtari et al. (2021) show that an ESS of at least 400 guarantees a good identification of the posterior for models of many classes.

5 Empirical Results

In this section we present the results implied by the estimates of our model. We first present the model parameter estimates and then use the model to speak to theories of emerging market business cycles. Finally, we show results under alternative model specifications.

5.1 Examining the Model Estimates

Parameters. We first analyze the posterior distribution of the main parameters of the empirical model described in section 4.2. We do so with two purposes in mind. First, these parameter estimates offer information on latent features in the data such as growth, volatility, the persistence of shocks, and measurement error. Second, our goal is to analyze g-shares across countries and periods, which are composed of four parameters $\sigma_z, \sigma_g, \rho_g$ and ρ_z —see equation (7). Therefore, looking at the individual components of the g-shares explains the origin of differences in our estimates across countries.

Table 4 displays the posterior mean for the parameters related to the trend and cycle processes g and z together with the standard deviation of the measurement error at the regional level.[14] Three patterns of the date become evident from the figures in the table.

First, the volatility of both trend and cycle shocks (σ^g and σ^z, respectively) has decreased in emerging economies, but to a similar proportion. For example, in Africa the volatility of both types of shocks has decreased by around 30% on average, in the Arab World by around 50%. On the other hand, in advanced economies the standard deviation of trend innovations, σ^g, decreased while the volatility of cycle innovations, σ^z, increased. All else equal, these figures already suggest that the share of variance explained by permanent shocks in emerging economies have remained relatively constant, while they have decreased in advanced economies —we will be discussing the details and implications momentarily in subsection 5.2. Reassuringly, this also shows that the decline in volatility we have documented in section 3 using simple rolling standard deviations remains intact when viewed through a model with stochastic volatility, quantitatively the extent of the moderation is also similar.

Second, our estimates indicate that, comparing the periods 1980-99 and 2000-19, trend growth μ increased in emerging markets, while it decreased in advanced economies. In emerging markets, average trend growth increased from 3.0% to 3.7% in 2000-19 (considering the simple average across emerging market regions). These figures are consistent with a pattern that has been documented before using simple average growth rates (Arsov and Watson, 2019; Kose and Ohnsorge, 2020; Kremer et al., 2022). Our econometric approach accounts for cycle and trend shocks, so it shows that this pattern appears struc-

[14] In the case of country-specific parameters —indexed with an i— we present the posterior distribution of the (unweighted) regional average.

Table 4. Average Parameter Estimates

Parameter	Americas	Arab World	Asia & the Pacific	Europe	Sub-Saharan Africa	Advanced Economies
Trend innovations $g_{i,t}$						
Growth $\mu_{i,1980-99}$	2.61	3.18	3.85	2.26	2.95	2.98
	(0.26)	(0.35)	(0.53)	(0.48)	(0.21)	(0.17)
Growth $\mu_{i,2000-19}$	3.04	3.59	4.31	3.17	4.22	2.23
	(0.21)	(0.27)	(0.51)	(0.37)	(0.17)	(0.13)
Autocorrelation $\rho_{R,g}$	0.52	0.40	0.89	0.59	0.48	0.60
	(0.05)	(0.06)	(0.08)	(0.06)	(0.04)	(0.05)
S.D. $\sigma^g_{i,1980-99}$	3.31	8.09	1.31	4.05	3.88	1.64
	(0.25)	(0.55)	(0.35)	(0.44)	(0.22)	(0.13)
S.D. $\sigma^g_{i,2000-19}$	2.44	3.96	0.84	2.30	2.78	0.99
	(0.19)	(0.23)	(0.16)	(0.23)	(0.16)	(0.21)
Cycle innovations $z_{i,t}$						
Autocorrelation $\rho_{R,z}$	0.75	-0.04	0.69	0.80	-0.02	0.93
	(0.15)	(0.28)	(0.11)	(0.15)	(0.08)	(0.06)
S.D. $\sigma^z_{i,1980-99}$	1.59	2.23	1.71	2.03	1.87	1.05
	(0.23)	(0.25)	(0.28)	(0.38)	(0.15)	(0.13)
S.D. $\sigma^z_{i,2000-19}$	1.31	1.21	1.22	1.19	1.23	1.28
	(0.18)	(0.18)	(0.13)	(0.24)	(0.11)	(0.14)

Notes: This table reports the average posterior mean, across countries, of the parameters in the model described in subsection 4.2. Standard deviations are reported in parenthesis. For country-specific parameters (subindex i) we show the posterior distribution of the (unweighted) regional average.

tural and is not driven by as series of *"fortunate"* shocks. In section 6, we return to this finding to study its impact on emerging and advanced economy welfare.

Third, the autocorrelation of trend shocks ρ_g is similar in emerging and advanced economies, while the the autocorrelation of cycle shocks ρ_z tends to be higher in advanced economies. Our estimates of ρ_g are positive and close to the ones found by García-Cicco et al. (2010) and Drechsel and Tenreyro (2018) for Argentina, who also use annual data, they are higher than the estimates of Aguiar and Gopinath (2007) in quarterly data, which indicate an autocorrelation of trend shocks of around 0. With regards to ρ_z, our estimates indicate a cyclical persistence of about 70-90% (with the exception of the Arab World and Sub-Saharan Africa), in line with the articles cited in this paragraph.

Long-run risks. To add to our discussion on parameter estimates, we underscore a natural connection between our estimates of the autocorrelation parameter ρ_g and the literature on long-run risk and hysteresis (Cerra et al., 2023; Cerra and Saxena, 2008; Bansal and Yaron, 2004).[15] In our setting, ρ_g summarizes the long-run effect of a trend

[15]The long-run risk literature posits that if growth is persistent enough, several asset pricing puzzles may be resolved (Bansal and Yaron, 2004). On the other hand, the hysteresis literature has found permanent effects from different types of crises (Cerra and Saxena, 2008; Cerra et al., 2023).

shock on income: a geometric series $\sum_{k=0}^{\infty} \rho_g^k = (1-\rho_g)^{-1}$ indicates the permanent effect of a 1% trend shock on output. As Table 4 shows, emerging market regions display a trend shocks are estimated to be relatively persistent, with an autocorrelation of around 0.6. This means that the permanent shock 1% trend shock increases output by 2.5% in the long run, making these shocks potentially very costly for these economies. Intuitively, this parameter is mainly identified by the autocorrelation of output growth: If output growth is very persistent, this means that high growth today predicts high growth tomorrow and shocks to trend fade out slowly.

After accounting for the uncertainty around our estimates, we can rule out the possibility of ρ_g being less than or equal to zero for all regions. This highlights that given the parameters we estimate, the model we study is capable of replicating empirical patterns previously documented in the literature. For example, Cerra and Saxena (2008) document that crises have negative effects that build over time and continue to persist for at least a decade without any signs of fading out, which is in line with what our output process predicts when $\rho_g > 0$.

Fit to the data. Next, we show that our model is able to capture key features of emerging market business cycles. We begin by directly showing our estimates of permanent and transitory shocks for four economies that have been studied extensively in the international business cycle literature in Figure 4; Argentina, Canada, Finland, and Mexico. In the figure, we plot measured output growth $\Delta y_{i,t}^{obs}$ together with the latent trend $g_{i,t}$ estimated by our model. The difference between both is the cycle $z_{i,t}$ and measurement error.

From the plots it becomes clear immediately that the two emerging economies are far more volatile than the advanced economies. Moreover, in these countries the estimated latent trend is also more volatile and moves closely with output growth. In contrast, in advanced economies, we find a smaller role for trend shocks, especially in the past 20 years. Large economic shocks, such as the financial crisis in 2008 have mostly transitory effects, and the trend is relatively unchanged. This figure also clarifies what identifies the cycle and the trend in our model. As Figure E11 shows, trend shocks leave persistent scars in output growth. As such, crises that leave economies depressed for a sustained period (such as the Latin American Debt crises in 1981) are identified as shocks to the trend. When economies recover swiftly from a shock (such as Canada and Finland during the 2008 financial crisis), these crises are mostly transitory shocks.

This exercise also offers some insights into the nature of permanent and transitory shocks. Although our estimation is agnostic about the causes of these shocks, we can compare our estimated series to narrative accounts of the economic history of these economies (Kehoe and Nicolini, 2022). Analyzing the two cases of Argentina and Mexico leads us to conclude that many of the negative permanent shocks in emerging economies are characterized by financial crises, while the positive shocks often appear to be accompanied by important institutional reforms.

For Argentina, we can observe negative shocks in the early 1980s, leading up to the

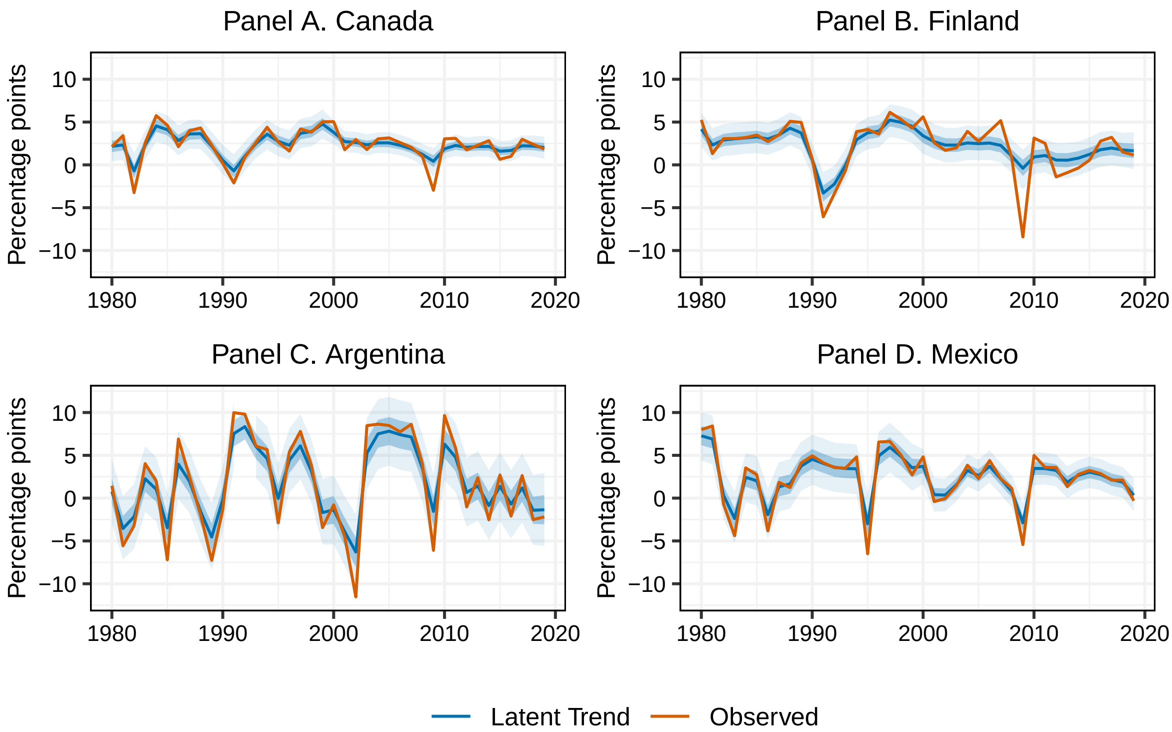

Figure 4. Observed Growth and Latent Trend for Four Economies

Notes: This figure shows output growth and the estimated latent trends for four representative economies: Canada, Germany, Mexico and Argentina. The trend corresponds to the estimated trend component in equation (9) in the model from section 4.2. Shaded areas indicated 50% and 95% confidence intervals.

default in 1982, followed by a decade marked by hyperinflation and extreme volatility. This appears to end in 1989, when the Argentine government implements the 'Bonex Plan', ushering in a short period of relative monetary dominance (Buera and Nicolini, 2019). This ends in 1998, when Argentina is hit by a series of negative shocks, beginning with the emerging market crisis and the associated capital flight in 1998 and culminating in another banking crash in 2001-2002.

In Mexico, again, the Latin American debt crisis in 1982 and the subsequent lost decade is clearly visible. The situation starts to improve in the late 1980s with a number of agreements (*"pactos"*) between the government and different stakeholder groups with the goal of inflation reduction, here we register a number of positive shocks. Interestingly, the Tequila crisis in 1993 leaves a relatively smaller dent in the trend, which observers have attributed the independence of the central bank in 1993 and the associated monetary dominance (Meza, 2018). After the 2000s, both output growth and trend growth remain relatively stable, with smaller trend shocks observed in the global financial crisis.

We find that advanced economies have become more resilient in recent years. The experience of Finland is instructive. In 1991-93, Finland experiences a deep economic recession as a result of the fall of the Soviet Union and the associated trade collapse

(Gorodnichenko et al., 2012). GDP growth is negative for 3 straight years and the Finnish economy does not appear to recover. Our model classifies this largely as a permanent shock. In contrast, the global financial crisis, although even deeper than the 1991 recession is associated with a much faster recovery and there is catch-up growth following the crisis. This reflects our finding that permanent shocks have decreased in size in advanced economies.

In a second step, we show that the model fits the properties of the business cycles in the countries we consider. We do so by simulating, for each country, 20 years of output growth for $B = 5,000$ samples using the estimated parameters for the growth process. We then compute the implied volatility in each bootstrap sample and compare it with the realized volatility in that period and country in Figure D9. Consistently, we are able to match the realized volatility across countries. Generally, the estimated volatility is below the volatility in the data, this is because our estimation attributes some of the volatility in emerging economies to measurement error. However, in general, the volatility of the simulated economy matches the realized volatility closely.

5.2 Evolution of the g-Share

We now study the changes in the contribution of permanent shocks to output volatility, i.e., to the g-share as defined in (7). For every country i and period p, we compute the posterior mean of the g-share and its change from 1980-99 to 2000-19. The evolution of the g-shares, shown in Table 5, allows us to make a preliminary assessment of the validity of emerging market business cycle theories based on trend shocks in explaining the facts we have documented.

Our estimates show that from 1980-99 to 2000-19, g-shares decreased in advanced economies, while they remained unchanged in emerging markets. Therefore, in line with Proposition 1, one should expect to observe an improvement in consumption smoothing and a less countercyclical trade balance in advanced economies, but relatively unchanged levels in emerging economies. In section 3.3 we have documented that that the volatility of consumption relative to output indeed decreased in advanced, but not in emerging. The cyclicality of the trade balance remained relatively unchanged across both. Our estimates suggest that canonical theories of emerging market business cycles appear capable of explaining patterns of consumption smoothing around the globe. At the same time, our findings indicate that these theories may be an insufficient mechanism to explain the differences in the cyclicality of trade balance between emerging and advanced economies.

A perhaps surprising feature of the estimates of the g-shares is that during the 1980-99 period, their average is very close in emerging and advanced economies. This pattern has been found before in the business cycle literature and does not contradict Proposition 1, which predicts that —all else equal— consumption smoothing in an economy will increase

TABLE 5. AVERAGE g-SHARE ACROSS REGIONS

	1980-99	2000-19	Change
Emerging economies	82.58	82.00	-0.58
	(7.74)	(8.16)	(8.48)
Americas	84.72	84.02	-0.70
	(4.55)	(4.67)	(6.41)
Arab World	88.66	88.81	0.15
	(4.09)	(2.96)	(4.73)
Asia and the Pacific	77.37	71.26	-6.10
	(9.93)	(8.97)	(11.98)
Europe	85.42	84.89	-0.53
	(6.26)	(6.04)	(8.74)
S.S. Africa	76.73	81.02	4.28
	(3.65)	(3.28)	(4.62)
Advanced economies	81.34	57.21	-24.12
	(4.81)	(9.71)	(10.68)

Notes: This table reports the posterior mean of the average g-share (share of output variance explained by the trend component) in each region during 1980-99 and 2000-19 in columns 2 and 3. Column 4 corresponds to their difference. Standard deviations are in parenthesis and are based on the posterior distributions.

if its g-share increases.[16]

As a formal test to Proposition 1, we study how the share of permanent shocks in output fluctuations covaries with excess consumption volatility and the cyclicality of the trade balance by estimating regressions of the form

$$y_{i,p} = \alpha + \beta_g \cdot (g\text{-share})_{i,p} + \gamma' X_{i,p} + u_{i,p}. \tag{16}$$

In this specification, $y_{i,p}$ corresponds to one of two outcome variables: the log of the ratio of consumption to output volatility (consumption smoothing), and the correlation between the trade balance and output (trade balance cyclicality).[17] We are interested in the coefficient β_g, expected to be positive when the outcome variable is the the consumption-output volatility ratio, and negative when it is trade balance cyclicality. We start by reporting the simple regression and then progressively add country-level controls.

[16] Boz et al. (2011) find a very similar g-share for Mexico and Canada and conclude that this is inconsistent with the different levels of consumption smoothing observed in the data. Thus, they reject the theory of Aguiar and Gopinath. In the proof of Proposition 1 we recon

[17] In the case of consumption smoothing, we use the logarithm of the definition of consumption smoothing so that for both moments, consumption smoothing and trade balance cyclicality, β_g measures the average percentage change in them following a one percent increase in the g-share.

Table 6. Regression Results

	Consumption Smoothing $y_{i,p} \equiv \log(\sigma_c/\sigma_y)_{i,p}$			Trade Balance cyclicality $y_{i,p} \equiv \text{corr}_{i,p}(NX/Y, \Delta y)$		
	(1)	(2)	(3)	(1)	(2)	(3)
g-share$_{i,p}$	1.145***	0.924***	0.767**	-0.227	-0.206	-0.020
	(0.189)	(0.255)	(0.320)	(0.140)	(0.193)	(0.216)
Region × Period	✗	✓	✓	✗	✓	✓
Controls	✗	✗	✓	✗	✗	✓
R-squared	0.107	0.238	0.258	0.009	0.123	0.137
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 (g-share). 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.

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.[18] First, we consider simple regressions of the outcome variables on the g-share. In the second specification, we add region-period fixed effects to soak up variation from period-invariant factors that affect all countries in a region (taking advanced economies as one region). Finally, in the third specification, we add the country-period mean and standard deviation of GDP growth, inflation, and trade openness index, to show that our estimates of the permanent component affect business cycle properties over and above the macroeconomic conditions of the countries.

Our estimates of coefficient β_g indicate that, in line with what canonical emerging market business cycle theories predict, countries displaying higher with a higher share of permanent shocks display larger ratios of consumption-output volatility and tend to have a more counter-cyclical net exports. Specifically, the regression results reveal that at the country level, a 1 percentage point increase g-share of an economy is related to a 0.75-1.15% increase in the consumption-output volatility ratio σ_c/σ_y. This finding holds very robustly at the 1% confidence level across specifications. The magnitudes matches the dynamics observed in advanced economies, where both the ratio of consumption to output volatility and the g-share fell by around 20%. On the other hand, we find that a 1 percentage point increase in the g-share is related to a 0-0.25% decrease in trade balance cyclicality; although this relationship is not statistically significant in any of the specifications considered.

[18]The regression results we show in this subsection use the full sample. In Appendix D.2 we show that these results change only in the second decimal when using winsorization schemes at the 2% and 5% lower and upper tails. We also show that the results hold if equation (16) is estimated in differences.

In short, our estimates confirm that permanent shocks account for the majority of output fluctuations in emerging economies. In the modern period, permanent shocks are also more important in emerging than in advanced, although this does not hold historically. Across countries, shocks to the trend are important explaining the volatility of consumption fluctuations. To a lesser degree, they may also provide information about movements in the trade balance. Hence, these estimates are broadly consistent with the mechanisms in emerging market business cycle models, but the large relevance of permanent shocks in advanced in the historical period remains puzzling.

5.3 Robustness of the Empirical Model

We estimate other versions of the model to check for the robustness of our results.

Stochastic volatility. The results presented in sections 5.1-5.2 were derived from the estimates of our baseline model, in which volatility changes every twenty years. We estimate a model in which volatility is allowed every year in Appendix D.3.1, which specifies a more general model in which output volatility changes every year.

The alternative model leads to similar results to the ones we presented in subsections 3.1 and 5.1-5.2. The model identifies a clear decline in volatility for emerging economies, with most of it temporally located in the 1980s and 1990s (see Figure D10). Consistent with our baseline results, we find that the contribution of permanent shocks to output volatility in emerging economies is high and has remained at a relatively similar level over time (see Table D3). In contrast, for advanced economies, the contribution of permanent shocks falls strongly (even more than in the baseline model). The biggest difference is that contribution of permanent shocks is lower than in the baseline model, around 65% relative to 80% in emerging economies in the baseline model.

Autocorrelations. The posterior distributions of the autocorrelation ρ_z varies widely across regions. For two region —the Arab World and Sub-Saharan Africa— the posterior mean of ρ_z is located near zero, in contrast to (an assumption that holds for the other four clusters of economies). We explore how sensitive our findings are to these parameters in Appendix D. To do so, we impose $\rho_z = 0.9$ and $\rho_g = 0.6$ for all regions, similar to estimates in annual data in García-Cicco et al. (2010). Table D4 shows that the results we obtain under this parameterization are consistent with what we find using the baseline model, emerging economies display a high share of trend shocks in overall fluctuations, with little change over time.

Structural dependence between $\boldsymbol{\sigma^z}$ and $\boldsymbol{\sigma^g}$. Assumption (15) imposes a linear relationship between σ^g and σ^z. In Appendix D.3.3 we estimate the model without this assumption, which results in parameter estimates that are relatively similar, but considerably more imprecise. However, the Appendix Table D5 show that re-estimating equation (16) using the alternative model results in similar results in terms of sign and statistical significance as Table 6. The main difference lies in that the coefficients are now smaller, which could be explained by attenuation bias induced by the increased uncertainty.

6 Welfare Cost of Business Cycles

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

6.1 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 consistent with our evidence on the presence of long-run risks in emerging market output, we allow for hysteresis, so that macroeconomic fluctuations are not neutral for long-run growth.

We use an endowment economy version of Aguiar and Gopinath (2007) and consider small open economy that faces income risk using the process described in section 4.2 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, the full model and calibration is described in appendix E.1. In particular, we use a CRRA utility function with a low coefficient of relative risk aversion of 2. 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 use the estimated parameters for every country to calibrate the income process in the given country for the two time periods we study, 1980-99 and 2000-19.

6.2 Welfare and the Emerging Market Great Moderation

Within this model, we evaluate the welfare cost of business cycles. 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 5 shows the implied welfare costs for

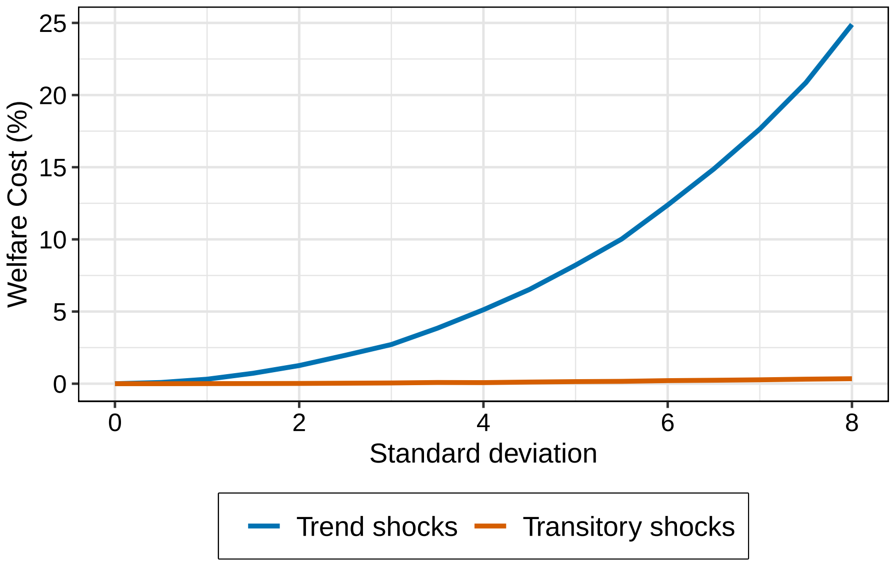

Figure 5. Welfare Cost of Business Cycles by Type of Shock

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 the model is given in table E1, we set $\rho_z = 0.9$ and $\rho_g = 0.6$ for the figure.

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.

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).[19] 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. This mechanism makes business cycles driven by volatile permanent shocks more costly in welfare terms.

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.[20] This gives us a measure of the welfare cost of business cycles in each period, λ_{1980} and λ_{2000}, defined as the amount of consumption agents would be willing to give up in order to eliminate fluctuations each period. We then calculate the welfare gains from the moderation in each country as

$$\text{Welfare Gain from Moderation} = \lambda_{1980} - \lambda_{2000}.^{21}$$

We show that the vast majority of emerging economies experienced a substantial increase in welfare over the course of the moderation in Figure 6, which plots the welfare

[19] Reis (2009) similarly notes that the persistence of consumption fluctuations has strong implications for the welfare costs of business cycles. Barro (2009) shows that rare disasters that leave permanent scars

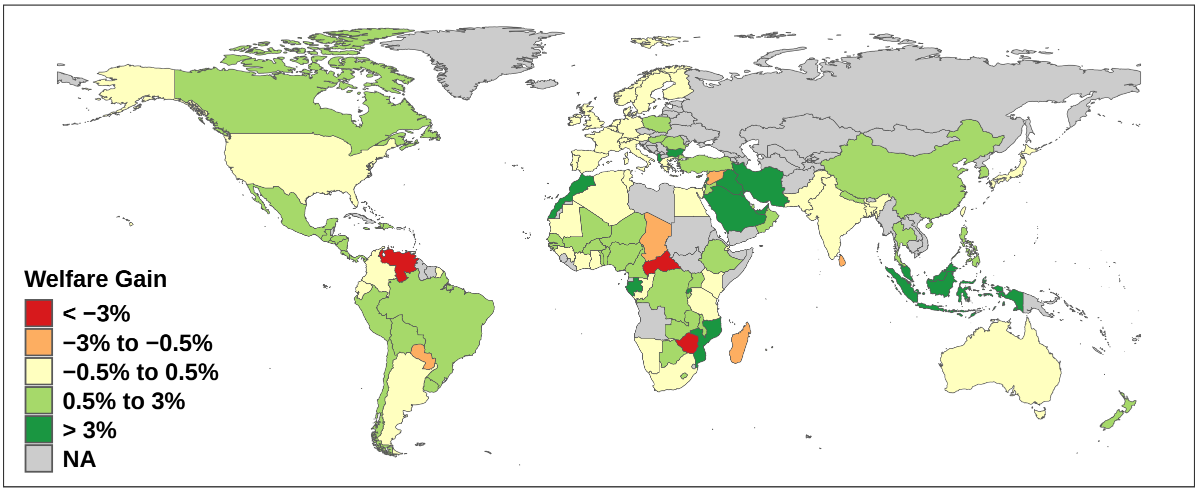

Figure 6. Welfare Gains from Moderation

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 E2 provides the numbers underlying the figure.

gains across countries. The welfare gains in emerging markets are not only positive, but also large, often exceeding 3% of steady state consumption - also large given the relatively low risk aversion of $\sigma = 2$ that we use. Examples for large gainers in terms of welfare include Morocco, Mozambique, or Peru. As with the moderation itself, welfare gains are broad based and present in all continents and along the path of the development. The big winners in terms of welfare see strongly reduced uncertainty about the long-term growth path, which used to be extremely unstable before the 2000s.

On the other hand, there are some countries which fail to see any welfare improvements, such as Argentina, Madagascar and Venezuela. In these countries we estimate welfare decreases, which can be very negative and up to -7% of steady state consumption for instance for Venezuela. Many of the countries in which we find welfare losses also prove to be exceptions to the rule of reduced volatility in emerging economies.

In contrast, advanced economies see smaller welfare changes, because their volatility was already relatively low in the earlier period. Moreover, in these countries, a larger share of fluctuations is driven by transitory shocks, particularly in the recent period, which do not have large welfare losses associated with them, as shown in Figure 5.

Table 7 reports the distribution of welfare gains across advanced and emerging. We emphasize three results. First, the median emerging market experienced roughly a 1%

also carry large welfare costs.

[20] We use the posterior mean of the model estimates.

[21] Note for small λ, this is equivalent to the consumption an agent would to give up to move from the 1980s income process to the 2000s income process, holding trend growth rates fixed (the derivation is in equation (E36) in the appendix). We study the impact of changes in trend growth in an extension below.

Table 7. Distribution of Welfare Gains

	Mean	Median	p25	p75
Emerging Economies	3.55	1.03	0.25	2.43
Americas	0.55	0.83	0.42	1.22
Arab World	14.00	3.07	0.44	6.19
Asia and the Pacific	1.58	1.66	-0.18	2.94
Europe	2.87	1.09	0.60	3.50
Sub-Saharan Africa	1.05	0.99	0.09	2.01
Advanced Economies	0.35	0.27	0.16	0.41

Notes: This table shows the implied welfare gains from moving from the 1980-99 volatility regime to the 2000-19 regime across different groups of countries. The figures for emerging markets refer to all emerging economies in our sample.

increase in welfare since the 1980-99 period. This figure hides that there is significant positive skew in the distribution of welfare gains, with the mean being a lot larger than the median. This is driven by the fact that welfare gains are nonlinear in volatility, such that economies with the largest reductions in volatility in absolute terms (especially in Middle-Eastern countries) see even larger welfare gains. Second, our estimates indicate that for 76 of the 92 emerging economies in our sample (i.e., 83% of emerging economies), welfare increased. This implies that the Emerging Market Great Moderation constitutes a broad-based improvement in welfare. Third, although volatility remained relatively constant in advanced economies, these economies generally also experienced increases in welfare, though to a smaller extent than emerging markets.

In Appendix E.2 we additionally allow trend growth to vary across countries and over time according to our empirical estimates. The welfare gains from reduced volatility remain important even when taking into account that trend growth increased in most emerging economies according to our estimates. Table E3 shows that for the median emerging economy, gains from reduced volatility are roughly one third of the gains from higher growth (for the average emerging economy this figure is around 15%). Numbers for all countries are in table E2.

7 Drivers of the Moderation

The evidence we present in previous sections calls for an answer about the origin of the decline in emerging market macroeconomic volatility. Is the source of the moderation country-specific, regional, or global? What economic and political fundamentals are linked to the moderation? In this section we offer answers to these questions.

7.1 Locating the decline in volatility

We generalize our baseline empirical model from section 4 to allow for regional and global shocks. Although this does not provide evidence on the true causes of the moderation, it allows us to narrow down the source of the moderation to country-specific shocks. We extend the output process to include regional and world shocks as in Kose et al. (2003),[22]

$$Y_{i,t} = \mathcal{T}_{i,t} \cdot Z_{i,t}, \tag{18}$$
$$\mathcal{T}_{i,t} \equiv \mathcal{T}_{i,t-1} \exp(g_{i,t} + \psi_i g_{R,t} + \zeta_i g_{W,t})$$
$$\mathcal{Z}_{i,t} \equiv \exp(z_{i,t} + \psi_i z_{R,t} + \zeta_i z_{W,t}). \tag{19}$$

In this specification we consider country-specific innovations ($g_{i,t}$,$z_{i,t}$), regional innovations ($g_{R,t}$,$z_{R,t}$) and world innovations ($g_{W,t}$, $z_{W,t}$). For each country, the loadings on the region and world processes are given by $\psi_i \geq 0$, and $\zeta_i \geq 0$ respectively. As before, we use g and z to denote trend and cycle innovations, respectively. This model nests the model in subsection 4.2 by turning off regional and world shocks, i.e., by setting ψ_i and ζ_i to zero.

Similar to our baseline model, we assume an AR(1) on the processes,

$$g_{i,t} = (1 - \rho_{R,g})\mu_{i,p} + \rho_{R,g} \cdot g_{i,t-1} + \sigma^g_{i,p}\eta^g_{i,t}, \tag{20}$$
$$z_{i,t} = \rho_{R,z} \cdot z_{i,t-1} + \sigma^z_{i,p}\eta^z_{i,t}, \tag{21}$$
$$g_{R,t} = \gamma_{R,g} \cdot g_{R,t-1} + \sigma^g_{R,p}\eta^g_{R,t}, \tag{22}$$
$$z_{R,t} = \gamma_{R,z} \cdot z_{R,t-1} + \sigma^z_{R,p}\eta^z_{R,t}, \tag{23}$$
$$g_{W,t} = \delta_{W,g} \cdot g_{W,t-1} + \sigma^g_{W,p}\eta^g_{W,t}, \tag{24}$$
$$z_{W,t} = \delta_{W,z} \cdot z_{W,t-1} + \sigma^z_{W,p}\eta^z_{W,t}, \tag{25}$$

where the volatility of all types of innovation is allowed to vary by period, the η's are unit variance shocks, and the γ and δ parameters represent autocorrelations lying in the interval $(-1, 1)$. The estimation is as in our baseline model, the prior distributions are in Appendix C.2.

Taking first differences of output in (18) iterating forward yields the share of output variance explained by domestic, global, and regional shocks:

$$\omega^{\text{dom}}_{i,p} = \left(\frac{\left(\sigma^g_{i,p}\right)^2}{1 - \rho_{R,g}} + \frac{\left(\sigma^z_{i,p}\right)^2}{1 + \rho_{R,z}} \right) \Big/ \left(\sigma^{\Delta y}_{i,p}\right)^2, \tag{26}$$
$$\omega^{\text{reg}}_{i,p} = \left(\frac{\left(\psi_i\sigma^g_{R,p}\right)^2}{1 - \gamma_{R,g}} + \frac{\left(\psi_i\sigma^z_{R,p}\right)^2}{1 + \gamma_{R,z}} \right) \Big/ \left(\sigma^{\Delta y}_{i,p}\right)^2, \tag{27}$$
$$\omega^{\text{glob}}_{i,p} = \left(\frac{\left(\zeta_i\sigma^g_{W,p}\right)^2}{1 - \delta_{W,g}} + \frac{\left(\zeta_i\sigma^z_{W,p}\right)^2}{1 + \gamma_{R,z}} \right) \Big/ \left(\sigma^{\Delta y}_{i,p}\right)^2, \tag{28}$$

[22] Note that the cycle and trend in this section are not same as in section 4.1, but their meaning remains very close. We do not change the notation to keep the discussion simple without overloading it with more mathematical symbols.

Table 8. 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 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.

where total output volatility is

$$\left(\sigma_{i,p}^{\Delta y}\right)^2 \equiv \frac{\left(\sigma_{i,p}^{g}\right)^2}{1-\rho_{R,g}^2} + \frac{\left(\psi_i\sigma_{R,p}^{g}\right)}{1-\gamma_{R,g}^2} + \frac{\left(\zeta_i\sigma_{W,p}^{g}\right)^2}{1-\delta_{W,g}^2} + \frac{\left(\sigma_{i,p}^{z}\right)^2}{1+\rho_{R,z}} + \frac{\left(\psi_i\sigma_{R,p}^{z}\right)}{1+\gamma_{R,z}} + \frac{\left(\zeta_i\sigma_{W,p}^{z}\right)^2}{1+\delta_{W,z}}. \quad (29)$$

Table 8 reports our estimates of output volatility (as measured by (29)) and the shares $\omega_{i,p}^{\text{dom}}$, $\omega_{i,p}^{\text{reg}}$, and $\omega_{i,p}^{\text{glob}}$ for emerging and advanced economies during the two periods under study. As we show below, 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.

Across economies, output volatility is accounted for mostly by domestic shocks, which generally account for more than 50% of output volatility. The contribution of domestic shocks is higher in emerging markets, but has generally declined by around 10-20% (except for Sub-Saharan Africa). Given that output volatility declines in general, this means that the volatility of domestic shocks has declined *more* than regional or world shocks. The share of output variance explained by regional shocks remained relatively constant, so that the volatility of regional factors has declined as well, although to a smaller extent than country-specific shocks. Together, these observations imply that the EMGM resulted from the moderation in the magnitude of country-specific and regional shocks.

In contrast, the influence of global shocks in emerging economies has nearly tripled over time, from around 5% in most regions to around 15%. Again this means that, in levels, the standard deviation of global shocks influencing emerging economies was higher during the 2000-19 period than in the preceding 20-year period, so that global shocks did not contribute to the decline in volatility. 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 et al. (2003) use a model with country-specific, regional, and global dynamic factors and find that country-specific explained around two-thirds of output variation in a sample of 32 emerging economies from 1960-1990, and that global shocks explained only 10%. These figures are close to the ones we find for the 1980-99 period.

Qualitatively, country-specific shocks have been less important for advanced economies than for emerging economies, and these 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 connect to the literature on globalization and international business cycles. Specifically, we include the United States in Table 8 and observe that, for the U.S., 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 findings, consistent with recent evidence showing that shocks in the United States generate movements in real macroeconomic aggregates (Miranda-Agrippino and Rey, 2020; Boehm and Kroner, 2023), is that U.S.-specific shocks directly spill over into financial markets and economies across the world.

7.2 Structural Drivers: Correlational Evidence

The results from the previous section indicate that the shocks that accounted for the majority of the moderation are country specific shocks, rather than a decline in global or regional shocks. A natural question is what political, economic or structural features of a country are associated with a decline in volatility. We present panel evidence suggesting that the improvement of monetary and political institutions were key for the increase in stability in emerging economies.

We study the role of changes in political and economic fundamentals in explaining the changes in aggregate output volatility by estimating the equation

$$\sigma^{\Delta y}_{c,t+h} - \sigma^{\Delta y}_{c,t-1} = \lambda_{c,h} + \lambda_{R\times t,h} + \boldsymbol{\beta}'_h \cdot \Delta \boldsymbol{F}_{c,t} + \boldsymbol{\delta}'_h \cdot \boldsymbol{X}_{c,t} + \varepsilon_{c,t+h}, \tag{30}$$

where the dependent variable indicates the change in volatility —measured in percentage points— from $t-1$ to $t+h$; $\boldsymbol{F}_{c,t}$ is a vector of measurements of fundamentals; $\boldsymbol{X}_{c,t}$ is a vector of lags of the one-year changes in volatility in country c; $\varepsilon_{c,t+h}$ represents the unmodeled influences of the outcome variable; $\lambda_{c,h}$ and $\lambda_{R\times t,h}$ are country and region-year fixed effects to soak the variation stemming from invariant country-specific factors and from time-varying factors affecting the volatility of all countries in the region of country c. We study the vectors $\boldsymbol{\beta}_h$ ($h = 1, 2, ...$) which measure how a change in a fundamental i relates to output volatility in the next h years.

We measure yearly output volatility, $\sigma^{\Delta y}_{c,t+h}$, using the stochastic volatility version of our model, described in Appendix D.3.1. The vector of fundamentals, $\boldsymbol{F}_{c,t}$, includes indicators for the rule of law (V-Dem dataset; Coppedge et al. 2025) and democracy (Polity V database; Marshall and Gurr 2020) as proxies for political fundamentals. As proxies for economic fundamentals, we include trade openness (trade-to-GDP), financial openness (proxied by the capital account openness index; Chinn and Ito 2006), private credit-to-GDP (Müller and Verner 2024), public debt-to-GDP (Abbas et al., 2010), agricultural output-to-GDP, an index of central bank independence (Romelli, 2022), and an indicator for the year in which a country adopts inflation targeting (Duncan et al., 2022).

Table 9 reports the results for changes in volatility at the short, medium and long-run. Overall, the regression coefficients suggest that improvements in economic and political institutions are associated with lower volatility, both in terms of magnitude and statistical significance.[23] Because of the many predictors, we focus on those with the strongest association in the main text and report the remainder in Appendix Table F.1.

Our estimates imply that improvements in monetary institutions (i.e., more central bank independence or the adoption of inflation targeting) lead to lower levels of volatility, in particular at longer horizons. For instance, central bank independence in emerging economies has increased by around 0.15 units (on a 0-1 scale). Taken at face value, our estimates imply that this is associated with a drop in volatility by around 50 basis points. Similarly, the adoption of inflation targeting leads to a decline in volatility of 60 basis points at $h = 10$ and 90 basis points at $h = 20$.[24]

Turning to political indicators, an improvement in the rule of law (measured by an index ranging from zero to one) is associated with a statistically significant decline in volatility at very short horizons (e.g., after one year). At longer horizons ($h \geq 5$ years), statistical significance is lost, although the magnitude of the estimated coefficients remains similar to that at $h = 1$. Increasing rule of law by 0.01 (measured on a 0-1 scale) is associated with a 2 basis points reduction in volatility. Taken at face value, the 0.08 increase in rule of law for the average emerging economy from 1980–99 to 2000–19 would imply a 16 basis points decline in volatility.

For the democracy indicator we do not find a statistically significant effects, despite the increase in democracy in emerging economies (see Figure B6 in the Appendix). This result

[23] This is not due to the measurement units, similar results hold when standardizing all predictors.

[24] Note that most emerging countries adopted inflation targeting only after 2005, so that long-run effects of inflation targeting are noisily estimated.

Table 9. Predictors of the Moderation

	Dependent variable: $\sigma^y_{c,t+h} - \sigma^y_{c,t-1}$				
	$h = 1$	$h = 5$	$h = 10$	$h = 15$	$h = 20$
Economic indicators					
Central bank independence	-0.715	-0.970	-2.634**	-1.725*	-3.049***
	(1.542)	(1.068)	(1.081)	(0.993)	(1.100)
Adopts inflation targeting	-0.132	0.196	-0.659*	-0.950***	-0.855
	(0.230)	(0.251)	(0.351)	(0.249)	(0.626)
Financial openness	0.266	0.411	0.682**	-0.337	-0.940**
	(0.206)	(0.555)	(0.318)	(0.479)	(0.396)
Political indicators					
Rule of law	-2.570***	-2.115***	-0.853	-1.072	-2.064
	(0.927)	(0.742)	(1.007)	(1.289)	(1.796)
Democracy	0.012	0.026	-0.040*	-0.014	0.014
	(0.025)	(0.034)	(0.024)	(0.027)	(0.020)
Fixed effects					
Country	✓	✓	✓	✓	✓
Region × Year	✓	✓	✓	✓	✓
R-squared	0.306	0.406	0.489	0.557	0.604
Observations	2,698	2,698	2,530	2,271	1,456

Notes: The table reports the entries of vector $\boldsymbol{\beta}_h$ defined in equation (30). Each entry of $\boldsymbol{\beta}_h$ measures the effect of a change in a fundamental on output volatility h-years from now. Driscoll and Kraay (1998) standard errors are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

may appear surprising given previous estimates in the democracy-volatility literature, which suggest that democracy reduces volatility (Mobarak, 2005; Acemoglu et al., 2003). In our extended sample, there appears to be no economically or statistically significant relationship between the two. This result also holds when comparing the volatility of democracies and non-democracies without controls (see Figure B6).

In terms of other dimensions of economic policy, financial openness is linked to lower levels of volatility in the long run, as shown in Table F.1. While openness tends to be associated with higher volatility in the short run (Diaz-Alejandro, 1985), the long-run effects suggest in the long run, openness in assocated with reduced volatility. The coefficient reported for $h = 20$ years implies that the increase in the average financial openness index from 1980-99 to 2000-19 is related to a 15 basis points decrease in emerging market volatility. The Table also shows that trade openness tends to be associated with reduced volatility (Caselli et al., 2020), though the evidence is stronger at shorter than at long horizons.

In sum, improvements in central bank independence, the adoption of an inflation targeting regime, and an increase in financial openness stand out as potential drivers of the decline in output volatility. The estimates discussed above suggest that monetary institutions account for a meaningful share of the observed moderation, indicating that institutional and policy reforms, especially in the conduct of monetary policy, have played an important role in stabilizing emerging economies.

8 Conclusion

We document a Great Moderation in emerging markets, characterized by a fall in output volatility by around 40% since the 1980s. 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.

We then present a first evaluation of the moderation through the lens of the canonical account of emerging market business cycles by Aguiar and Gopinath (2007) based on output growth data alone. Using our empirical model of economic fluctuations, we find evidence of trend shocks in emerging economies, a key prediction of the Aguiar and Gopinath (2007) model. However, we find that 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. Viewed through the lens of standard business cycle models, the moderation implies important welfare gains for emerging economies, around 1% of steady state consumption for the median emerging country.

Finally, we show that he moderation is mainly explained by a reduction in the volatility of domestic and regional sources of variation. Additionally, we present evidence underscoring that the improvement of monetary institutions was key for emerging economies to become more stable. Our analysis is agnostic about why these institutions are so correlated with the moderation, we are investigating these questions in ongoing work.

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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 from the national accounts (variables q_{gdp}, q_c, q_g, q_i, q_x, q_m).[25] 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.

[25] In particular, we do not adjust for PPP.

A.2 Quarterly 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 national statistical offices 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 Subcomponents	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, both in terms of GDP and for the sub-components of GDP. 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. [26]

[26]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.

B Appendix to Section 3

B.1 Details on the Moderation

B.1.1 Moderation across Emerging Countries

Figure 1 shows the average output volatility in advanced and emerging economies. Below, we further show that this holds not only at the average, but also at the median and other quantiles of the distribution, supporting for instance table 2 in the main text. Figure B1 adds to the volatility of the average emerging economy the volatility of the median emerging country, as well as the interquartile range. Volatility has decreased across emerging countries, in roughly similar proportions. If anything, the median emerging market has moderated more in terms of output volatility than the average.

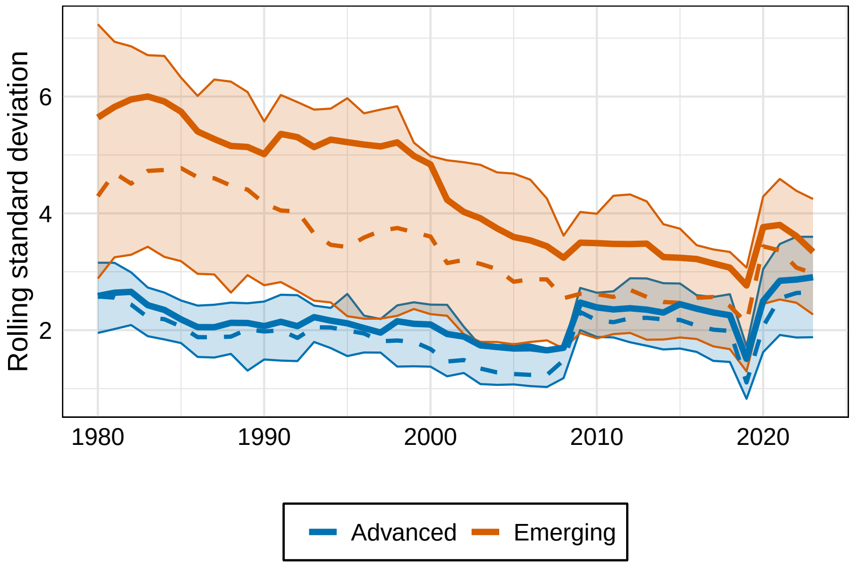


FIGURE B1. ROLLING STANDARD DEVIATION OF GDP GROWTH, 1980-PRESENT

Notes: The plot shows the average backward 10-years rolling standard deviation of output growth for 92 emerging markets (orange) and 24 advanced markets (blue). 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. Dashed lines indicate the median, and shaded areas indicate the interquartile range.

B.1.2 Moderation in macroeconomic aggregates

In Panel A of Figure B2, 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 plot shows that volatility fell for all macroeconomic aggregates —between 30% (imports) and 50% (productivity).

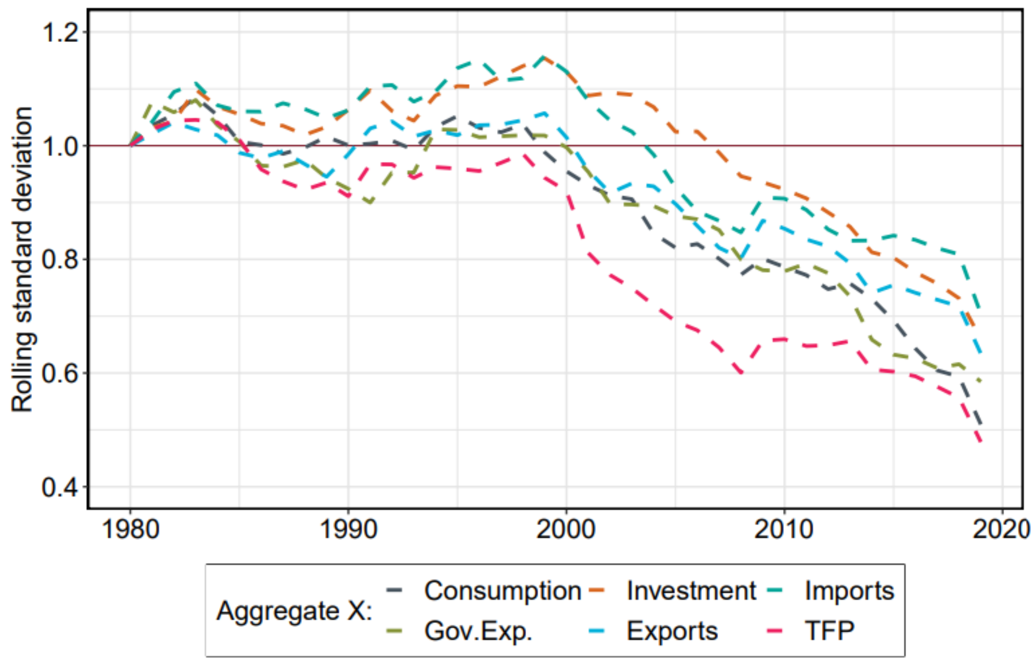


FIGURE B2. VOLATILITY OF OTHER AGGREGATES (1980 = 1)

Notes: This figure reports the 10–year rolling standard deviation of macroeconomic aggregates. Data is from the Penn World tables for the baseline sample of 92 emerging economies described in Section 2. TFP stands for total factor productivity, measured as the solow residual.

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

The moderation we document exists for all aggregates at the country level. In what follows, we summarize the changes in volatility of different aggregates across countries, in the spirit of Figure 3.

- *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%) 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.

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 GDP growth,

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

We then estimate break points in the standard deviation of the residuals $\hat{\epsilon}_{i,t}$ of the AR(1). To do so, 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. This specification using absolute values is more robust to deviations from normality (Davidian and Carroll, 1987) and is therefore commonly used in the literature on the Great Moderation in advanced economies (McConnell and Perez-Quiros, 2000; Gadea et al., 2018).

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

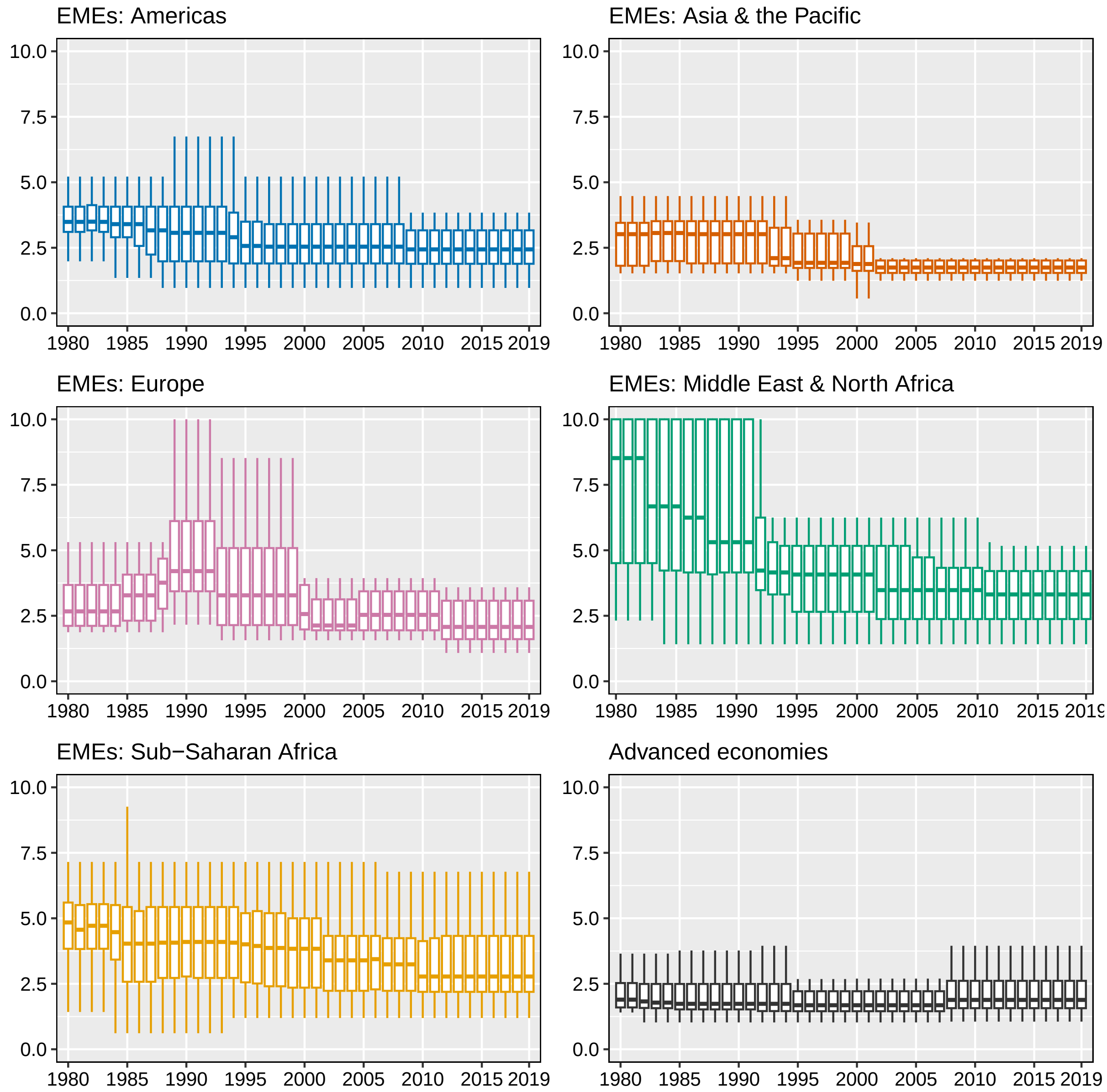


Figure B3. GDP Volatility Regimes, 1980-2019

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.

innovations in the output growth process.[27] We follow this procedure separately for each

[27] McConnell and Perez-Quiros (2000) use F-tests instead, which test for the presence of one structural

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 et al., 2023).

Figure B3 summarizes the distribution properties of the time series of latent GDP volatility in emerging and advanced economies via a dynamic box plot, in which we plot the volatility regimes over time. Each box corresponds to the 25% and 75% percentiles of the data from the corresponding year and region under study. Between these, the median is depicted as a bold horizontal line. The whiskers 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.

One key finding emerges from Figure B3: the most noticeable changes in emerging market volatility occurred before the year 2000. The panels show that the median, 25% and 75% percentile, and extreme values of the distribution of output 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 decreasing monotonically over time. In the remaining region (Europe), the figure shows that volatility increased around the 1990s and then fell again in the 2000s, corresponding to the fall of the iron curtain and the associated turmoil in emerging Europe.

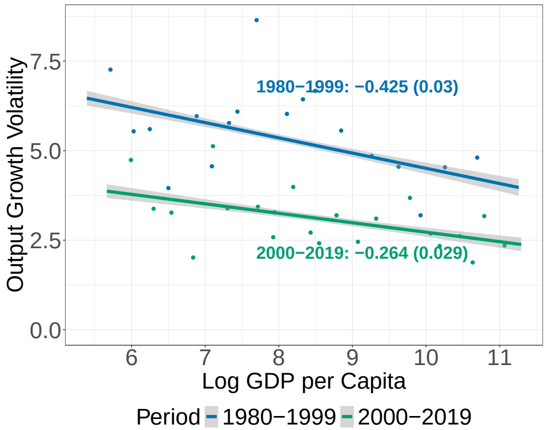
The panels in Figure B3 reveal another piece of information that aids in describing the time series dynamics that led to the EMGM. After the year 2000, GDP volatility stabilized in Asia & the Pacific; decreased in the Americas, the Arab World, and Sub-Saharan Africa (although more slowly than in the period 1980-99); and remained below the 1980-99 levels in Europe. On the other hand, the lower-right panel of Figure B3 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

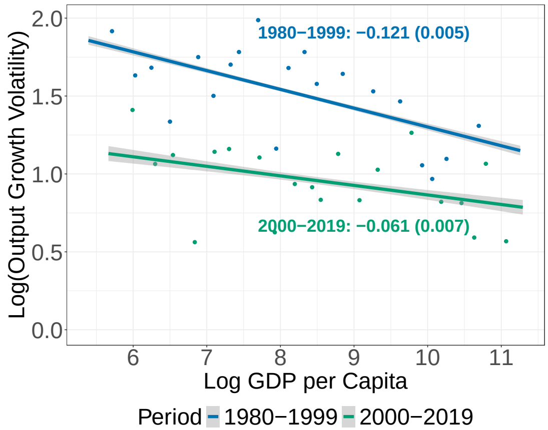
Another way of viewing the emerging market great moderation we document is as a decline in the gradient between volatility and development (Koren and Tenreyro, 2007). Figure B4 shows this explicitly. Both panels present binscatter plots using cross-country regressions showing the relationship between volatility and development for the periods 1980-99 and 2000-19 of the form

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

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.



(a) Volatility–Develop. Relation



(b) Log Volatility–Develop. Relation

FIGURE B4. 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.

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, data only starts later in the 1960s, leading to an unbalanced sample at the beginning. First, we extend the evidence on the development of output volatility in Figure 1 back to 1960. Region-specific results are in Table B1.

In line with the trend suggested by Figure B5, 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

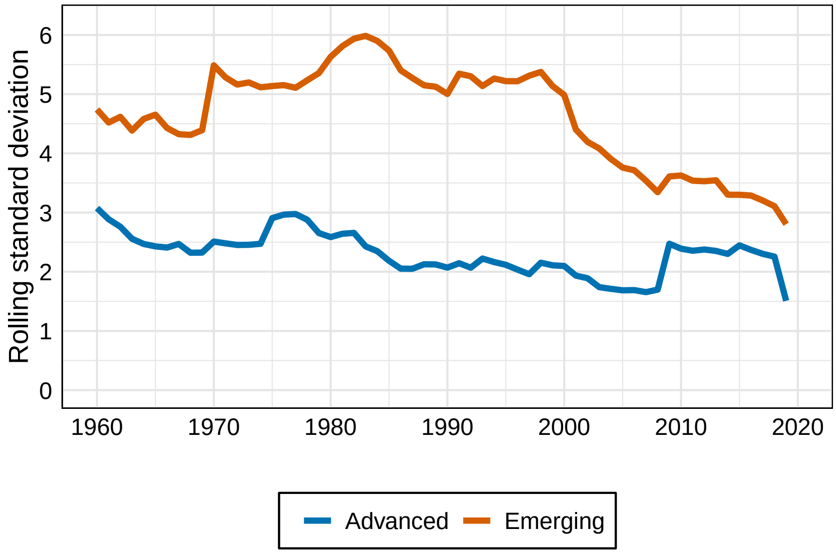


Figure B5. Output Volatility: Advanced vs. Emerging since 1980

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.

the two periods 1960-79 and 1980-99. Output volatility drops by around 27%, from around 2.7 to 2.1 percent, but has remained relatively constant since then. 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.

B.2.4 The Frequency of Crises

To shed light on the sources of the moderation, we examine the frequency of crises in emerging countries. Across different kinds of crises, we find that volatility in emerging economies is associated with an *reduction* of crises. Table B2 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. The frequency of these crises has fallen strongly in emerging markets.

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

Table B1. Output Volatility: 1960-1979, 1980-1999, 2000-2019

Region	1960-1979	1980-1999	2000-2019
Emerging economies	6.07	5.50	3.50
	(0.23)	(0.24)	(0.19)
Americas	3.86	4.16	3.20
	(0.22)	(0.26)	(0.24)
Asia & Pacific	3.99	2.96	1.79
	(0.33)	(0.38)	(0.15)
Europe	3.21	5.17	3.13
	(0.45)	(0.69)	(0.35)
Arab World	10.98	9.61	4.71
	(1.00)	(0.90)	(0.40)
Sub-Saharan Africa	6.32	5.18	3.70
	(0.25)	(0.30)	(0.23)
Advanced economies	2.80	2.21	2.08
	(0.21)	(0.13)	(0.34)

Notes: This table reports the average output volatility for the periods 1980-1999 and 2000-2019, together with the difference in volatility in levels and percent terms. Standard errors in parenthesis are computed as in Table 1.

Table B2. Relative frequency (%) of Crises

	1980-1999						2000-2019					
	Bank	Currency	Sov.Debt	War	Conflict	Coup	Bank	Currency	Sov.Debt	War	Conflict	Coup
Emerging economies	4.3	5.2	2.2	2.9	6.3	5.4	0.7	1.2	0.7	1.2	3.1	2.0
Americas	6.0	8.3	3.8	1.2	6.7	5.0	1.0	2.1	1.7	0.0	1.2	1.2
Arab World	3.8	4.4	2.5	1.2	5.0	2.5	2.5	0.6	1.2	0.6	0.6	0.6
Asia & the Pacific	4.5	6.8	2.3	0.1	5.1	9.7	0.3	2.4	0.4	0.0	1.3	5.1
Europe	2.5	3.1	1.2	11.2	4.1	4.1	0.0	0.9	0.0	2.8	1.6	0.6
S.S. Africa	5.0	3.2	0.9	0.9	10.9	5.9	0.0	0.0	0.0	2.7	10.9	2.3
Advanced economies	1.5	2.0	0.0	0.4	0.0	0.2	3.0	0.0	0.0	0.0	0.2	0.0

Notes: The table reports the frequency (in percentage points) of five types of crises in emerging economies. For each region, we report the simple average. Financial crises (banks, currency and sovereign debt) are from Laeven and Valencia (2020) and refer to the year when a crisis started. For political crises, we concentrate on interstate wars (fought within the territory) and coups d"etat (successful and unsuccessful). We classify wars using Federle et al. (2025), intrastate conflicts with more than 1,000 casualties using Gleditsch et al. (2002) and coups using Polity International V data.

it was during the 1980-99 period.

Emerging markets also experienced a pronounced decline in political crises. Coup attempts (successful and unsuccessful) occurred with a 6.2% probability in 1980-99; the frequency decreased to 2.1% in 2000-19. The marked decline in the relative frequency of wars and conflicts (fought within the territory) in emerging economies is perhaps the

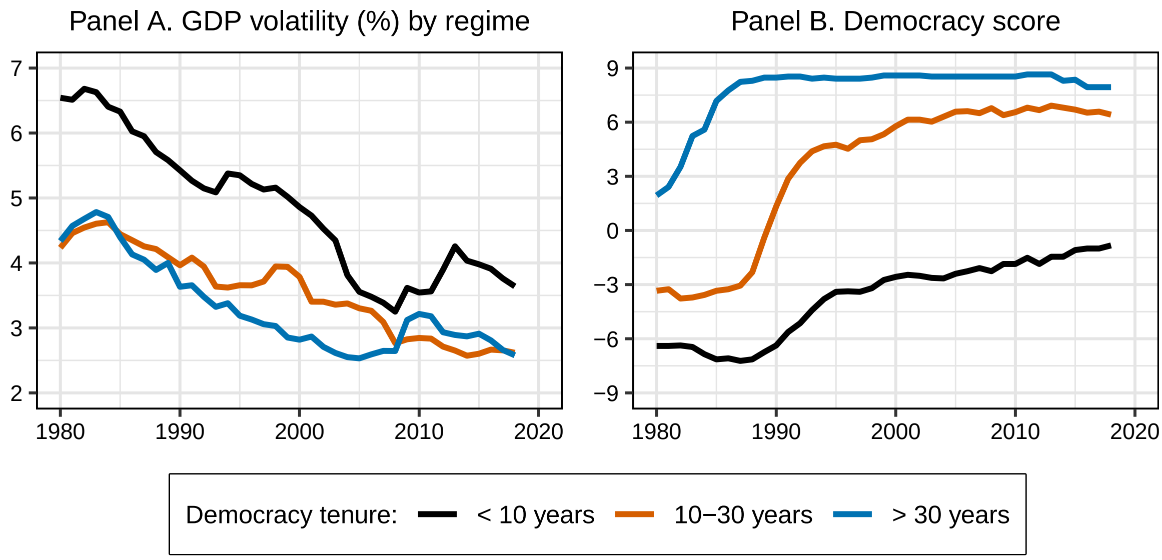


Figure B6. Democracy and the Moderation

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.

most positive implication from Table B2; the frequency of both fell by more than half.

In contrast to emerging markets, advanced economies were 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 according to standard classifications, emerging economies did not.

In Panel A of Figure B6 we show the 10-year rolling standard deviation of output for emerging economies. These economies are grouped based on their democratic status: democracies for more than 30 years, between 10 and 30 years (inclusive), and for less than 10 years.[28] Indeed, emerging economies that are more democratic see lower volatility than countries that those not classified as democracies in most years.

Despite this, output volatility has fallen for all three groups to a relatively similar extent. However, we note that even non-democracies have become more democratic, as shown in panel B, which tracks the polity2 score within the threee 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

[28]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.

all three groups of countries at the same time that they became more democratic.

B.3 Robustness of the Moderation

B.3.1 Robustness: Business Cycle Properties

In this section, test the robustness of business cycle facts we establish 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. We also report results excluding outliers (GDP growth rates above 15% in Table B5. Our results are robust to these alternative data treatments. In particular, we find an important reduction in output volatility, which drops by around 40% 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 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 in 2021, which consists of four categories (low, lower-middle, upper-middle, and high-income economies) and is based on national income per capita.[29] Table B6 summarizes results using the World Bank country classification, classifying high-income countries as advanced. There is a slightly larger decline in volatility in advanced economies using this classification, mainly because the World Bank classifies a number of 'new' advanced economies, such as Chile or Uruguay as advanced. The breakdown into categories allows us to shed further light on business cycles along the path of development in Tables B7 and B8. The moderation we document is not concentrated among more advanced emerging economies but rather applies across countries. 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. 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 B9.

Output is subject to measurement challenges in emerging economies. Therefore, we also consider other measures of economic activity. In particular, we add GDP adjusted for informality from Elgin et al. (2021), credit growth from Müller and Verner (2024)

[29] See here for further details.

and goods imports and exports from Tradhist (Fouquin and Hugot, 2016).[30] We start by plotting the standard deviation of these aggregates in figure B7, and show volatility across emerging markets in table B10. Throughout, the moderation continues to hold.

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	3.42	2.74	3.11	1.06	1.82	3.72	7.35
	2000-2019	1.94	1.52	1.52	0.66	1.03	2.14	5.08
$\sigma(c)/\sigma(y)$	1980-1999	1.68	1.36	1.04	0.72	1.08	2.00	3.55
	2000-2019	1.72	1.26	1.34	0.65	0.91	2.09	4.56
$\rho(nx/y, y)$	1980-1999	-0.19	-0.23	0.39	-0.82	-0.47	0.04	0.47
	2000-2019	-0.15	-0.17	0.39	-0.77	-0.43	0.14	0.45
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
$\rho(nx/y, y)$	1980-1999	-0.38	-0.37	0.24	-0.76	-0.52	-0.22	0.01
	2000-2019	0.03	0.06	0.48	-0.70	-0.37	0.41	0.73

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

[30]The country coverage in these data sets is also global, but slightly varies. In particular, we only lose Palestine in the trade data; Hong Kong, Haiti, Djibouti, Iraq, Palestine and Taiwan in the informality–adjusted data; and Uruguay, Albania, Iraq, Palestine, Guinea, Guinea-Bissau, Mauretania, Namibia and Simbabwe in the credit data as countries with incomplete observations since 1980.

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
$\rho(nx/y, y)$	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
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
$\rho(nx/y, y)$	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

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

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	4.24	4.33	1.46	1.94	3.22	5.27	6.82
	2000-2019	2.97	2.65	1.39	1.21	1.92	3.76	5.83
$\sigma(c)/\sigma(y)$	1980-1999	1.73	1.43	1.00	0.89	1.10	2.06	3.20
	2000-2019	1.65	1.25	1.21	0.66	1.00	1.97	3.44
$\rho(nx/y, y)$	1980-1999	-0.05	-0.01	0.33	-0.58	-0.32	0.20	0.48
	2000-2019	-0.06	-0.08	0.35	-0.60	-0.33	0.16	0.49
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
$\rho(nx/y, y)$	1980-1999	0.07	0.13	0.31	-0.37	-0.17	0.26	0.46
	2000-2019	0.05	0.09	0.26	-0.42	-0.07	0.27	0.31

Notes: The table reports first-difference filtered business cycle moments for emerging and advanced economies, dropping years in which GDP changes by more than 15%. The table reports the mean, median, standard deviation, 5th, 25th, 75th, and 95th percentiles across the countries in each category.

Table B6. Business Cycles: 1980-99 vs 2000-19, World-Bank Classificatiom

Statistic	Period	Emerging Markets						
		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
$\rho(nx/y, y)$	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
Statistic	Period	Advanced Economies						
		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
$\rho(nx/y, y)$	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

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

Table B7. Business Cycles: 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
$\rho(nx/y, y)$	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
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
$\rho(nx/y, y)$	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

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

Table B8. Business Cycles: 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
$\rho(nx/y, y)$	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
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
$\rho(nx/y, y)$	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

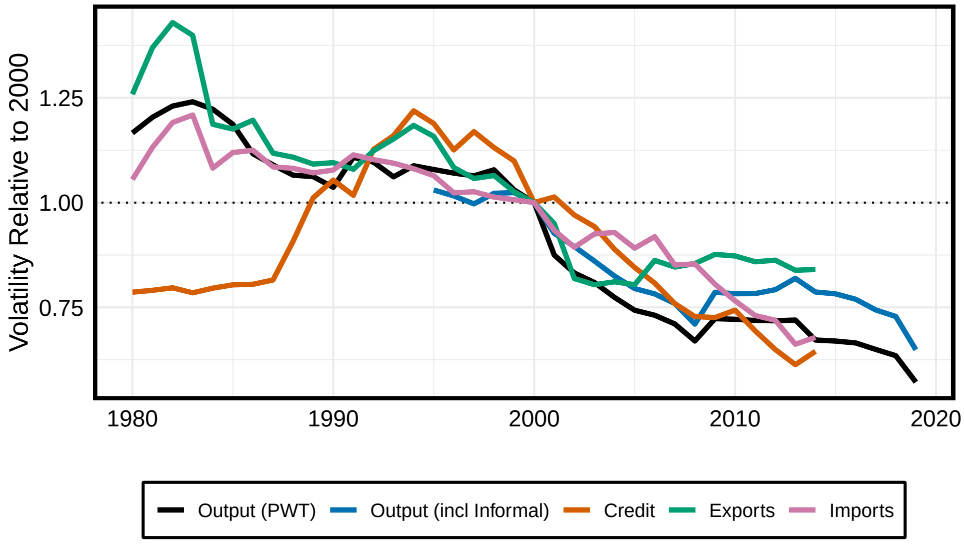
Notes: The table reports first-difference filtered business cycle moments for lower-middle-income and low-income countries from 1980-1999 and 2000-2019, using the classification by the World Bank. The table reports the mean, median, standard deviation, 5th, 25th, 75th, and 95th percentiles across the countries in each category.

Table B9. 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
$\rho(nx/y, y)$	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
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
$\rho(nx/y, y)$	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

Notes: The table reports first-difference filtered business cycle moments for emerging and advanced economies. 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.

Figure B7. Volatility of Alternative Activity Measures



Notes: This figure shows 10-year rolling standard deviation of different aggregates in emerging markets. Output is from the Penn World Tables, informality adjusted GDP from Elgin et al. (2021), credit growth from Müller and Verner (2024), and exports and imports from Tradhist (Fouquin and Hugot, 2016). The informality-based measure starts in 1992 only, so the initial years are computed on a smaller window.

Table B10. Volatility of Other Variables: 1980-99 vs 2000-2019

Statistic	Period	Mean	Median	p5	p25	p75	p95
Output	1980-1999	5.50	4.62	1.95	3.31	5.86	10.25
	2000-2019	3.50	2.71	1.22	1.93	3.89	9.52
Output (incl Informal)	1980-1999	4.34	3.57	1.17	2.29	5.20	8.95
	2000-2019	3.39	2.70	1.22	1.94	3.94	7.68
Credit	1980-1999	21.48	16.32	4.85	10.31	23.79	67.24
	2000-2019	13.51	10.98	4.50	7.43	15.07	26.47
Exports	1980-1999	24.34	19.96	13.46	15.65	27.02	53.62
	2000-2019	18.88	16.24	9.67	11.69	20.92	41.37
Imports	1980-1999	24.12	21.54	14.26	17.68	28.29	42.18
	2000-2019	19.17	14.32	9.16	11.38	20.03	45.82

Notes: This table shows the volatility of different macroeconomic aggregates across emerging markets. For each variable compute the standard deviation of first differences in each country and period and report the mean, median, and percentiles of the distribution. Output is from the Penn World Tables, informality adjusted GDP from Elgin et al. (2021), credit growth from Müller and Verner (2024), and exports and imports from Tradhist (Fouquin and Hugot, 2016). Note that in contrast to the national accounts, tradhist covers only goods trade.

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 B8 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.

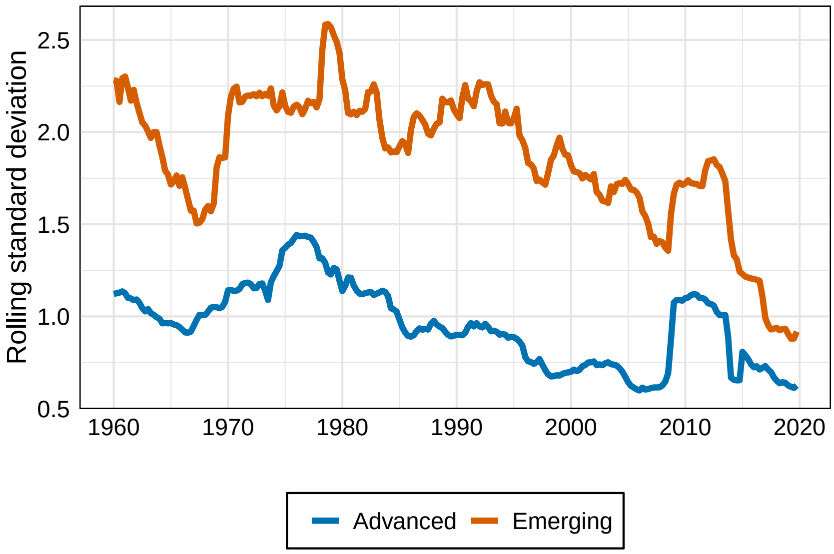


FIGURE B8. Output Volatility in Quarterly Data: Advanced versus Emerging

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 B11 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 B11. 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 Proof to Proposition 1

Proof. We do this proof in several steps.

Step 1: Approximate problem. For a general expected utility function with time separability

$$\mathcal{U}_t = \mathbb{E}_t \sum_{s=t}^{\infty} \beta^{s-t} u(C_s),$$

one can approximate $u(C_s)$ using a second order polynomial, that is,

$$u(C_s) \approx u(0) + \gamma_1 C_s - \gamma_2 \frac{C_s^2}{2}$$

using the usual assumptions of a utility function $u(\cdot)$, $\gamma_1 \equiv u'(0) > 0$ and $-\gamma_2 \equiv u''(0) < 0$.

Then, it follows that up to a second-order approximation, the representative household solves the problem

$$\max_{\{C_s, B_{s+1}\}_{s \geq t}} - \mathbb{E}_t \sum_{s=t}^{\infty} \beta^{s-t} \cdot \left(\gamma_1 C_s - \gamma_2 \cdot \frac{C_s^2}{2} \right)$$

subject to the constraints

$$C_s = Y_s + \exp(r) B_s - B_{s+1}, \quad s \geq t. \tag{C2}$$

where C_s and Y_s indicate consumption and income, B_s is the borrowing position of the household at time s ($B_s > 0$ represents a net creditor), and r is the continuously compounded interest rate which is fixed. For simplicity, we assume $B_t = 0$ and $\beta \exp(r) = 1$.

Step 2: First order conditions. Set the Lagrangian

$$\mathcal{L} = - \mathbb{E}_t \sum_{s=t}^{\infty} \beta^{s-t} \left(\gamma_1 C_s - \gamma_2 \cdot \frac{C_s^2}{2} + \lambda_s \left[C_s - Y_s - \exp(r) B_s + B_{s+1} \right] \right)$$

The first order condition with respect to consumption at time s leads to

$$\gamma_2 C_s = \gamma_1 + \lambda_s \tag{C3}$$

and the first order condition with respect to B_{s+1} gives

$$\lambda_s = \beta \exp(r) \, \mathbb{E}_s[\lambda_{s+1}] = \mathbb{E}_s[\lambda_{s+1}]. \tag{C4}$$

Condition (C4) implies that λ_s is a martingale. Therefore, it follows from such a fact and condition (C3) that C_s is also a martingale, that is,

$$\mathbb{E}_t[C_s] = \mathbb{E}_t[\mathbb{E}_{s-1}[C_s]] = \mathbb{E}_t \left[C_{s-1} \right] = \mathbb{E}_t \left[\mathbb{E}_{s-2}[C_{s-1}] \right] = \mathbb{E}_t[C_{s-2}] = \cdots = C_t. \tag{C5}$$

Step 3: Derive the consumption at t as a function of discounted income. Notice that from the budget constraint (C2) at $s = t, t+1$

$$C_t = Y_t + \exp(r)B_t - B_{t+1},$$
$$B_{t+1} = \exp(-r)\left(C_{t+1} - Y_{t+1}\right) + \exp(-r)B_{t+2},$$

So putting these expressions together results in

$$C_t + \exp(-r)C_{t+1} = Y_t + \exp(-r)Y_{t+1} - \exp(-r)B_{t+2}.$$

Again, with from (C2) at $t+2$ we know

$$B_{t+2} = \exp(-r)\left(C_{t+2} - Y_{t+2}\right) + \exp(-r)B_{t+3},$$

so we can substitute B_{t+2} in the previous expression to obtain

$$\sum_{s=t}^{t+2}(\exp(-r))^{s-t}C_s = -(\exp(-r))^2 B_{t+3} + \sum_{s=t}^{t+2}(\exp(-r))^{s-t}Y_s.$$

We can repeat the process iteratively to obtain

$$\sum_{s=t}^{t+K}(\exp(-r))^{s-t}C_s = -(\exp(-r))^{t+K} B_{t+K+1} + \sum_{s=t}^{t+K}(\exp(-r))^{s-t}Y_s.$$

Under the no-Ponzi scheme assumption,

$$\lim_{K\to\infty}(\exp(-r))^{t+K} B_{t+K+1} = 0,$$

it follows that the lifetime budget constraint of the household is

$$\sum_{s=t}^{\infty}(\exp(-r))^{s-t}C_s = \sum_{s=t}^{\infty}(\exp(-r))^{s-t}Y_s. \tag{C6}$$

Take expectations in (C6) and use (C5) to obtain

$$\begin{aligned}
&\sum_{s=t}^{\infty}(\exp(-r))^{s-t}\,\mathbb{E}_t\,C_s = \sum_{s=t}^{\infty}(\exp(-r))^{s-t}\,\mathbb{E}_t\,Y_s \\
\Rightarrow\ &\sum_{s=t}^{\infty}(\exp(-r))^{s-t}C_t = \sum_{s=t}^{\infty}(\exp(-r))^{s-t}\,\mathbb{E}_t\,Y_s \\
\Rightarrow\ &\frac{C_t}{1-\exp(-r)} = \sum_{s=t}^{\infty}(\exp(-r))^{s-t}\,\mathbb{E}_t\,Y_s,
\end{aligned}$$

meaning that consumption at time t can be written as

$$C_t = (1-\exp(-r))\sum_{s=t}^{\infty}(\exp(-r))^{s-t}\,\mathbb{E}_t\,Y_s. \tag{C7}$$

Step 4: Approximate $\mathbb{E}_t\, Y_s$. Notice that

$$\mathbb{E}_t\, Y_s = \mathbb{E}_t \left[\mathcal{T}_t \cdot \exp\left(\mu(s-t) + \sum_{j=t+1}^{s} g_j \right) \exp(z_s) \right]. \tag{C8}$$

Recalling that $x \in \{z, g\}$ are defined as

$$x_j = \rho_x \cdot x_{j-1} + \epsilon_j^x$$

with $\epsilon_j^x \equiv \sigma^x \eta_j^x$, we next do a series of algebraic approximations to get an close expression for $\mathbb{E}_t\, Y_s$. We do this in three sub-steps:

i) *Expectation on exponential of z_s.* We write

$$\begin{aligned}
\mathbb{E}_t[\exp(z_s)] &= \mathbb{E}_t \left[\exp\left(\rho_z^{s-t} z_t + \sum_{j=t+1}^{s} \rho_z^{s-j} \epsilon_j^z \right) \right] \\
&= \exp(\rho_z^{s-t} z_t) \prod_{j=t+1}^{s} \mathbb{E}_t \left[\underbrace{\exp\left(\rho_z^{s-j} \epsilon_j^z\right)}_{\sim \log\mathcal{N}\left(0, (\rho_z^{s-j}\sigma_z)^2\right)} \right] \\
&= \exp(\rho_z^{s-t} z_t) \prod_{j=t+1}^{s} \exp\left(\frac{(\rho_z^2)^{s-j} \sigma_z^2}{2} \right) \\
&= \exp(\rho_z^{s-t} z_t) \exp\left(\frac{\sigma_z^2}{2} \sum_{j=t+1}^{s} (\rho_z^2)^{s-j} \right) \\
&= \exp(\rho_z^{s-t} z_t) \exp\left(\frac{\sigma_z^2}{2} \sum_{j=0}^{s-t-1} (\rho_z^2)^{j} \right) \\
&= \exp(\rho_z^{s-t} z_t) \exp\left(\frac{\sigma_z^2}{2} \frac{1-(\rho_z^2)^{s-t}}{1-\rho_z^2} \right) \\
&\approx \exp(\rho_z^{s-t} z_t) \exp\left(\frac{\sigma_z^2}{1+\rho_z} (s-t) \right),
\end{aligned}$$

where the third equality follows from the formula for the mean of a log-normal random variable, and the last line follows from the Taylor approximation of first degree for $f(\rho_z) \equiv (\rho_z^2)^{s-t} \approx 1 + 2(s-t)(\rho_z - 1)$. Grouping terms it follows that

$$\mathbb{E}_t[\exp(z_s)] \approx \exp(\rho_z^{s-t} z_t) \left\{ \exp\left(\frac{\sigma_z^2}{1+\rho_z} \right) \right\}^{s-t}. \tag{C9}$$

ii) *Expectation on exponential of $\sum_{j=t+1}^{s} g_j$.* Notice that

$$\begin{aligned}
&\mathbb{E}_t \left\{ \exp\left(\sum_{j=t+1}^{s} g_j \right) \right\} \\
&= \mathbb{E}_t \exp\left[\sum_{j=t+1}^{s} \left(\rho_g^{j-t} g_t + \sum_{k=t+1}^{j} \rho_g^{j-k} \epsilon_k^g \right) \right]
\end{aligned}$$

$$
\begin{aligned}
&= \exp\left[g_t \sum_{j=t+1}^{s} \rho_g^{j-t}\right] \mathbb{E}_t \left[\exp\left(\sum_{j=t+1}^{s} \sum_{k=t+1}^{j} \rho_g^{j-k} \epsilon_k^g\right)\right] \\
&= \exp\left[g_t \rho_g \sum_{j=0}^{s-1} \rho_g^{j}\right] \mathbb{E}_t \left[\exp\left(\sum_{j=t+1}^{s} \left(\frac{1-\rho_g^{s-j+1}}{1-\rho_g}\right) \epsilon_j^g\right)\right] \\
&= \exp\left[\left(\frac{1-\rho_g^{s-t}}{1-\rho_g}\right)\rho_g g_t\right] \exp\left[\frac{\sigma_g^2}{2(1-\rho_g)^2} \sum_{j=t+1}^{s} (1-\rho_g^{s-j+1})^2\right] \\
&= \exp\left[\left(\frac{1-\rho_g^{s-t}}{1-\rho_g}\right)\rho_g g_t\right] \times \\
&\quad \exp\left[\frac{\sigma_g^2}{2(1-\rho_g)^2}\left((s-t) - 2\rho_g\left(\frac{1-\rho_g^{s-t}}{1-\rho_g}\right) + \rho_g^2\left(\frac{1-(\rho_g^2)^{s-t}}{1-\rho_g^2}\right)\right)\right] \\
&\approx \exp\left[(s-t)\rho_g g_t\right] \times \\
&\quad \exp\left[\frac{\sigma_g^2}{2(1-\rho_g)^2}\left((s-t) - 2\rho_g(s-t) + \frac{2\rho_g^2}{1+\rho_g}(s-t)\right)\right],
\end{aligned}
$$

where, as before, the approximation follows from using first degree Taylor approximations, now for $f(\rho_g) \equiv \rho_g^{s-t} \approx 1 + (s-t)(\rho_g - 1)$ and $g(\rho_g) \equiv (\rho_g^2)^{s-t} \approx 1 + 2(s-t)(\rho_g - 1)$. Hence,

$$
\mathbb{E}_t \exp\left(\sum_{j=t+1}^{s} g_j\right) = \left\{\exp\left[\rho_g g_t + \frac{\sigma_g^2}{2(1-\rho_g)^2}\left(1 - 2\rho_g + \frac{2\rho_g^2}{1+\rho_g}\right)\right]\right\}^{s-t} \tag{C10}
$$

Plugging (C9) and (C10) into (C8) results in

$$
\begin{aligned}
\mathbb{E}_t Y_{t+s} &\approx \mathcal{T}_t(\exp(\mu))^{s-t} \\
&\quad \times \left\{\exp\left[\rho_g g_t + \frac{\sigma_g^2}{2(1-\rho_g)^2}\left(1 - 2\rho_g + \frac{2\rho_g^2}{1+\rho_g}\right)\right]\right\}^{s-t} \\
&\quad \times \exp(z_t)\left\{\exp\left(\frac{\sigma_z^2}{1+\rho_z}\right)\right\}^{s-t} \\
&\approx \mathcal{T}_t \times \exp(\rho_z^{s-t} z_t) \times \exp\left[\left(\frac{1-\rho_g^{s-t}}{1-\rho_g}\right)\rho_g g_t\right] \\
&\quad \times \left\{\exp\left[\mu + \frac{\sigma_g^2}{2(1-\rho_g)^2}\left(1 - 2\rho_g + \frac{2\rho_g^2}{1+\rho_g}\right) + \frac{\sigma_z^2}{1+\rho_z}\right]\right\}^{s-t},
\end{aligned}
$$

which implies that

$$
\begin{aligned}
\mathbb{E}_t Y_{t+s} &\approx \mathcal{T}_t \times \left(1 + \rho_z^{s-t} z_t + \left(\frac{1-\rho_g^{s-t}}{1-\rho_g}\right)\rho_g g_t\right) \\
&\quad \times \left\{\exp\left[\mu + \frac{\sigma_g^2}{2(1-\rho_g)^2}\left(1 - 2\rho_g + \frac{2\rho_g^2}{1+\rho_g}\right) + \frac{\sigma_z^2}{1+\rho_z}\right]\right\}^{s-t}.
\end{aligned} \tag{C11}
$$

Step 5: Derive an expression for log-consumption. Let

$$
q \equiv \exp\left[\mu + \frac{\sigma_g^2}{2(1-\rho_g)^2}\left(1 - 2\rho_g + \frac{2\rho_g^2}{1+\rho_g}\right) + \frac{\sigma_z^2}{1+\rho_z} - r\right],
$$

then we can re-write expression (C11) as

$$(\exp(-r))^{s-t}\,\mathbb{E}_t\,Y_s \approx \mathcal{T}_t \cdot \left(1+\rho^{s-t}z_t+\left(\frac{1-\rho_g^{s-t}}{1-\rho_g}\right)\rho_g g_t\right)q^{s-t},$$

and plugging the resulting expression into (C7) results in

$$C_t \approx (1-\exp(-r))\mathcal{T}_t \cdot \sum_{s=t}^{\infty}\left(1+\rho^{s-t}z_t+\left(\frac{1-\rho_g^{s-t}}{1-\rho_g}\right)\rho_g g_t\right)q^{s-t}. \tag{C12}$$

Using the convergence condition

$$\mu+\frac{\sigma_g^2}{2(1-\rho_g)^2}\left(1-2\rho_g+\frac{2\rho_g^2}{1+\rho_g}\right)+\frac{\sigma_z^2}{1+\rho_z}<r, \tag{C13}$$

and the basic properties of geometric sums, it follows that

$$\begin{aligned}
C_t &\approx (1-\exp(-r))\mathcal{T}_t \cdot \left[\frac{1}{1-q}+\frac{z_t}{1-\rho q}+\frac{\rho_g g_t}{1-\rho_g}\left(\frac{1}{1-q}-\frac{1}{1-\rho_g q}\right)\right] \\
&= (1-\exp(-r))\mathcal{T}_t \cdot \frac{1}{1-q}\left[1+\left(\frac{1-q}{1-\rho q}\right)z_t+\frac{\rho_g}{1-\rho_g}\left(1-\frac{1-q}{1-\rho_g q}\right)g_t\right] \\
&= (1-\exp(-r))\mathcal{T}_t \cdot \frac{1}{1-q}\left[1+\left(\frac{1-q}{1-\rho q}\right)z_t+\frac{\rho_g q}{1-\rho_g}\left(\frac{1-\rho_g}{1-\rho_g q}\right)g_t\right],
\end{aligned}$$

which implies that log-consumption can be approximated by

$$\log C_t \approx \log(1-\exp(-r))+\log\mathcal{T}_t-\log(1-q)+\left(\frac{1-q}{1-\rho_z q}\right)z_t+\frac{\rho_g q}{1-\rho_g}\left(\frac{1-\rho_g}{1-\rho_g q}\right)g_t. \tag{C14}$$

Step 6: Derive an expression for the consumption-output ratio. Based on the expression for consumption (C12) and the definition of output, it follows that the ratio of consumption C_t to output C_t can be approximated by

$$\begin{aligned}
\frac{C_t}{Y_t} &\approx \frac{(1-\exp(-r))\mathcal{T}_t \cdot \sum_{s=t}^{\infty}\left(1+\rho_z^{s-t}z_t+\left(\frac{1-\rho_g^{s-t}}{1-\rho_g}\right)\rho_g g_t\right)q^{s-t}}{\mathcal{T}_t \cdot \exp(z_t)} \\
&= (1-\exp(-r))\exp(-z_t)\cdot\frac{1}{1-q}\left[1+\left(\frac{1-q}{1-\rho_z q}\right)z_t+\frac{\rho_g q}{1-\rho_g}\left(\frac{1-\rho_g}{1-\rho_g q}\right)g_t\right] \\
&\approx (1-\exp(-r)-(1-\exp(-r))z_t) \\
&\quad\cdot\frac{1}{1-q}\left[1+\left(\frac{1-q}{1-\rho_z q}\right)z_t+\frac{\rho_g q}{1-\rho_g}\left(\frac{1-\rho_g}{1-\rho_g q}\right)g_t\right]
\end{aligned}$$

and muting cross-multiplied shocks (i.e., $z_t^2\approx 0$ and $z_t g_t \approx 0$), we obtain

$$\frac{C_t}{Y_t}\approx\frac{1-\exp(-r)}{1-q}\left\{1+\left(\frac{1-q}{1-\rho_z q}-1\right)z_t+\left(\frac{\rho_g q}{1-\rho_g q}\right)g_t\right\}. \tag{C15}$$

Step 7: Consumption smoothing as a function of the g-share. From (C14) it follows that consumption growth is

$$\Delta c_t \equiv \log C_{t+1}-\log C_t$$

$$
\begin{aligned}
&= \mu + \underbrace{\log \mathcal{T}_{t+1} - \log \mathcal{T}_t}_{=g_{t+1}} + \left(\frac{1-q}{1-\rho_z q}\right)\Delta z_{t+1} + \left(\frac{\rho_g q}{1-\rho_g q}\right)\Delta g_{t+1} \\
&= \mu + g_{t+1} + \left(\frac{1-\rho_z q + \rho_z q - q}{1-\rho_z q}\right)\Delta z_{t+1} + \left(\frac{\rho_g q}{1-\rho_g q}\right)\Delta g_{t+1} \\
&= \mu + g_{t+1} + \Delta z_{t+1} - q\left(\frac{1-\rho_z}{1-\rho_z q}\right)\Delta z_{t+1} + \left(\frac{\rho_g q}{1-\rho_g q}\right)\Delta g_{t+1} \\
&= \mu + g_{t+1} + \Delta z_{t+1} - \left(\frac{1-\rho_z}{(1/q)-\rho_z}\right)\Delta z_{t+1} + \left(\frac{\rho_g q}{(1/q)-\rho_g}\right)\Delta g_{t+1}. \qquad \text{(C16)}
\end{aligned}
$$

Applying the variance operator we obtain

$$
\begin{aligned}
\operatorname{var}(\Delta c_{t+1}) = \operatorname{var}(\underbrace{g_{t+1} + \Delta z_{t+1}}_{=\Delta y_{t+1}}) &+ \left(\frac{1-\rho_z}{(1/q)-\rho_z}\right)^2 \operatorname{var}(\Delta z_{t+1}) \\
&+ \left[\frac{\rho_g}{1-\rho_g}\left(\frac{1-\rho_g}{(1/q)-\rho_g}\right)\right]^2 \operatorname{var}(\Delta g_{t+1}) \\
&+ 2\left[\frac{\rho_g}{1-\rho_g}\left(\frac{1-\rho_g}{(1/q)-\rho_g}\right)\right] \underbrace{\operatorname{cov}(g_{t+1}, \Delta g_{t+1})}_{=\operatorname{cov}(\rho_g g_t + \epsilon^g_{t+1}, (\rho_g - 1) g_t + \epsilon^g_{t+1})} \\
&- 2\left(\frac{1-\rho_z}{(1/q)-\rho_z}\right)\operatorname{cov}(\Delta z_{t+1}, \Delta z_{t+1}) \\
= \operatorname{var}(\Delta y_{t+1}) &+ \left(\frac{1-\rho_z}{(1/q)-\rho_z}\right)^2 \operatorname{var}(\Delta z_{t+1}) \qquad \text{(C17)} \\
&+ \left[\frac{\rho_g}{1-\rho_g}\left(\frac{1-\rho_g}{(1/q)-\rho_g}\right)\right]^2 \operatorname{var}(\Delta g_{t+1}) \\
&+ 2\left[\frac{\rho_g}{1-\rho_g}\left(\frac{1-\rho_g}{(1/q)-\rho_g}\right)\right] \left(\sigma_g^2 + \rho_g(\rho_g - 1)\operatorname{var}(g_t)\right) \\
&- 2\left(\frac{1-\rho_z}{(1/q)-\rho_z}\right)\operatorname{var}(\Delta z_{t+1}).
\end{aligned}
$$

Since g_t is an AR(1) process, the following identities hold true:

$$\operatorname{var}(\Delta g_{t+1}) = 2(1-\rho_g)\operatorname{var}(g_{t+1}), \qquad \text{(C18)}$$

$$\sigma_g^2 + \rho_g(\rho_g - 1)\operatorname{var}(g_t) = (1-\rho_g)\operatorname{var}(g_{t+1}), \qquad \text{(C19)}$$

where we use the unconditional variance property $\operatorname{var}(g_t) = \operatorname{var}(g_{t+1})$ for all t.

Plugging (C18) and (C19) into (C17) and dividing by $\operatorname{var}(y_{t+1})$ results in

$$
\begin{aligned}
\frac{\operatorname{var}(\Delta c_{t+1})}{\operatorname{var}(\Delta y_{t+1})} = 1 &+ \left(\frac{1-\rho_z}{(1/q)-\rho_z}\right)^2 (1-\Lambda_{t+1}) \qquad \text{(C20)} \\
&+ 2\left[\frac{\rho_g}{1-\rho_g}\left(\frac{1-\rho_g}{(1/q)-\rho_g}\right)\right]^2 (1-\rho_g)\Lambda_{t+1} \\
&+ 2\left[\frac{\rho_g}{1-\rho_g}\left(\frac{1-\rho_g}{(1/q)-\rho_g}\right)\right] (1-\rho_g)\Lambda_{t+1} \\
&- 2\left(\frac{1-\rho_z}{(1/q)-\rho_z}\right)(1-\Lambda_{t+1}),
\end{aligned}
$$

where

$$\Lambda_{t+1} \equiv \frac{\text{var}(g_{t+1})}{\text{var}(\Delta y_{t+1})}$$

denotes the g-share.[31]

Simplifying (C20) further, we write

$$\begin{aligned}
\frac{\text{var}(\Delta c_{t+1})}{\text{var}(\Delta y_{t+1})} &= 1 + \left(\frac{1-\rho_z}{(1/q)-\rho_z}\right)\left[\frac{1-\rho_z}{(1/q)-\rho_z} - 2\right](1-\Lambda_{t+1}) \\
&\quad + 2\left[\frac{\rho_g}{1-\rho_g}\left(\frac{1-\rho_g}{(1/q)-\rho_g}\right)\right]^2 (1-\rho_g)\Lambda_{t+1} \\
&\quad + 2\left[\frac{\rho_g}{1-\rho_g}\left(\frac{1-\rho_g}{(1/q)-\rho_g}\right)\right](1-\rho_g)\Lambda_{t+1}, \\
&= 1 + \left(\frac{1-\rho_z}{(1/q)-\rho_z}\right)\left[\frac{1-\rho_z}{(1/q)-\rho_z} - 2\right] \qquad\qquad \text{(C21)} \\
&\quad + \underbrace{\left\{-\left(\frac{1-\rho_z}{(1/q)-\rho_z}\right)\left[\frac{1-\rho_z}{(1/q)-\rho_z} - 2\right]\right\}}_{(+)} \cdot\Lambda_{t+1} \\
&\quad + \underbrace{2\left[\frac{\rho_g}{1-\rho_g}\left(\frac{1-\rho_g}{(1/q)-\rho_g}\right)\right]^2 (1-\rho_g)}_{(+)} \cdot\Lambda_{t+1} \\
&\quad + \underbrace{2\left[\frac{\rho_g}{1-\rho_g}\left(\frac{1-\rho_g}{(1/q)-\rho_g}\right)\right](1-\rho_g)}_{(+)} \cdot\Lambda_{t+1},
\end{aligned}$$

where the sign of the coefficients follows from q, ρ, and ρ_g all inside $(0, 1)$. Moreover, using the assumption that

$$\mu + \frac{\sigma_g^2}{2(1-\rho_g)^2}\left(1 - 2\rho_g + \frac{2\rho_g^2}{1+\rho_g}\right) + \frac{\sigma_z^2}{1+\rho_z} - r$$

is negative but close to zero, we can use $q \approx 1$ to obtain

$$\frac{\text{var}(\Delta c_{t+1})}{\text{var}(\Delta y_{t+1})} = \left\{1 + 2\cdot\frac{\rho_g^2}{1-\rho_g} + 2\cdot\rho_g\right\}\Lambda_{t+1},$$

which in turn, under the approximations used, implies the expression for consumption smoothing

$$CS_{t+1} \equiv \sqrt{\frac{\text{var}(\Delta c_{t+1})}{\text{var}(\Delta y_{t+1})}} = \sqrt{\left(\frac{1+\rho_g}{1-\rho_g}\right)\Lambda_{t+1}}. \qquad \text{(C22)}$$

Then consumption smoothing is increasing in the g-share Λ_{t+1} when one holds ρ_g fixed.

Step 8: Trade balance ciclicality as a function of the *g*-share. We are now interested in finding an expression for

$$TBC_{t+1} \equiv \text{cor}(\Delta y_{t+1}, NX_{t+1}/Y_{t+1}) = \frac{\text{cov}(\Delta y_{t+1}, NX_{t+1}/Y_{t+1})}{\sqrt{\text{var}(\Delta y_{t+1})}\sqrt{\text{var}(NX_{t+1}/Y_{t+1})}}, \qquad \text{(C23)}$$

[31] We use Λ instead of writing g-share because it saves space and characters in an already long proof.

so we need to take some intermediate steps.

First, in our model, net exports are simply output less consumption, so

$$\frac{NX_{t+1}}{Y_{t+1}} = \frac{Y_{t+1} - C_{t+1}}{Y_{t+1}} = 1 - \frac{C_{t+1}}{Y_{t+1}},$$

which plugged into (C23) implies

$$TBC_{t+1} = -\frac{\operatorname{cov}(\Delta y_{t+1}, C_{t+1}/Y_{t+1})}{\sqrt{\operatorname{var}(\Delta y_{t+1})}\sqrt{\operatorname{var}(C_{t+1}/Y_{t+1})}}. \tag{C24}$$

The above expression shows that trade balance ciclicality depends on three statistical moments. One of them, $\operatorname{var}(\Delta y_{t+1})$, is already known. Hence, in the following two sub-steps we derive expressions for the other two moments:

i) *Expression for cov*$(\Delta y_{t+1}, C_{t+1}/Y_{t+1})$. Recalling $\Delta y = \Delta z + g$ and using (C15) evaluated at $t+1$ to substitute C_{t+1}/Y_{t+1} we obtain

$$\begin{aligned}
&\operatorname{cov}(\Delta y_{t+1}, C_{t+1}/Y_{t+1}) \\
&= \operatorname{cov}\Big\{\Delta z_{t+1} + g_{t+1}, \\
&\qquad \frac{1-e^{-r}}{1-q}\left(\frac{1-q}{1-\rho_z q} - 1\right) z_{t+1} + \frac{1-e^{-r}}{1-q}\frac{\rho_g q}{1-\rho_g}\left(\frac{1-\rho_g}{1-\rho_g q}\right) g_{t+1}\Big\} \\
&= \frac{1-e^{-r}}{1-q}\left\{\left(\frac{1-q}{1-\rho_z q} - 1\right)\operatorname{cov}(\Delta z_{t+1}, z_{t+1}) + \left(\frac{\rho_g q}{1-\rho_g}\cdot\frac{1-\rho_g}{1-\rho_g q}\right)\operatorname{var}(g_{t+1})\right\} \\
&= \frac{1-e^{-r}}{1-q}\left\{\left(\frac{q(\rho_z - 1)}{1-\rho_z q}\right)(1-\rho_z)\operatorname{var}(\Delta z_{t+1}) + \left(\frac{\rho_g q}{1-\rho_g}\cdot\frac{1-\rho_g}{1-\rho_g q}\right)\operatorname{var}(g_{t+1})\right\} \\
&= \frac{1-e^{-r}}{1-q}\left\{-\left(\frac{q(1-\rho_z)^2}{1-\rho_z q}\right)\operatorname{var}(\Delta z_{t+1}) + \left(\frac{\rho_g q}{1-\rho_g}\cdot\frac{1-\rho_g}{1-\rho_g q}\right)\operatorname{var}(g_{t+1})\right\},
\end{aligned} \tag{C25}$$

where the third equality follows from

$$\begin{aligned}
\operatorname{cov}(\Delta z_{t+1}, z_{t+1}) &= \operatorname{cov}(z_{t+1}, z_{t+1}) - \operatorname{cov}(z_t, z_{t+1}) \\
&= \operatorname{var}(z_{t+1}) - \operatorname{cov}(z_t, \rho_z z_t + \epsilon^z_{t+1}) \\
&= \operatorname{var}(z_{t+1}) - \rho_z \operatorname{var}(z_{t+1}) \\
&= (1-\rho_z)\operatorname{var}(z_{t+1}).
\end{aligned}$$

ii) *Expression for var*(C_{t+1}/Y_{t+1}). Again, we take advantage of (C15) evaluated at $t+1$ to obtain

$$\begin{aligned}
&\operatorname{var}(C_{t+1}/Y_{t+1}) \\
&= \operatorname{var}\left\{\frac{1-e^{-r}}{1-q}\left(\frac{q(1-\rho_z)}{1-\rho_z q}\right) z_{t+1} + \frac{1-e^{-r}}{1-q}\left(\frac{\rho_g q}{1-\rho_g q}\right) g_{t+1}\right\} \\
&= \left(\frac{1-e^{-r}}{1-q}\right)^2\left\{\left(\frac{q(1-\rho_z)}{1-\rho_z q}\right)^2 \operatorname{var}(z_{t+1}) + \left(\frac{\rho_g q}{1-\rho_g q}\right)^2 \operatorname{var}(g_{t+1})\right\}
\end{aligned}$$

$$= \left(\frac{1-e^{-r}}{1-q}\right)^2 \left\{ \left(\frac{q(1-\rho_z)}{1-\rho_z q}\right)^2 \frac{\sigma_z^2}{1-\rho_z^2} + \left(\frac{\rho_g q}{1-\rho_g q}\right)^2 \mathrm{var}(g_{t+1}) \right\}$$

$$= \left(\frac{1-e^{-r}}{1-q}\right)^2 \left\{ \left(\frac{q(1-\rho_z)}{1-\rho_z q}\right)^2 \frac{\sigma_z^2}{1-\rho_z^2} \frac{2(1+\rho_z)}{2(1+\rho_z)} + \left(\frac{\rho_g q}{1-\rho_g q}\right)^2 \mathrm{var}(g_{t+1}) \right\}$$

$$= \left(\frac{1-e^{-r}}{1-q}\right)^2 \left\{ \left(\frac{q(1-\rho_z)}{1-\rho_z q}\right)^2 \frac{\mathrm{var}(\Delta z_{t+1})}{2(1-\rho_z)} + \left(\frac{\rho_g q}{1-\rho_g q}\right)^2 \mathrm{var}(g_{t+1}) \right\}. \tag{C26}$$

Then, substituting (C25) and (C26) into (C24) results in

$$TBC_{t+1}$$

$$= -\frac{\frac{1-e^{-r}}{1-q}\left\{-\left(\frac{q(1-\rho_z)^2}{1-\rho_z q}\right)\mathrm{var}(\Delta z_{t+1}) + \left(\frac{\rho_g q}{1-\rho_g}\cdot\frac{1-\rho_g}{1-\rho_g q}\right)\mathrm{var}(g_{t+1})\right\}}{\sqrt{\mathrm{var}(\Delta y_{t+1})\cdot\left(\frac{1-e^{-r}}{1-q}\right)^2\left\{\left(\frac{q(1-\rho_z)}{1-\rho_z q}\right)^2\frac{\mathrm{var}(\Delta z_{t+1})}{2(1-\rho_z)} + \left(\frac{\rho_g q}{1-\rho_g q}\right)^2\mathrm{var}(g_{t+1})\right\}}}$$

$$= \frac{\left(\frac{q(1-\rho_z)^2}{1-\rho_z q}\right)\mathrm{var}(\Delta z_{t+1}) - \left(\frac{\rho_g q}{1-\rho_g}\cdot\frac{1-\rho_g}{1-\rho_g q}\right)\mathrm{var}(g_{t+1})}{\sqrt{\mathrm{var}(\Delta y_{t+1})\cdot\left\{\left(\frac{q(1-\rho_z)}{1-\rho_z q}\right)^2\frac{\mathrm{var}(\Delta z_{t+1})}{2(1-\rho_z)} + \left(\frac{\rho_g q}{1-\rho_g q}\right)^2\mathrm{var}(g_{t+1})\right\}\cdot\frac{\mathrm{var}(\Delta y_{t+1})}{\mathrm{var}(\Delta y_{t+1})}}}$$

$$= \frac{\left(\frac{q(1-\rho_z)^2}{1-\rho_z q}\right)\frac{\mathrm{var}(\Delta z_{t+1})}{\mathrm{var}(\Delta y_{t+1})} - \left(\frac{\rho_g q}{1-\rho_g}\cdot\frac{1-\rho_g}{1-\rho_g q}\right)\frac{\mathrm{var}(g_{t+1})}{\mathrm{var}(\Delta y_{t+1})}}{\sqrt{\left(\frac{q(1-\rho_z)}{1-\rho_z q}\right)^2\frac{1}{2(1-\rho_z)}\frac{\mathrm{var}(z_{t+1})}{\mathrm{var}(\Delta y_{t+1})} + \left[\frac{\rho_g q}{1-\rho_g}\left(\frac{1-\rho_g}{1-\rho_g q}\right)\right]^2\frac{\mathrm{var}(g_{t+1})}{\mathrm{var}(\Delta y_{t+1})}}}$$

$$= \frac{\left(\frac{q(1-\rho_z)^2}{1-\rho_z q}\right)(1-\Lambda_{t+1}) - \left(\frac{\rho_g q}{1-\rho_g}\cdot\frac{1-\rho_g}{1-\rho_g q}\right)\Lambda_{t+1}}{\sqrt{\left(\frac{q(1-\rho_z)}{1-\rho_z q}\right)^2\frac{1}{2(1-\rho_z)}(1-\Lambda_{t+1}) + \left[\frac{\rho_g q}{1-\rho_g}\left(\frac{1-\rho_g}{1-\rho_g q}\right)\right]^2\Lambda_{t+1}}}$$

so, using the assumption that q is negative but close to zero, we have $q \approx 1$ and then

$$TBC_{t+1} = \frac{(1-\rho_z) - \left[(1-\rho_z) + \frac{\rho_g}{1-\rho_g}\right]\Lambda_{t+1}}{\sqrt{\frac{1}{2(1-\rho_z)} + \left\{\left(\frac{\rho_g}{1-\rho_g}\right)^2 - \frac{1}{2(1-\rho_z)}\right\}\Lambda_{t+1}}}. \tag{C27}$$

We now prove that under such an approximation, and holding positive ρ_g and ρ_z fixed, the trade balance ciclicality is decreasing. For this, first rewrite

$$TBC_{t+1} = \frac{A - B\Lambda}{\sqrt{C + (D-C)\Lambda}}.$$

where

$$A \equiv (1-\rho_z) > 0,$$

$$
\begin{aligned}
B &\equiv (1-\rho_z) + \frac{\rho_g}{1-\rho_g} > 0, \\
C &\equiv \frac{1}{2(1-\rho_z)} > 0, \\
D &\equiv \left(\frac{\rho_g}{1-\rho_g}\right)^2 > 0 \\
\Lambda &\equiv \Lambda_{t+1} \in [0,1].
\end{aligned}
$$

Then, we take the derivative

$$
\begin{aligned}
&\frac{d\,TBC_{t+1}}{d\,\Lambda_{t+1}} \\
&= -\frac{A-B\Lambda}{2}\left(C+(D-C)\Lambda\right)^{-3/2}(D-C) - B\left(C+(D-C)\Lambda\right)^{-1/2} \\
&= -\left(C+(D-C)\Lambda\right)^{-3/2}\left[\frac{A-B\Lambda}{2}(D-C) + B\left(C+(D-C)\Lambda\right)\right] \\
&\propto -\left[\frac{D(A-B\Lambda)}{2} - \frac{C(A-B\Lambda)}{2} + BC + BD - BC\Lambda\right] \\
&= -\left[\frac{D(A-B\Lambda)}{2} - \frac{C(A-B\Lambda)}{2} + BD + BC(1-\Lambda)\right] \\
&= -\left[\frac{AD}{2} + BD\left(1+\frac{\Lambda}{2}\right) - \frac{C(A-B\Lambda)}{2} + BC(1-\Lambda)\right] \\
&= -\left[\frac{AD}{2} + BD\left(1+\frac{\Lambda}{2}\right) + \frac{C(B\Lambda-A)}{2} + BC(1-\Lambda)\right] \\
&= -\left[\frac{AD}{2} + BD\left(1+\frac{\Lambda}{2}\right) + C\left(\frac{B\Lambda-A}{2} + B(1-\Lambda)\right)\right] \\
&= -\left[\frac{AD}{2} + BD\left(1+\frac{\Lambda}{2}\right) + C\left(B - \frac{B\Lambda}{2} - \frac{A}{2}\right)\right] \\
&= -\left[\frac{AD}{2} + BD\left(1+\frac{\Lambda}{2}\right) + C\left(\frac{2B-B\Lambda-A}{2}\right)\right] \\
&= -\left[\frac{AD}{2} + BD\left(1+\frac{\Lambda}{2}\right) + C\left(\frac{B(2-\Lambda)-A}{2}\right)\right].
\end{aligned}
$$

In summary, the above sequence gives

$$
\frac{d\,TBC_{t+1}}{d\,\Lambda_{t+1}} = -\left[\frac{AD}{2} + BD\left(1+\frac{\Lambda}{2}\right) + C\left(\frac{B(2-\Lambda)-A}{2}\right)\right] < 0, \tag{C28}
$$

where the inequality follows from $A > 0$, $B > 0$, $D > 0$, $\Lambda \in [0,1]$, and noting that

$$
B(2-\Lambda) - A \geq B - A = (1-\rho_z) + \frac{\rho_g}{1-\rho_g} - (1-\rho_z) = \frac{\rho_g}{1-\rho_g} > 0.
$$

Importantly, inequality (C28) proves that for positive ρ_g and ρ_z, trade balance ciclicality is decreasing in the g-share. With this, we conclude the proof of the proposition. $\square$

C.2 Specification of prior distributions

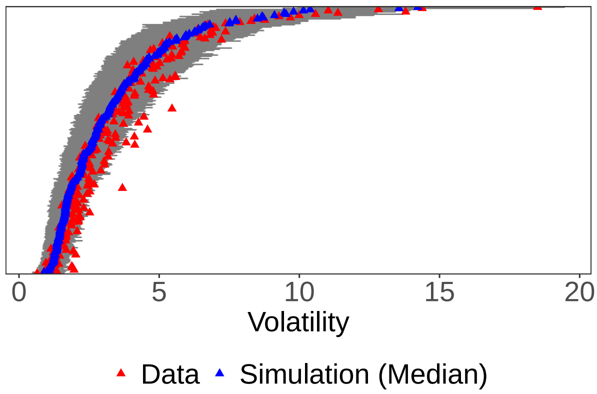
Table C1 reports the prior distributions that we used in the estimation procedure of the baseline model that we discuss in section 4.2. It also includes the prior distribution for the parameters of the international model described in section 7.1. We tried several alternative specifications to study how sensitive to priors our estimates were. The general conclusion was that the posterior distributions of the parameters of interest look very similar.

TABLE C1. PRIOR DISTRIBUTIONS

	Prior	Mean	S.D.	Q 2.5%	Q 97.5%
Panel A. Baseline model					
Autocorrelations:					
$\rho_{R,z}$, $\rho_{R,z}$	$\mathcal{U}(-0.995, 0.995)$	0.0	0.33	-0.95	0.95
Standard deviations (%):					
$\sigma^z_{i,p}$	$\mathcal{N}^{[0,\infty)}(0,4)$	1.6	1.2	0.06	4.50
$\sigma^\nu_{R,p}$,	$\mathcal{N}^{[0.2,\infty)}(0.5, 0.25)$	0.55	0.26	0.21	1.20
Coefficients linking $\sigma^g_{i,p}$ to $\sigma^z_{i,p}$:					
$\theta^{(1)}_{R,p}$, $\theta^{(2)}_{R,p}$	$\mathcal{N}^{[0,\infty)}(0, 0.25)$	0.4	0.3	0.02	1.12
Growth (%) and sensitivity parameters:					
$\mu_{i,p}$	$\mathcal{N}(3,4)$	3.0	2.0	-0.95	6.90
Panel B. International model					
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 (%):					
$\sigma^z_{i,p}$, $\sigma^z_{R,p}$, $\sigma^z_{W,p}$, $\sigma^\nu_{R,p}$,	$\mathcal{N}^{[0,\infty)}(0,4)$	1.6	1.2	0.06	4.50
Coefficients linking $\sigma^g_{i,p}$ to $\sigma^z_{i,p}$:					
$\theta^{(1)}_{R,p}$, $\theta^{(2)}_{R,p}$	$\mathcal{N}^{[0,\infty)}(0, 0.25)$	0.4	0.3	0.02	1.12
Growth (%) and sensitivity parameters:					
$\mu_{i,p}$	$\mathcal{N}(2,3)$	2.0	3.0	-3.85	7.85
ψ_i, ζ_i, ϕ_i	$\mathcal{N}^{[0,\infty)}(0,4)$	1.6	1.2	0.06	4.50

Notes: $\mathcal{U}([a,b])$ denotes a uniform distribution on the interval $[a,b]$; $\mathcal{N}(m,s^2)$ denotes a normal distribution with mean m and variance s^2; and $\mathcal{N}^I(m,s^2)$ corresponds to a $\mathcal{N}(m,s^2)$ distribution truncated by the bounds of interval I. b) The indices i, R, and p correspond to country, region and period indices.

FIGURE D9. Volatility in the Model and the Data



Notes: This figure shows, for each country and period in our sample the realized volatility in red. In blue, we show the median volatility for the same country and period in $B = 5000$ samples from the posterior distribution of the model, shaded lines indicate 95% quantiles from the simulations.

D Appendix to section 5

D.1 Model Fit to the Data

We give further information on how the model parameters fit the data in figure D9. For each of the two time periods (1980-99 and 2000-19) we simulate a series of 20 years of output growth using the model posterior and calculate the standard deviation of growth. We then repeat this procedure $B = 5000$ times and compare the estimated volatility from the simulation to the volatility in the data for each country period. Figure D9 shows the comparison for each of the country periods. As the figure shows, we are able to match the realized output volatility closely with the model. In general, the estimated volatility is slightly lower than the realized volatility, because the model attributes part of the volatility to measurement error.

D.2 Business Cycle Regressions: Robustness

Outlier Winsorization. In Section 5.2, 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, g-share. Similarly, we underscore that there is a negative relationship between the g-share and the cyclicality of the trade balance. Both results were obtained with data on the outcome variables and the g-share without removing any potential outliers. In what follows, we show that our results hold in magnitude and significance after removing the influence of outliers; which ensures that our results are not driven by a few countries.

Specifically, in Table D1 we present the results for our business cycle regressions (explained in Section 5.2) by winsorizing the upper and lower tails of the distribution of

Table D1. Testing the Cycle is the Trend Hypothesis, Robustness

	Consumption smoothing $y_{i,p} \equiv \log(\sigma_c/\sigma_y)_{i,p}$			Net exports cyclicality $y_{i,p} \equiv \text{corr}_{i,p}(NX/Y, \Delta y)$		
	(1)	(2)	(3)	(1)	(2)	(3)
Panel A. Results with winsorized data by period at the 2% tails						
g-share$_{i,p}$	1.161***	1.038***	1.129***	-0.275*	-0.249	-0.199
	(0.213)	(0.256)	(0.281)	(0.146)	(0.191)	(0.195)
Region × Period	✗	✓	✓	✗	✓	✓
Controls	✗	✗	✓	✗	✗	✓
R-squared	0.105	0.260	0.267	0.012	0.128	0.138
Observations	232	232	232	232	232	232
Panel B. Results with winsorized data by period at the 5% tails						
g-share$_{i,p}$	1.147***	1.042***	1.121***	-0.251	-0.206	-0.163
	(0.220)	(0.257)	(0.276)	(0.153)	(0.195)	(0.195)
Region × Period	✗	✓	✓	✗	✓	✓
Controls	✗	✗	✓	✗	✗	✓
R-squared	0.102	0.265	0.271	0.010	0.128	0.139
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.

g-shares and dependent variables at 2% and 98% quantiles (Panel A) and at the 5% and 95% quantiles (Panel B). The winsorization procedure is done by period; otherwise we would be systematically dropping observations only from the 1980-99 period. The figures in the table confirm that the results presented in the main body of the article hold after having dealt with the outliers using standard procedures.

Estimation in differences. We estimate regression equations of the form

$$\Delta y_i = \alpha + \beta_g \cdot \Delta(g\text{-share})_i + \gamma' \Delta X_i + u_i, \tag{D29}$$

which is the *"differences"* version of equation (16). Similar to the baseline specification, Δy_i corresponds to the change from 1980-99 to 2000-19 of one of 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.

Table D2. Regression Results, in Differences

	Consumption smoothing $\Delta y_i \equiv \Delta \log(\sigma_c/\sigma_y)_i$			Net exports cyclicality $\Delta y_i \equiv \Delta \text{corr}_i(NX/Y, \Delta y)$		
	(1)	(2)	(3)	(1)	(2)	(3)
Δg-share$_{i,p}$	1.422***	1.865***	1.749***	-0.043	0.122	0.127
	(0.221)	(0.301)	(0.291)	(0.213)	(0.316)	(0.325)
Region FE	✗	✓	✓	✗	✓	✓
Controls	✗	✗	✓	✗	✗	✓
R-squared	0.178	0.220	0.285	0.000	0.088	0.127
Observations	116	116	116	116	116	116

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 (g-share). 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.

In Table D2 we show the results of our regressions for three different specifications of the vector of controls $X_{i,p}$, each nesting the previous. First, we consider simple regressions of Δy_i on the g-share. In the second specification, we add region fixed effects to soak up variation from invariant factors that affect all countries in a region. Finally, in the third specification, we add the country-period mean and standard deviation of GDP growth, inflation, and trade openness index, to show that our estimates of the permanent component affect business cycle properties over and above the macroeconomic conditions of the countries.

Our estimates of coefficient β_g indicate that economies that experienced an increase in their g-share also experienced an increase in their consumption-output volatility ratios. Specifically, the regression results reveal that at the country level, a 1 percentage point increase g-share of an economy is related to a 1.75% increase in the consumption-output volatility ratio σ_c/σ_y —a finding which holds very robustly at the 1% confidence level across specifications.

D.3 Robustness under Alternative Model Specifications

D.3.1 Stochastic Volatility Model

Model. The theoretical setting is the same as in section 4.1, but we now allow σ_t^z and σ_t^g to be stochastic. Despite such feature, we assume that households take the current value of such parameters as constant so that Proposition 1 holds for this model. We have to make such an assumption on the grounds that an analytical result cannot be obtained due to the increased complexity of the household decision problem once stochastic volatility is introduced. This assumption not only simplifies the math, but it seems plausible that from the household's perspective, volatility is a constant.

Empirical counterpart. 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:

$$Y_{i,t} = \underbrace{\Gamma_{i,t-1} \exp\left(\mu_{i,p} + g_{i,t}\right)}_{\equiv \text{Trend } \Gamma_{i,t}} \cdot \underbrace{\exp\left(z_{i,t}\right)}_{\equiv \text{Cycle } Z_{i,t}}, \tag{D30}$$

where we model processes g and z simply as

$$g_{i,t} = \rho_{R,g} \cdot g_{i,t-1} + \sigma^g_{i,t}\eta^g_{i,t}, \tag{D31}$$

$$z_{i,t} = \rho_{R,z} \cdot z_{i,t-1} + \sigma^z_{i,t}\eta^z_{i,t}, \tag{D32}$$

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

$$\log \sigma^z_{i,t} = \log \sigma^z_i + \gamma_R \cdot \left(\log \sigma^z_{i,t-1} - \log \sigma^z_i\right) + \omega_z \eta^\sigma_{i,t}, \tag{D33}$$

$$\sigma^g_{i,t} = \Lambda_{R,p}\sigma^z_{i,t}, \tag{D34}$$

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 pooled regionally.

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

$$\Delta y^{obs}_{i,t} = \Delta y_{i,t} + \nu_{i,t} \tag{D35}$$

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 Hoffman and Gelman (2014)'s Hamiltonian Monte Carlo (HMC) with No U-Turn Sampler (NUTS), just as we did with the baseline model. We also 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 $\mathcal{N}(3, 2)$ 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^z_i, representing the long-run volatility if volatility shocks ($\eta^\sigma_{i,t}$) 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

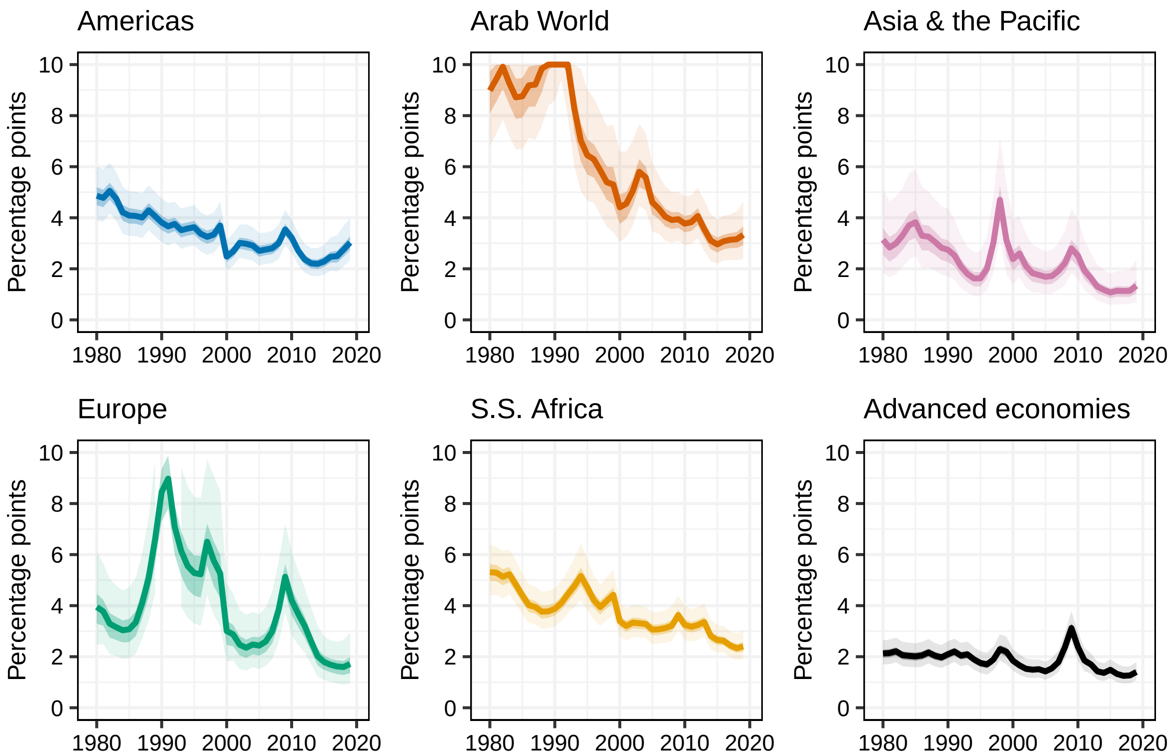


Figure D10. GDP Volatility, 1980-2019

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. The values for the Arab World are truncated at 10%.

implies that there is more than 5% probability of the cycle explaining all variation in economies with GDP volatility of 5%.

Volatility at yearly frequency. In line with our findings on GDP period volatility, we identify a fall in volatility at the regional level. Figure D10 shows average GDP volatility across each of the regions defined for this study. The dark (light) shaded areas show the 70% (95%) confidence interval.[32] 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 5%), 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 in which average volatility in the Americas increased from 3% in 2008 to 4% in 2009, but when it rapidly returned to average levels of less than 3%. Therefore, this gradual decrease in volatility coincides with the gradual improvement in the institutions of American economies, as well as their shift towards inflation targeting

[32]For expositional purposes we truncated the extreme values observed in the Arab World at 10%. This does not have an impact on our discussion.

regimes, and increased global participation in trade.

The decrease in volatility in the Arab World is remarkable. Eyeballing their volatility time series in Figure D10, we can see that volatility was around 10% or above during the 1980s, coinciding with many political and warfare episodes that likely spanned economic instability. After the first half of the 1990s, average GDP volatility started to decrease from 6% until it reached the current level of 3%. Moreover, despite the political turmoil across the region sparked by the Arab Spring at the start of the 2010s, regional volatility 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 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 emerging market regions.

In the case of Sub-Saharan Africa, there is a trend towards a decrease in volatility since the 1980s (going from around 5% 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 3.5%. Bearing this in mind, our high-frequency estimates of volatility suggest

Table D3. Implied g-Shares from the Stochastic Volatility Model

	1980-99	2000-19	Change
Emerging economies	86.83	77.74	-9.09
	(6.15)	(7.16)	(6.89)
Americas	90.99	78.69	-12.30
	(3.28)	(7.06)	(4.90)
Arab World	87.43	85.22	-2.21
	(12.18)	(5.66)	(9.97)
Asia and the Pacific	65.70	53.34	-12.36
	(11.95)	(14.90)	(16.98)
Europe	94.49	86.21	-8.28
	(3.40)	(6.50)	(5.86)
S.S. Africa	88.95	79.28	-9.67
	(3.74)	(5.65)	(3.65)
Advanced economies	81.23	68.84	-12.39
	(5.07)	(8.74)	(6.10)

Notes: This table reports the posterior mean of the average g-share (share of output variance explained by the trend component) in each region during 1980-99 and 2000-19 in columns 2 and 3. Column 4 corresponds to their difference. Standard deviations are in parenthesis and are based on the posterior distributions.

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.

Share of output variance explained by the trend component (g-share). Taking first log-differences in (D30) we obtain

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

Using the assumption that households take $\sigma^g_{i,t}$ and $\sigma^z_{i,t}$ as constant, we can iterate the previous identity forward ad infinitum and take the variance to approximate the share of variance explained by the trend component (g-share) as

$$g\text{-share}_{i,t} = \frac{\dfrac{\left(\sigma^g_{i,t}\right)^2}{1-\rho_g^2}}{\dfrac{\left(\sigma^g_{i,t}\right)^2}{1-\rho_g^2} + 2\dfrac{\left(\sigma^z_{i,t}\right)^2}{1+\rho_z}} = \frac{\dfrac{\Lambda^2_{R,p}}{1-\rho_g^2}}{\dfrac{\Lambda^2_{R,p}}{1-\rho_g^2} + \dfrac{2}{1+\rho_z}},$$

where the second equality follows from assumption (D34). Hence, this model shares with the baseline model the property of a constant g-share across the periods studied.

Table D3 shows our estimates of the g-share for periods 1980-99 and 2000-19. As with our baseline model, we observe that the it is highly likely that the g-share remained

Table D4. g-Shares Estimated with Fixed Autocorrelations

	1980-99	2000-19	Change
Emerging economies	79.72	76.81	-2.91
	(3.30)	(2.90)	(4.44)
Americas	81.69	81.24	-0.45
	(5.18)	(5.26)	(7.30)
Arab World	92.13	86.47	-5.66
	(2.05)	(3.67)	(4.28)
Asia and the Pacific	66.96	61.43	-5.53
	(12.01)	(9.74)	(15.07)
Europe	78.37	79.11	0.73
	(7.28)	(6.95)	(10.27)
S.S. Africa	79.46	75.80	-3.66
	(4.97)	(4.79)	(6.79)
Advanced economies	80.97	55.77	-25.20
	(4.94)	(9.00)	(9.88)

Notes: This table reports the posterior mean of the average g-share (share of output variance explained by the trend component) in each region during 1980-99 and 2000-19 in columns 2 and 3. Column 4 corresponds to their difference. Standard deviations are in parenthesis and are based on the posterior distributions. These estimates correspond to the same models as the baseline model, with the difference that ρ_g and ρ_z are set to 0.6 and 0.9, respectively.

quite unchanged —or decreased only a bit— in emerging markets at levels around 80%, while in advanced economies the g-share went from 81.2% in 1980-99 to 68.8% in 2000-19, with such decrease having a likelihood of more than 95% of being negative according to posterior estimates. These estimates, like the ones from the baseline model, support the view that emerging markets are more exposed to trend shocks, consistent with the predictions from the class of models that we synthesize in our model.

D.3.2 Baseline Model with Fixed Autocorrelations

Table D4 show the g-shares for our baseline model estimated under the assumption that $\rho_g = 0.6$ and $\rho_z = 0.9$. These estimates show that once we drop all the uncertainty surrounding the autocorrelation parameters, including that of the autocorrelation ρ_z of cycle shocks, the patterns in the g-shares across regions are not very different from those that we find in the model with full uncertainty.

D.3.3 Model with No Dependence Between Trend and Cycle Volatility

We estimate a version of the baseline model without assumption (15),

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

We use the posterior mean of the country-specific g-shares to estimate the coefficient β in equation (16). We trim the distribution of the dependent variables at the 1 and 99% percentiles. Table D5 shows the results of the corresponding regressions. The sign and statistical significance of these results coincide with the baseline results shown in Table 6.

TABLE D5. REGRESSION RESULTS, NO DEPENDENCE BETWEEN σ^g AND σ^z

	Consumption smoothing $y_{i,p} \equiv \log(\sigma_c/\sigma_y)_{i,p}$			Net exports cyclicality $y_{i,p} \equiv \text{corr}_{i,p}(NX/Y, \Delta y)$		
	(1)	(2)	(3)	(1)	(2)	(3)
g-share$_{i,p}$	0.224*	0.278**	0.238*	-0.142	-0.142	-0.117
	(0.133)	(0.129)	(0.129)	(0.090)	(0.094)	(0.097)
Region × Period	✗	✓	✓	✗	✓	✓
Controls	✗	✗	✓	✗	✗	✓
R-squared	0.012	0.218	0.252	0.010	0.128	0.143
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 (corr$(NX/Y, \Delta y)$) on the share of variance explained by the trend component (g-share). 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.

E Appendix to section 6

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.

E.1 Emerging market business cycle model

We employ the standard emerging market business cycle model, as put in Aguiar and Gopinath (2006, 2007). We model an endowment economy, which borrows from abroad and faces permanent and transitory income shock. To simplify the model as much as possible, there is no possibility of default.

Model Environment. Output Y_t consists 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. Figure E11 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 and 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

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

Calibration. We calibrate the model to annual frequency. The calibration follows standard values in the literature and is summarized in table E1. We take a number of

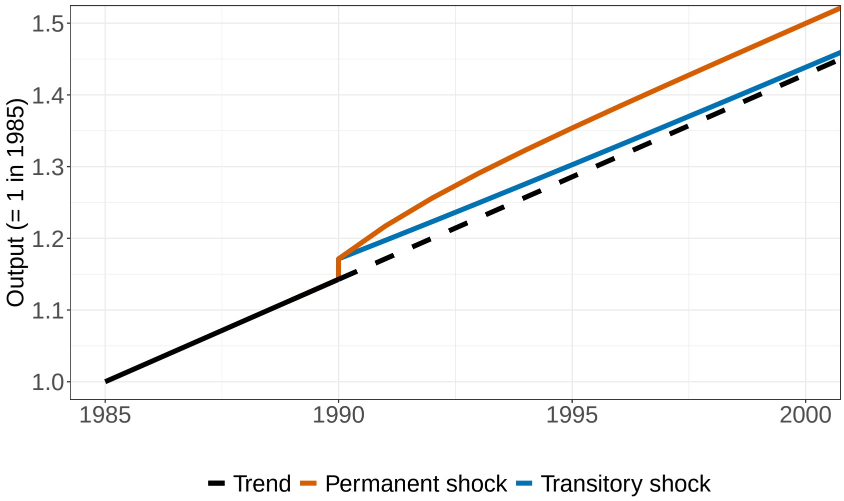


FIGURE E11. The impact of permanent and transitory shocks on the growth path

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 $\rho_z = 0.9$, following our empirical model.

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). We fix the deterministic growth rate at 3% across countries to facilitate comparisons for our baseline figures (this corresponds to the median across periods in our estimation), but let it vary across countries below.

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 in each country directly from our empirical model in section 4, which only targets the volatility and structure of output fluctuations.

A Note on Welfare Costs. In the text, we state that the welfare gain from moving from the 1980s income process to the 2000s income process is equivalent to the difference in the welfare costs of business cycles of both processes. To this more formally, denote $\bar{U}$ is the certainty equivalent consumption, $E[U_t]$ as the expected utility given the income process in t and λ_t as the welfare cost of business cycles in time t. Defining γ as the welfare gain of moving from the historical to the modern income process we have that

$$(1+\gamma)^{1-\sigma} \equiv \frac{E[U_{2000}]}{E[U_{1980}]} = \frac{\bar{U}(1+\lambda_{1980})^{\sigma-1}}{\bar{U}(1+\lambda_{2000})^{\sigma-1}} \approx (1+\lambda_{2000}-\lambda_{1980})^{1-\sigma}, \tag{E36}$$

so that γ is equivalent to the change in the welfare cost of business cycles.

Table E1. Calibrated Parameters of the Economic Model

Param.	Value	Description	Source
β	0.922	Discount factor	Aguiar and Gopinath (2007)
b	0.100	Steady state normalized debt	Aguiar and Gopinath (2007)
ψ	0.001	Elasticity of interest rates	Aguiar and Gopinath (2007)
σ	2.000	Risk aversion	Aguiar and Gopinath (2007)
μ_g	0.03	Steady State Growth	Own Estimation
ρ_z	varies	Persistence transitory shocks	Own Estimation
ρ_g	varies	Persistence permanent shocks	Own Estimation
σ_z	varies	StD transitory Shocks	Own Estimation
σ_g	varies	StD permanent Shocks	Own Estimation

Notes: This table summarizes the parameter calibration for the endowment economy. For the computation of welfare gains in the main text, we fix steady state growth, but vary it by country in section E.2.

E.2 Welfare Gains under Alternative Parametrizations

In section 6, we compute the welfare gains from the great moderation in emerging markets. To make figures comparable, we use the same deterministic growth rate across countries in the main text. Below, we compute welfare gains using the deterministic growth rates that we estimate for every country during the 1980-2000s period, i.e. the deterministic growth rate varies by country.

The estimated welfare gains are shown in the first part of table E3, they are close to the the welfare gains in table 7. The second part of the table adds to this the change in welfare from the changes in *growth rates* observed in emerging markets.[33] Growth rates have increased for many emerging economies over the period we study, further adding to the welfare gains from reduced volatility. Nevertheless, the gains from reduced volatility remain non-trivial even when compared to the gains from higher growth. For the median emerging economy, gains from reduced volatility are roughly one third of the gains from higher growth, for the average economy this figure is around 15%. This shows that even compared to changes in growth rates, reductions in volatility have made a meaningful difference for welfare in emerging countries.[34]

Table E2. Welfare Gains from Moderation of Business Cycles

Country	Welfare Gains	Welfare Gains (μ_g varies)	Country	Welfare Gains	Welfare Gains (μ_g varies)

[33]We compute this as the percentage change in expected utility from the consumption path under the 1980s income process and the 2000s income process.

[34]Welfare gains from changing growth rates are higher at the mean than at the median, because the increase in growth in emerging markets has not been as widespread as the reduction in volatility.

Albania	11.67	11.66	Kenya	0.00	0.04
Algeria	0.27	0.23	Kuwait	56.15	59.23
Argentina	-0.24	-0.37	Lebanon	55.04	54.02
Australia	0.49	0.44	Lesotho	1.24	1.17
Austria	0.16	0.14	Madagascar	-0.91	-1.06
Bahrain	3.96	4.18	Malawi	2.65	2.58
Bangladesh	-0.18	-0.18	Malaysia	3.52	3.34
Belgium	0.31	0.33	Mali	2.95	2.65
Benin	0.85	0.76	Mauritania	0.30	0.29
Bolivia	0.65	0.73	Mauritius	0.72	0.62
Botswana	1.06	0.84	Mexico	1.22	1.14
Brazil	1.01	1.00	Morocco	3.17	3.12
Bulgaria	5.55	6.48	Mozambique	3.28	3.23
Burkina Faso	1.25	1.10	Namibia	0.00	-0.06
Burundi	1.69	1.84	Nepal	2.10	2.01
C.A.R	-5.74	-6.56	Netherlands	0.19	0.21
Cameroon	0.99	1.11	New Zealand	0.60	0.70
Canada	0.54	0.48	Nicaragua	1.09	1.26
Chad	-2.60	-2.67	Niger	1.99	2.29
Chile	2.33	2.19	Nigeria	0.99	1.15
China	1.66	1.39	Norway	0.26	0.30
Hong Kong	0.98	0.85	Oman	1.23	1.00
Colombia	0.42	0.46	Pakistan	-0.17	-0.12
Congo	0.16	-0.08	Palestine	3.07	2.67
Costa Rica	0.95	0.99	Panama	1.39	1.28
Cyprus	0.61	0.66	Paraguay	-0.74	-0.58
D.R. Congo	1.90	2.49	Peru	2.92	2.94
Denmark	0.24	0.28	Philippines	2.98	3.09
Djibouti	0.16	0.12	Poland	2.81	3.21
Dom. Rep.	0.78	0.72	Portugal	0.37	0.37
Ecuador	0.40	0.38	Qatar	1.30	1.13
Egypt	0.44	0.37	Romania	1.38	1.41
El Salvador	0.83	0.98	Rwanda	15.26	15.27
Ethiopia	2.14	2.18	Saudi Arabia	7.17	8.02
Finland	0.28	0.21	Senegal	2.03	1.93
France	0.19	0.22	Singapore	0.68	0.52
Gabon	3.03	3.17	South Africa	0.45	0.47
Gambia	0.01	0.06	South Korea	1.42	1.21
Germany	0.08	0.13	Spain	0.11	0.16
Ghana	0.39	0.39	Sri Lanka	-0.69	-0.50

Greece	-0.42	-0.59	Sweden	0.13	0.19
Guatemala	0.53	0.53	Switzerland	0.22	0.33
Guinea	-0.29	-0.25	Syria	-1.88	-2.22
Guinea-Bissau	3.00	3.18	Taiwan	-0.29	-0.23
Haiti	1.63	2.00	Tanzania	0.25	0.30
Honduras	0.67	0.68	Thailand	2.90	2.94
Hungary	0.81	0.89	Togo	2.36	2.74
India	0.15	0.18	Trin. & Tobago	0.11	0.20
Indonesia	5.38	5.99	Tunisia	0.25	0.23
Iran	4.75	4.88	Turkey	0.58	0.76
Iraq	94.49	103.11	Uganda	0.66	0.54
Ireland	-0.24	-0.15	UAE	6.19	6.46
Israel	0.37	0.40	United Kingdom	0.31	0.34
Italy	0.09	0.11	United States	0.38	0.44
Ivory Coast	0.03	0.22	Uruguay	1.14	1.22
Jamaica	1.33	1.45	Venezuela	-6.89	-7.86
Japan	0.13	0.11	Zambia	1.19	1.26
Jordan	2.16	2.18	Zimbabwe	-6.45	-5.99

Notes: This table shows the welfare gainsfrom a reduction in volatility of business cycles for each country. Welfare Gains are calculated under two scenarios: First, we employ the standard calibration of EM business cycle models from Table E1. Second, we use the deterministic growth rate estimated in each country in the period 1980-2000.

Table E3. Welfare Gains from Change in Volatility and Growth

	Changing Volatility				Changing Volatility + Growth			
	Mean	Median	p25	p75	Mean	Median	p25	p75
Emerging Economies	3.69	1.05	0.23	2.60	11.00	8.28	1.29	17.25
Americas	0.54	0.98	0.46	1.26	4.23	3.70	1.17	6.07
Arab World	14.63	2.67	0.37	6.46	18.96	13.23	-7.50	21.48
Asia and the Pacific	1.63	1.39	-0.15	3.02	5.93	8.23	-3.42	12.07
Europe	3.06	1.15	0.74	4.03	12.25	15.01	6.27	19.58
Sub-Saharan Africa	1.06	0.84	0.14	2.23	12.51	10.10	3.87	19.69
Advanced Economies	0.35	0.32	0.18	0.44	-5.92	-6.05	-8.17	-3.50

Notes: This table shows the implied welfare gains from moving from the 1980-99 volatility regime to the 2000-19 regime across different groups of countries. The figures for emerging markets refer to all emerging economies in our sample.

F Appendix to section 7

F.1 Coefficients on all Fundamentals

Table F1. Predictors of the Moderation

	Dependent variable: $\sigma^y_{c,t+h} - \sigma^y_{c,t-1}\%$				
	$h = 1$	$h = 5$	$h = 10$	$h = 15$	$h = 20$
Economic indicators					
Central bank independence	-0.715	-0.970	-2.634**	-1.725*	-3.049***
	(1.542)	(1.068)	(1.081)	(0.993)	(1.100)
Adopts inflation targeting	-0.132	0.196	-0.659*	-0.950***	-0.855
	(0.230)	(0.251)	(0.351)	(0.249)	(0.626)
Private credit (% of GDP)	0.022*	0.009	-0.008	0.005	-0.009
	(0.012)	(0.014)	(0.015)	(0.025)	(0.011)
Agriculture (% of GDP)	0.008	0.015	0.020	-0.010	-0.016
	(0.015)	(0.020)	(0.019)	(0.022)	(0.026)
Trade (% of GDP)	-0.012**	-0.017**	-0.001	0.003	-0.005
	(0.005)	(0.007)	(0.006)	(0.008)	(0.007)
Financial openness	0.266	0.411	0.682**	-0.337	-0.940**
	(0.206)	(0.555)	(0.318)	(0.479)	(0.396)
Public debt (% of GDP)	0.003	-0.007**	0.003	0.004	-0.001
	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)
Political indicators					
Rule of law	-2.570***	-2.115***	-0.853	-1.072	-2.064
	(0.927)	(0.742)	(1.007)	(1.289)	(1.796)
Democracy	0.012	0.026	-0.040*	-0.014	0.014
	(0.025)	(0.034)	(0.024)	(0.027)	(0.020)
Fixed effects					
Country	✓	✓	✓	✓	✓
Region × Year	✓	✓	✓	✓	✓
R-squared	0.306	0.406	0.489	0.557	0.604
Observations	2,698	2,698	2,530	2,271	1,456

Notes: The table reports the entries of vector $\boldsymbol{\beta}_h$ defined in equation (30). Each entry of $\boldsymbol{\beta}_h$ measures the effect of a change in a fundamental on output volatility h-years from now. Driscoll and Kraay (1998) standard errors are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.