

# Africa's Great Moderation

Sebastian Krantz\*

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## Abstract

Over the past 30 years, African economies have experienced remarkable improvements in macroeconomic conditions, characterized by higher and more stable real per-capita growth rates, and lower and more stable inflation. This paper documents the persistent decline in macroeconomic volatility at the aggregate and sectoral levels and seeks to provide explanations. Sectoral analysis shows a particularly strong reduction of growth volatility in agriculture and, to a lesser extent, in services. Classical structural change only explains a small fraction of the moderation. Analysis of further factors yields that changes in structural characteristics such as institutions, trade intensity and diversification, natural resource dependence, or conflict incidence do not explain the moderation. On the positive side, the paper provides evidence to suggest that changes in the external environment, improved macroeconomic policy frameworks, and 'softer' structural improvements, such as the deepening of the domestic financial sector, were important in reducing macroeconomic volatility on the continent.

**Keywords:** macroeconomic stability and resilience, growth, inflation, volatility, structural change, macroeconomic policy

**JEL Classification:** O11; E30; E60

## 1 Introduction

In both academic literature and policy discourse, Africa has long been conceived as a continent of unstable macroeconomic conditions, where a majority of countries suffer from volatile growth rates, high and volatile inflation, and a multitude of other macroeconomic problems, including fiscal spending, debt levels, and exchange rate management. But, as documented by [Calderon & Boreux \(2016\)](#), [Rodrik \(2018\)](#), and others, starting around 1995, many African economies have experienced real growth rates above 5%, well above the levels of the 1970s and '80s. Whereas real growth has slowed a bit again to around 3-4% from 2012 onwards, the past 30 years from around 1990 show a much more persistent and pronounced process of macroeconomic moderation in Africa, where real growth volatility was cut in half, and inflation volatility is less than a third of its initial level.

This paper investigates macroeconomic volatility in Africa over the last 30 pre-COVID years (1990-2019). It documents the decline of macroeconomic volatility at the aggregate and sector levels and then seeks to draw links to changes in production, external conditions, macroeconomic policy, and structural characteristics of African economies. It draws from a variety of empirical methods spanning time series analysis, sectoral decompositions of volatility, panel regressions to assess policy changes, and machine learning models to assess a wide variety of structural characteristics. The paper contributes to a broad literature on the causes and consequences of macroeconomic volatility in developing countries such as [Ramey & Ramey \(1995\)](#), [Rodrik \(1999\)](#), [Easterly et al. \(2001\)](#), [Acemoglu et al. \(2003\)](#), [Auffret \(2003\)](#), [Koren & Tenreyro \(2007\)](#), [Loayza et al. \(2007\)](#), [Malik & Temple \(2009\)](#), [Papageorgiou & Spatafora \(2012\)](#). It differs from most of this literature by endeavoring a comprehensive examination of developments on the African continent.

Declining volatility in macroeconomic aggregates, popularized as 'The Great Moderation' by [Bernanke \(2004, 2012\)](#), has also been widely studied in economic literature. Most studies focus

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\*Kiel Institute for the World Economy, Research Center International Development  
Address: Haus Welt-Club, Duesternbrooker Weg 148, D-24105 Kiel  
E-mail: sebastian.krantz@ifw-kiel.de

on the US, such as [McConnell & Perez-Quiros \(2000\)](#), [Blanchard & Simon \(2001\)](#), [Ahmed et al. \(2004\)](#) and [Galí & Gambetti \(2009\)](#), but some authors such as [Horan \(2006\)](#) and [Schmidt-Hebbel \(2009\)](#) also examine the wider global context. [Burger \(2008\)](#) and [Du Plessis & Kotzé \(2010\)](#) discuss the Great Moderation in South Africa, the only country on the continent that has received much attention in this literature. [Schmidt-Hebbel \(2009\)](#) notes that moderation generally occurred with a significant lag in developing countries. The literature has not reached a consensus on the causes of moderation, and the paper provides evidence that the causes of moderation in Africa may be different from the causes studied in advanced and emerging economies.

The paper establishes two main findings. First, only a small fraction of the stark decline in macroeconomic volatility in Africa can be explained by structural change, i.e., the service sector's rise. Other changes in the structure of production and trade, conflict incidence, and political institutions also only assume secondary roles. Secondly, evidence suggests that changes in the external environment, improved internal policy frameworks, and 'softer' structural improvements, such as the deepening of the financial sector, were important in reducing volatility on the continent. Overall, the results are stronger on the negative side, providing compelling evidence that macroeconomic moderation in Africa was largely a within-sector phenomenon, with minor roles for structural change and economic diversification. Structural characteristics such as institutions and resource/commodity dependence remain important for explaining volatility differences in a cross-section of African economies, but they cannot explain the persistent and profound process of macroeconomic stabilization in Africa over the last 30 years.

The paper proceeds as follows: Section 2 characterizes broad trends in the volatility of real per-capita growth rates and CPI inflation in Africa and the world and develops the stylized facts that motivate the analysis. Section 3 goes down to the sector level and analyzes growth volatility in Africa from the production side, seeking to quantify the contribution of different sectors to the moderation and the role of structural change. Section 4 examines changes in the external environment faced by African economies, the domestic financial sector, and macroeconomic policies. Section 5 complements this analysis by assessing a broad range of structural characteristics of African economies. Key contributions from the literature referenced above are reviewed within these sections to contextualize the analysis. Section 6 summarizes the findings and concludes.

## 2 Aggregate Relationships and Trends

The decline in macroeconomic volatility in the median African country since 1990 has been profound. Figure 1 shows 10-year rolling medians and median absolute deviations (MADs) of real per capita growth and inflation in Africa and the rest of the world (ROW), using data from 1980 where available, calculated at the country-level and aggregated across countries for each year using quartiles. While the whole world has experienced a sizeable macroeconomic moderation in terms of lower inflation and lower volatility of real growth and inflation, this moderation has been particularly strong in Africa, which experienced larger declines in growth and inflation volatility alongside higher growth rates. The bulk of the African transformation occurred between 1995 and 2012, with median per capita growth almost zero in 1986-95, rising to 2.8% in 2003-12. At the same time, the MAD of growth fell from 2.2% to 1.3%, median inflation fell from ~8% to ~5%, and the MAD of inflation fell from 3.8% to 1.8%. After 2003-12, per capita growth in Africa slowed down to 2% in the most recent decade (in line with ROW) alongside further improvements in inflation and volatility, with median inflation coming as low as 4.2% and the MAD dropping to 1.25% in the 2010-2019 period. These trends are robust to weighting countries by GDP or population, as shown in Appendix Figure C3.

Documenting the decline in US output volatility, [Blanchard & Simon \(2001\)](#) run a rolling autoregression of the GDP growth rate over a 20-quarter window to gauge whether the decrease in volatility is due to a decrease in the persistence of shocks, as measured by the AR1 coefficient. They also add a crisis dummy (NBER recessions) to control for large shocks. [Blanchard & Simon \(2001\)](#) find that the US decline in output volatility is due to declines in the magnitude of shocks, reflected in the volatility of the residual, and this holds also when controlling for NBER recessions.

Figure 2 shows the results of a similar analysis conducted for Africa, where I have estimated

autoregressions at the country level using a 15-year rolling window and again aggregated the results quartiles. The crisis definition is adapted from the IMF country risk assessment for LICs (Syed et al., 2017; IMF, 2021), a crisis having occurred if the 2-year average level of real output per capita post-shock ( $t$  and  $t+1$ ) falls below the pre-shock 3-year average level, and output per capita growth is negative in the year of the shock ( $t$ ) (see Figure C6).

Figure 1: Volatility Over Time

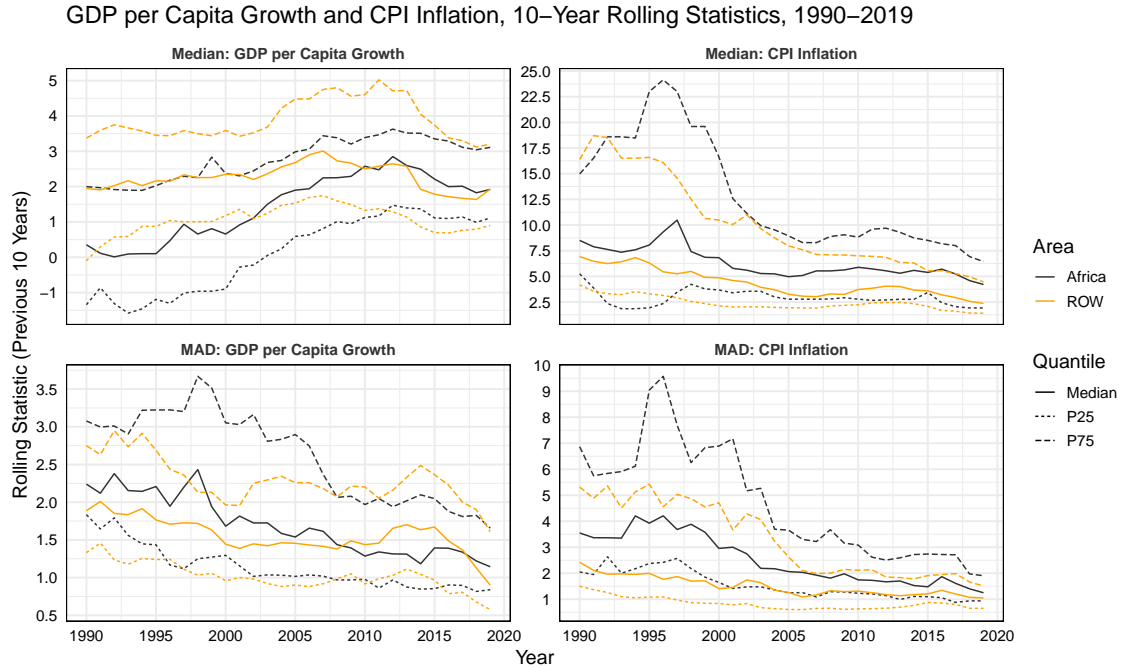


Figure 2 indicates that more or less the same conclusions hold for Africa. The persistence of real output growth even appears to have increased slightly,<sup>1</sup> thus the decline in volatility is primarily associated with factors captured in the residual of the model.

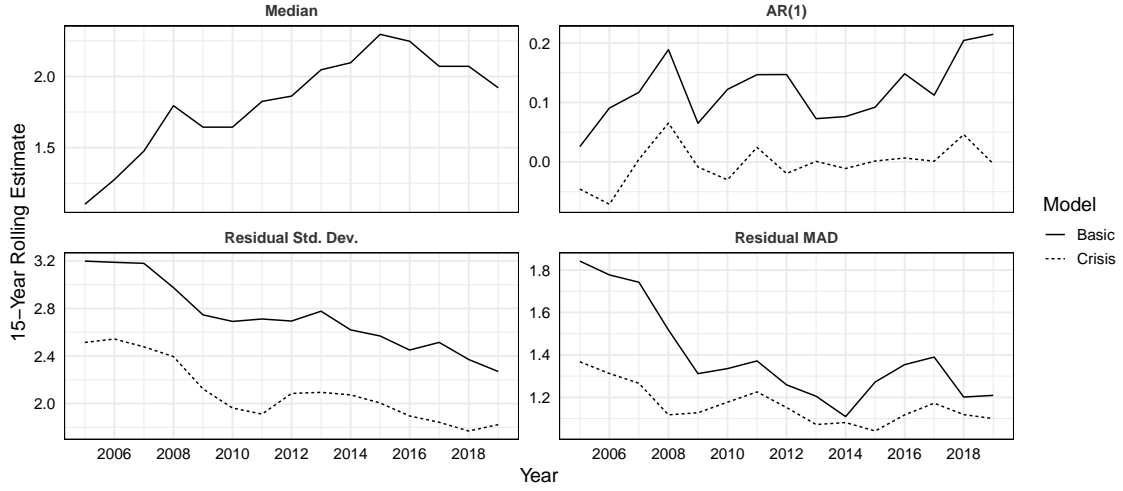
To uncover some heterogeneity, Table 1 compares changes for countries at different income levels, computing statistics over the 1990–2004 and 2005–2019 periods. In Africa, LICs experienced the largest growth acceleration from 1.1% in 1990–04 to 2.25% in 2005–19, alongside a remarkable stabilization of growth from a MAD of 2.43 down to 1.12, and a similar stabilization of inflation from a MAD of 4.34 down to 1.95. LMICs experienced a similar but slightly weaker development in both Africa and ROW. The aggregate statistics for Africa and ROW confirm the results of Figure 1, that in terms of real growth and volatility, Africa performed very similarly to ROW in the 2005–19 period. The only real difference remains the higher median level of inflation at 5.2% in Africa, compared to 2.8% in ROW. This difference is explicable by the Balassa-Samuelson effect.

Appendix Table C4 shows the same table but aggregated across countries using the MAD, indicating that African economies also converged in terms of volatility between these two periods. In ROW, volatility convergence is only evident for inflation. Appendix Figure C2 further shows the extent of moderation in all individual African counties, indicating that 2/3 of countries experienced a moderation in growth volatility, and nearly 90% experienced a moderation in inflation.

It remains to quantify the extent to which improvements in macroeconomic stability are also associated with larger growth and lower inflation within individual countries. Table 2 reports robust regressions of the difference in medians on the difference in the MADs of growth and inflation.

<sup>1</sup>This increase in persistence is even more visible in World Bank data, see Figure C7 in the Appendix.

Figure 2: AR1 Analysis of GDP per Capita Growth in Africa à la Blanchard & Simon (2001)



Data Source: IMF World Economic Outlook, October 2021

Notes: 15-year rolling autoregressions of GDP per capita growth on its lag are run for each African country, with or without a crisis dummy (definition following Syed et al. (2017) as described above, see Figure C6), and aggregated across countries using quartiles. The upper panels show the median 15-year growth rate and AR(1) coefficient across countries. The bottom panels show the Std. Dev. and MAD of the residuals. Figure C7 reports the same exercise with GDP per capita estimates from the World Bank.

Table 1: Volatility Over Time and Income Group

Area	Period	N	Per Capita Growth			Inflation		
			Median	MAD	IQR	Median	MAD	IQR
Africa	1990-04	50	1.103	1.950	4.352	6.510	3.110	6.400
	2005-19	50	2.158	1.443	2.884	5.214	1.764	3.406
Low income	1990-04	21	1.096	2.432	4.876	6.787	4.341	8.776
	2005-19	21	2.250	1.121	2.257	5.668	1.950	6.186
Lower middle income	1990-04	20	1.128	1.721	3.952	6.014	2.365	5.087
	2005-19	20	2.212	1.742	3.415	4.812	1.612	3.271
Upper middle income	1990-04	8	1.366	1.947	3.403	6.126	2.217	3.363
	2005-19	8	1.319	1.614	3.765	3.902	1.362	2.574
High income	1990-04	1	0.483	2.973	7.555	2.229	1.723	2.772
	2005-19	1	3.028	2.077	3.891	2.858	2.210	3.815
ROW	1990-04	118	2.278	1.658	3.350	5.086	1.874	4.002
	2005-19	119	2.043	1.446	3.060	2.806	1.201	2.538
Low income	1990-04	4	1.533	1.508	2.894	15.861	6.298	24.794
	2005-19	4	2.391	1.164	2.153	8.456	2.515	5.834
Lower middle income	1990-04	23	1.760	1.217	3.094	8.528	3.973	7.423
	2005-19	23	3.106	0.921	2.103	5.296	1.590	3.253
Upper middle income	1990-04	39	2.504	2.231	4.339	8.410	4.286	14.062
	2005-19	40	2.821	1.898	3.655	4.072	1.492	3.184
High income	1990-04	52	2.476	1.501	3.166	2.395	0.970	1.871
	2005-19	52	1.484	1.323	2.997	1.912	0.864	1.704

Data Source: IMF WEO, October 2021. Real GDP per capita growth is calculated using the constant national currency series (NGDPRPC), and inflation is based on average national consumer price indices (PCPIPCH).

Notes: Statistics calculated at country-level and aggregated across countries using the median. Countries with < 9 obs. for growth or inflation in 1990-04 or 2005-19 were excluded, in Africa Liberia, Somalia, South Sudan, and Zimbabwe.

The coefficients imply a negative correlation between volatility and growth and a positive relationship between inflation volatility and median inflation, which is sizeable for LICs and LMICs in Africa and ROW alike. Table 2 thus provides strong evidence that macroeconomic stabilization in these countries is associated with better macroeconomic performance.<sup>2</sup> These relationships

<sup>2</sup>See also Appendix Tables C2, C3, and Figures C3 and C9 for further cross-sectional analysis and correlations.

Table 2: Output and Inflation Volatility: 2005-19 – 1990-04 Difference

Area	N	GDP/Capita			Inflation		
		$\beta$	$P(\beta \neq 0)$	$R^2$	$\beta$	$P(\beta \neq 0)$	$R^2$
<b>Africa</b>	<b>50</b>	<b>-0.294</b>	<b>0.004</b>	<b>0.164</b>	<b>0.469</b>	<b>&lt;0.001</b>	<b>0.632</b>
Low income	21	-0.429	0.025	0.244	0.709	<0.001	0.747
Lower middle income	20	-0.111	0.379	0.043	0.322	<0.001	0.715
Upper middle income	8	0.218	<0.001	0.943	-0.108	0.743	0.020
<b>ROW</b>	<b>118</b>	<b>-0.126</b>	<b>0.018</b>	<b>0.046</b>	<b>0.713</b>	<b>&lt;0.001</b>	<b>0.890</b>
Lower middle income	23	-0.432	0.039	0.182	0.920	<0.001	0.761
Upper middle income	39	-0.035	0.756	0.003	0.701	<0.001	0.915
High income	52	-0.087	0.247	0.027	0.250	<0.001	0.364

*Data Source:* IMF WEO, October 2021. See also note to Table 1.

*Notes:* Regressions of the difference in medians on the difference in MADs of the country-series between the 1990-2004 and the 2005-2019 periods are run using a robust MM estimator following Koller & Stahel (2011), available in R package *robustbase* (Maechler et al., 2021). Table C3 shows corresponding cross-sectional results.

have been studied empirically, starting with Ramey & Ramey (1995), though mostly in a pure cross-country setting. Among the more detailed analyses, Hnatkovska & Loayza (2005) document that the correlation between volatility and growth is negative for low-income countries, basically zero for middle-income countries, and positive for advanced economies - reproduced for ROW in Table C3. Loayza et al. (2007) and Hallegatte & Przyluski (2011) also show that output volatility in developing countries is strongly related to consumption volatility and incurs a high welfare cost.

A final question regards the international synchronization of business cycles: Has the Great Moderation made African and ROW countries' growth and inflation more correlated? To study this, I compute pairwise Pearson's correlations between countries' per capita growth and inflation series, respectively, and compute an eigendecomposition of this matrix. The first eigenvector spans the first principal component, which I regard as a proxy for the international business cycle. The share of its eigenvalue in the sum of all eigenvalues corresponds to its share in the joint variance of the data. I do this separately with series for Africa, ROW, and all countries (World) for periods 1990-2004 and 2005-2019. In addition, I compute the average absolute correlation between African' and ROW countries as a measure of Africa's alignment with ROW. Table 3 reports the results.

Table 3: International Synchronization of Growth/Inflation Rates

Period	Per Capita Growth				Inflation			
	Africa	ROW	World	Corr	Africa	ROW	World	Corr
1990-2004	0.195	0.195	0.187	0.248	0.347	0.413	0.372	0.337
2005-2019	0.236	0.386	0.312	0.267	0.372	0.495	0.443	0.368
Overall (1990-2019)	0.160	0.221	0.178	0.188	0.331	0.382	0.345	0.289

*Data Source:* IMF WEO, October 2021. See also note to Table 1. Appendix Table C5 shows equivalent estimates using World Bank Data.

*Notes:* The numbers under 'Africa', 'ROW', and 'World' are the share of the first eigenvalue in the sum of eigenvalues, computed from a pairwise Pearson's correlation matrix of the country-series. They estimate the share of an international business cycle in the joint variance of the data. The 'Corr' column reports the average absolute correlation between African and ROW countries series and measures alignment between Africa and ROW.

International alignment has increased in Africa and ROW, with a more substantial gain in growth rates than in inflation. The gain in alignment in ROW is, however, much larger than in Africa, and the correlation between African and ROW growth and inflation remains low, indicating that the African Moderation has contributed little to international synchronization.

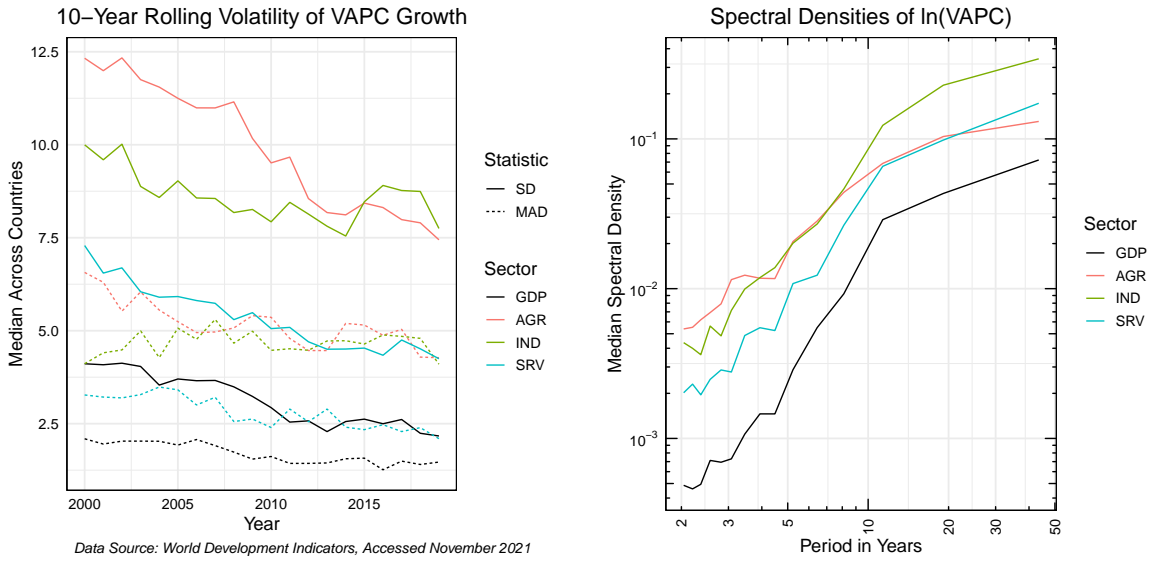
### 3 Decomposing Output Volatility

Structural change in Africa since the 1990s was characterized by an increasing GDP share of the services sector and a declining share of agriculture.<sup>3</sup> This pattern is strongly reflected in the sectors'

<sup>3</sup>See Figure C10.

contribution to GDP per capita growth rates.<sup>4</sup> For volatility analysis, I consider GDP at basic prices. Figure 3 provides a broad view of sectoral volatility, measured by sectoral value-added per capita (VAPC), across time and frequency. The left side of Figure 3 shows that growth volatility in all sectors has decreased over time. In the 1990-2000 decade, the agricultural sector was the most volatile, but volatility decreased rapidly in the 2000s, approaching the volatility of industry. Volatility in services is much lower and has also declined continuously. The right-hand side of Figure 3 shows that agriculture is only more volatile than industry over short-run fluctuations with periods of  $< 4$  years. Industry is the main source of volatility for longer-term variation with  $> 10$ -year periods, whereas the volatility of agriculture drops significantly at longer periods. The two sides of Figure 3 can be reconciled by considering, as shown by Shumway & Stoffer (2000) and in Appendix A,<sup>5</sup> that differencing data amounts to a high-pass filter that gives most weight to volatility at periods of 2 years and gradually down-weights higher periods.

Figure 3: Sectoral Volatility Across Time and Frequency



*Notes:* The LHS shows 10-year rolling SDs and MADs of GDP per capita growth at constant 2015 basic prices and its VA components (AGR, IND, SRV). The right side shows the spectral densities of the log levels of VA, computed by removing a linear trend, applying a cosine bell taper to 15% of the data on both sides, computing the periodogram using a Fast Fourier Transform, and smoothing the periodogram using modified Daniell smoothers with widths 3 and 7. The smoothed periodogram ordinates thus obtained at the country level are then aggregated across countries for each period ( $= 1/\text{frequency}$ ) using the median. For more details, see Appendix A.

The relationship between aggregate and sectoral volatility is only linear if sectoral growth rates are independent, which is not true in economic reality. Therefore, I also consider a decomposition of aggregate volatility incorporating sectoral covariances. Formally, let  $Y_t$  be the real GDP per capita at basic prices for a single country in period  $t$ . Aggregate GDP per capita is the sum of sectoral VAPC. Let there be  $K$  sectors indexed by  $k$ , then

$$Y_t = \sum_k y_{kt}. \quad (1)$$

Subtracting Eq. 1 at period  $t - 1$  from Eq. 1, and dividing through by  $Y_{t-1}$ , gives the GDP growth rate in terms of the contribution of sectoral shares, or, after multiplying and dividing by  $y_{k,t-1}$ , as the share-weighted sum of sectoral growth rates

$$\frac{\Delta Y_t}{Y_{t-1}} = \sum_k \frac{\Delta y_{kt}}{Y_{t-1}} = \sum_k \frac{y_{k,t-1}}{Y_{t-1}} \frac{\Delta y_{kt}}{y_{k,t-1}} = \sum_k \theta_{k,t-1} \frac{\Delta y_{kt}}{y_{k,t-1}}, \quad (2)$$

where  $\Delta Y_t = Y_t - Y_{t-1}$ . I now consider the variance of real GDP per capita growth over the entire sample period:  $\text{var}(\% \Delta Y) = E[(\% \Delta Y)^2] - E[\% \Delta Y]^2$ , where  $\% \Delta Y = \Delta Y / Y_{(t-1)}$ . Bienames

<sup>4</sup>See Figure C11, which also shows an increasing role of taxes.

<sup>5</sup>Appendix A contains a frequency domain analysis and discussion concerning volatility harmful to economic activity in Africa and shows that the volatility of growth rates provides an acceptable proxy for such volatility.



Identity gives the variance of a sum of random variables,<sup>6</sup> thus taking the variance of Eq. 2 yields

$$\text{var}(\% \Delta Y) = \sum_{k \in K} \sum_{j \in K} \text{cov} \left( \frac{\Delta y_k}{Y_{(t-1)}}, \frac{\Delta y_j}{Y_{(t-1)}} \right) \approx \sum_{k \in K} \sum_{j \in K} \bar{\theta}_k \bar{\theta}_j \text{cov}(\% \Delta y_k, \% \Delta y_j), \quad (3)$$

where  $\bar{\theta}_k = \frac{1}{T-1} \sum_{t=2}^T \theta_{kt}$  is the average lagged output share of sector  $k$  over the observed period  $T$ . If there is no structural change during the period of observation ( $\theta_{kt} = \bar{\theta}_k \forall t \in T$ ), the right side of Eq. 3 becomes an identity as well.

Computing Eq. 3 over the entire 1990-2019 period (Table C6), confirms that agriculture is the most volatile sector, followed closely by industry. The covariances are negative and significantly smaller, with the largest relationship between agriculture and industry and the smallest between agriculture and services. These patterns are broadly preserved when considering contributions to aggregate volatility. Accounting with robust estimates from Table C6 yields that aggregate volatility in the median African country is composed of 23.6% agriculture, 31.7% industry, and 59% services volatility, and their sum is reduced -14.6% by negative covariances.

I now consider the change in aggregate per-capita growth volatility  $\Delta \text{var}(\% \Delta Y)_\tau$ , computed between two periods  $\tau_1 = 1990 - 2004$  and as  $\tau_2 = 2005 - 2019$ . Following Eq. 3, this equals the sum of changes in the variances and covariances of the sectoral contributions to aggregate growth. To guard against outliers, I also use a comedian-based estimate<sup>7</sup> as a robust alternative to the classical estimator. Another methodological ambiguity regards aggregation. Sectoral shares can either be computed at the country level before aggregation or after aggregating the volatility differences across countries. One would think the former is better, but the data for some countries is of very poor quality. I thus implement both approaches and only report country-level shares aggregated across countries using the median. Together with the choice of covariance estimator, this leads to 6 different estimation strategies, reported in Table 4.

Table 4 shows that the reduction in volatility  $\Delta \text{var}(\% \Delta Y)_\tau$  is due to both reductions in sectoral variances and sectoral covariances.<sup>8</sup> The results differ a bit depending on the methodology: estimates involving Pearson's covariance generally satisfy the equation much more closely but are also most affected by outliers. To generate a representative estimate summarizing the exercise, I compute the median across all 6 strategies and report it in the final row of Table 4.

Table 4: Sectoral Contribution to Moderation in GDP Volatility

CovEst	AggFun	Fit	$\Delta \text{var}(\% \Delta Y)_\tau$	AGR	IND	SRV	$\sum \text{cov}_{jk}$	2AI	2AS	2IS
<i>Sectoral Shares Computed After Aggregation</i>										
Pearson	Mean	100%	-16.18	35%	3%	48%	13%	28%	-6.2%	-8.5%
Comedian	Mean	95%	-6.53	49%	-24%	37%	38%	9.7%	4.9%	24%
Pearson	Median	62%	-5.82	29%	0.84%	40%	31%	2.5%	11%	17%
Comedian	Median	29%	-1.25	45%	0.71%	18%	37%	7.9%	8.7%	20%
<i>Sectoral Shares Computed Before Aggregation</i>										
Pearson	Median	100%	-5.82	23%	14%	46%	17%	3.9%	3.5%	9.6%
Comedian	Median	68%	-1.25	20%	23%	31%	26%	5.9%	14%	6.8%
Median of 6 Estimates:		81%	-5.82	32%	1.9%	38%	28%	6.9%	6.8%	13%

*Notes:* The 'Fit' column signifies how closely Eq. 3 is satisfied. Columns AGR, IND, and SRV give the sectoral contribution to the aggregate volatility reduction in percentage terms, and  $\sum \text{cov}_{jk}$  gives the combined contribution of all covariance terms, which are also individually broken down in columns 2AI, 2AS, and 2IS. Estimates differ depending on the covariance estimator, aggregation function, and whether shares are computed before or after aggregation. The bottom row shows the median of all 6 reported estimates.

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$$\text{var}(\sum_k a_k y_k) = \sum_{i \in K} \sum_{j \in K} a_i a_j \text{cov}(y_i, y_j) = \sum_k a_k^2 \text{var}(y_k) + 2 \sum_{1 \leq i < j \leq K} a_i a_j \text{cov}(y_i, y_j).$$

<sup>7</sup>The comedian is defined as  $\text{com}(X, Y) = \text{med}((X - \text{med}(X))(Y - \text{med}(Y)))$ . It is not strictly a robust covariance estimator as it does not preserve the relative magnitude of variances and covariances. The implementation available in R package *robustbase* (Maechler et al., 2021) however uses the comedian to estimate the covariance, applying appropriate corrections.

<sup>8</sup>Mostly expressed through already negative covariances becoming more negative, so not a covariance reduction in absolute terms.

The outcome suggests that 32% of the aggregate reduction in per capita growth volatility between  $\tau_1$  and  $\tau_2$  was accounted for by agriculture, 38% by services, and 28% by a reduction in the covariances, of which, abbreviating sectors by their first letter, around 7% are accounted for by AI and AS, and 13-14% by IS. The idiosyncratic reduction in industrial volatility only accounts for 1.9% of the aggregate reduction. The results thus confirm a more than proportional role of agriculture in the African Moderation but also signify a shift towards greater sectoral independence, or rather, sectoral substitutability.<sup>9</sup>

A shortcoming of the results of Table 4, based on the left side of Eq. 3, is that they include the effects of structural change. To examine the contribution of structural change in isolation, I further develop the right side of Eq. 3 and decompose changes in aggregate volatility into changes in sectoral volatilities and changes in sectoral production shares. This is motivated by the consideration that the service sector is substantially less volatile than agriculture and industry, and the share of services in African GDP has been increasing; hence, a quantifiable fraction of the African Moderation must be a direct consequence of structural change. This type of decomposition is well-known in the structural change literature. McMillan et al. (2014) decompose changes in aggregate labor productivity as<sup>10</sup>

$$\Delta LP_t = \Delta \sum_k \theta_{kt} lp_{kt} = \sum_k \theta_{k,t-1} \Delta lp_{kt} + \sum_k \Delta \theta_k lp_{kt}, \quad (4)$$

where  $\theta_{k,t-1} \Delta lp_{kt}$  denotes the sectoral labor productivity changes weighted by sector shares at the beginning of the period, and  $\Delta \theta_k lp_{kt}$  denotes the changes in sectoral shares weighted by final period productivity levels. Applying Eq. 4 to the right side of Eq. 3 yields

$$\Delta var(\% \Delta Y)_\tau \approx \sum_{k \in K} \sum_{j \in K} \bar{\theta}_{kj, \tau-1} \Delta cov(\% \Delta y_k, \% \Delta y_j)_\tau + \sum_{k \in K} \sum_{j \in K} \Delta \bar{\theta}_{kj, \tau} cov(\% \Delta y_k, \% \Delta y_j)_\tau, \quad (5)$$

where  $\tau = (t, \dots, t + N - 1)'$ ,  $N \in 2, \dots, T$  denotes a time-window of size  $N$  over which the covariance is computed, and  $\bar{\theta}_{kj\tau} = \frac{1}{N-1} \left( \sum_{i=1}^{N-1} \theta_{k,t+i} \times \sum_{i=1}^{N-1} \theta_{j,t+i} \right) \forall k, j$  denotes the product of the average sectoral shares. The first weighted sum of covariances in Eq. 5 thus captures changes in aggregate volatility resulting from changes in volatility within sectors and the second changes due to the shifting of value-added between sectors at different levels of volatility. I estimate Eq. 5 considering again a single difference between periods  $\tau_1$  and  $\tau_2$ , using both classical and comedian estimators, and compute shares before and after aggregating across countries using the median.

Table 5 reports the results. Columns 'Within' and 'Between' give the median value of the respective components in Eq. 5, transformed into shares before aggregation if 'Trans = Share'. 'Fit' indicates how closely Eq. 5 is satisfied, and columns 'Within/Sum' and 'Between/Sum' provide the percentage shares of the two components in their sum i.e. relative to the overall fit, as in Table 4. If 'Trans = Share', these columns are also computed before aggregation. Table 5 shows that in the median country, structural change explains between 3% and 5.6% of the aggregate reduction in per-capita growth volatility in  $\tau_1 \rightarrow \tau_2$ . This result is robust across methodological choices.

A concern may be that the 3-sector setup is too broad to quantify the effects of structural change on aggregate volatility. Thus, I also repeat the exercise with a more detailed dataset used in the structural change literature: the Economic Transformation Database (Kruse et al., 2023) provides a disaggregation into 12 sectors for 21 African countries over the period 1990-2018. It can thus also be split between  $\tau_1$  and  $\tau_2$ . The bottom half of Table 5 reports the results, indicating that even with a finer sectoral disaggregation, the contribution of pure structural change to African moderation is smaller than 5%.

<sup>9</sup>Implied by an observed median increase in the negative covariance between AI and AS, and a shift from a small positive IS covariance in  $\tau_1$  to a small negative covariance in  $\tau_2$ .

<sup>10</sup>Equation 4 is derived as:  $\Delta LP_t = \sum_k \Delta(\theta_{kt} lp_{kt}) = \sum_k (\theta_{kt} lp_{kt} - \theta_{k,t-1} lp_{k,t-1}) = \sum_k (\theta_{kt} lp_{kt} - \theta_{k,t-1} lp_{k,t-1} + \theta_{k,t-1} lp_{kt} - \theta_{k,t-1} lp_{kt}) = \sum_k (\theta_{k,t-1} \Delta lp_{kt} + \Delta \theta_k lp_{kt})$ .



Table 5: Stuctural Change and African Moderation: à la [McMillan et al. \(2014\)](#)

CovEst	Trans	$\Delta var(\% \Delta Y)_\tau$	Within	Between	Fit	Within/Sum	Between/Sum
<i>World Bank Data</i> (3-Sectors, 41 Countries)							
Classical	None	-5.823	-2.390	-0.141	43.5%	94.4%	5.58%
Classical	Share	-5.823	0.958	0.019	102%	97.0%	2.98%
Comedian	None	-1.669	-2.506	-0.147	159%	94.5%	5.53%
Comedian	Share	-1.669	0.757	0.045	88.7%	96.9%	3.07%
<i>Economic Transformation Database</i> (12-Sectors, 21 Countries)							
Classical	None	-6.304	-5.002	-0.002	79.4%	100%	0.03%
Classical	Share	-6.304	0.993	0.001	105%	98.1%	1.85%
Comedian	None	-2.775	-3.413	-0.111	127%	96.8%	3.16%
Comedian	Share	-2.775	0.969	0.037	113%	96.9%	3.07%

*Notes:* The decomposition is computed at the country level for 41 African countries according to Eq. 5, comparing 1990-2004 to the 2005-2019 period. The two components are turned into shares if 'Trans = Share', and aggregated across countries using the median. Further descriptions of the columns are provided in the main text above. 13 countries with less than 10 observations for any sectoral growth rate in either period were excluded: Algeria, Angola, the Central African Republic, Djibouti, Equatorial Guinea, Eritrea, Kenya, Liberia, Libya, Madagascar, Somalia, South Sudan, and São Tomé & Príncipe. The ETD of [Kruse et al. \(2023\)](#) records 12 sectors for 21 African countries: BFA, BWA, CMR, EGY, ETH, GHA, KEN, LSO, MAR, MOZ, MUS, MWI, NAM, NGA, RWA, SEN, TUN, TZA, UGA, ZAF, ZMB.

A related exercise, established by [Stock & Watson \(2002\)](#) fixes the sectoral shares but maintains the sectoral growth rates to generate a pseudo-outcome GDP growth series reflecting the absence of structural change. Following their method, I generate two pseudo-outcome series with sectoral shares fixed at their average in periods  $\tau_1$  and  $\tau_2$ , respectively. I then compute various measures of volatility  $\sigma$  (variance, IQR, and MAD) across the two periods and series, yielding two actual (approximately) and two counterfactual volatility estimates. Following [Stock & Watson \(2002\)](#), I compute  $\psi = ([\sigma_{\tau_2}^{\tau_2} - \sigma_{\tau_2}^{\tau_1}] + [\sigma_{\tau_1}^{\tau_2} - \sigma_{\tau_1}^{\tau_1}])/2$ , where  $\sigma_{\tau_2}^{\tau_1}$  is the volatility of GDP in period  $\tau_2$ , computed using the sectoral shares of period  $\tau_1$ . The statistic  $\psi$  thus estimates the change in volatility due to a change in shares by averaging both possible ways of conducting the counterfactual exercise: comparing actual volatility in  $\tau_2$  to volatility in  $\tau_2$  if the sectoral shares are those of  $\tau_1$ , and comparing volatility in  $\tau_1$  with the shares of  $\tau_2$  to actual volatility of  $\tau_1$ . Further, I compute  $\Delta\sigma = \sigma_{\tau_2}^{\tau_2} - \sigma_{\tau_1}^{\tau_1}$  as the actual (approximate) change in GDP volatility. Table 6 reports the results.

Table 6: Stuctural Change and African Moderation: à la [Stock & Watson \(2002\)](#)

Statistic	AggFun	$\sigma_{\tau_1}^{\tau_1}$	$\sigma_{\tau_1}^{\tau_2}$	$\sigma_{\tau_2}^{\tau_2}$	$\sigma_{\tau_2}^{\tau_1}$	$\Delta\sigma$	$\psi$	$\frac{100\psi}{\Delta\sigma}$
<i>World Bank Data</i> (3-Sectors, 41 Countries)								
Variance	TrimmedMean (10%)	21.64	26.28	12.00	12.99	-6.67	2.39	-1.76
Variance	Median	17.83	19.40	6.94	7.44	-3.20	0.75	2.20
IQR	TrimmedMean (10%)	4.62	4.73	3.29	3.45	-1.23	-0.04	9.19
IQR	Median	3.90	4.21	3.26	3.21	-0.54	-0.01	5.11
MAD	TrimmedMean (10%)	2.28	2.48	1.70	1.78	-0.54	0.03	-6.64
MAD	Median	2.05	2.24	1.77	1.69	-0.30	-0.02	2.69
<i>Economic Transformation Database</i> (12-Sectors, 21 Countries)								
Variance	TrimmedMean (10%)	15.22	19.29	6.17	4.93	-9.10	1.58	0.97
Variance	Median	8.36	10.52	5.06	4.35	-4.25	0.70	6.49
IQR	TrimmedMean (10%)	4.17	4.40	2.74	2.46	-1.27	0.17	3.98
IQR	Median	3.72	3.51	2.29	2.54	-1.01	0.03	3.51
MAD	TrimmedMean (10%)	2.23	2.21	1.42	1.13	-0.72	0.10	5.32
MAD	Median	2.01	2.04	1.35	1.12	-0.46	0.05	8.76

*Notes:* Decomposition of GDP volatility by fixing sectoral shares and generating counterfactual series as in [Stock & Watson \(2002\)](#).  $\sigma_{\tau_2}^{\tau_1}$  is the volatility of GDP in period  $\tau_2$  = 2005-2019, computed using the sectoral shares of period  $\tau_1$  = 1990-2004.  $\psi = ([\sigma_{\tau_2}^{\tau_2} - \sigma_{\tau_2}^{\tau_1}] + [\sigma_{\tau_1}^{\tau_2} - \sigma_{\tau_1}^{\tau_1}])/2$  estimates the average volatility change due to structural change across the two periods.  $\Delta\sigma = \sigma_{\tau_2}^{\tau_2} - \sigma_{\tau_1}^{\tau_1}$  estimates the actual (approximate) change in GDP volatility. Results are aggregated across countries using either the median or a trimmed mean, removing 10% of the observation from both sides.

Overall, the results of Table 6 are very similar to those of Table 5. The counterfactual volatility estimates are very close to the actual ones, confirming that macroeconomic moderation in Africa was largely a within-sector phenomenon. The percentage share of the moderation attributable to structural change by this method, reported in the final column of Table 6, ranges between -6.6 and 9.2 %. The analysis presented in Tables 4 through 6 thus establishes that up to 30% of the aggregate African Moderation of real per-capita growth rates is due to changes in the covariance towards greater sectoral independence/substitution, and  $\sim 5\%$  can be attributed to pure structural change, with less volatile sectors like services becoming economically more important. The remaining 65-70% is due to other factors that mostly affected agriculture and services. As noted by [Stock & Watson \(2002\)](#), the increase in services employment could, through more stable incomes and demand, also have stabilizing effects on other sectors, which is not captured by these decompositions. The decompositions might thus understate the true general equilibrium effects of structural change on output stability.

In the great moderation literature, a frequently mentioned driver in advanced economies ([McConnell & Perez-Quiros, 2000](#); [Blanchard & Simon, 2001](#); [Horan, 2006](#)) is greater production efficiency through inventory management innovations. Given the small role of the industry sector in Africa's moderation, the results suggest that inventory management is unlikely to be an important driver.

Before examining other factors, I validate these results at the country level and uncover some heterogeneity by computing the MAD sector contribution to growth,  $MAD(\Delta y_t/Y_{t-1})$ , and sectoral growth volatility,  $MAD(\% \Delta y_t)$ , for each country. Computing  $MAD(\Delta y_t/Y_{t-1})$  over the whole 1990-2019 period yields a large group of 21 countries has services as the greatest contributor to aggregate volatility, followed by industry (17) and agriculture (13) (see Table C7). This metric thus broadly aligns with the pattern of structural change. Considering the sectoral growth volatility, however, leads to a large reallocation of countries to industry and agriculture, with 22 countries having the largest volatility in agriculture and 28 in industry, and only 1 country (Gabon) in the services category.<sup>11</sup> Table C8 summarizes both metrics for  $\tau_1$  and  $\tau_2$ , and Figure C16 visualizes the movement in  $MAD(\Delta y_t/Y_{t-1})$  for all countries, indicating a nearly ubiquitous and large stabilization of agriculture, as well as a sizeable stabilization of services in most countries. In industry, the developments are very heterogeneous, with some countries like Ghana experiencing greater volatility and others like South Africa experiencing significant stabilization. It is also interesting to compare different regions in Africa. Figure C17 and Table C10 provide a regional summary of sectoral volatility and show that all regions apart from southern Africa experienced a sizeable stabilization in agriculture. Overall, Eastern Africa experienced the largest stabilization in aggregate output, followed by Middle and Western Africa.

Disaggregated analysis hence confirms the results of aggregate analysis, indicating that stabilization of agriculture and services was a shared experience for most African countries since 1990. There is moderate regional heterogeneity, with the more developed regions of Northern and Southern Africa being affected less. Appendix B reports a similar decomposition from the expenditure side of GDP, indicating a decline in the volatility of all expenditure components, especially consumption, investment, and exports.

## 4 External, Financial, and Policy Factors

Since  $\sim 70\%$  of the African Moderation cannot be explained by structural change or changes in sectoral covariances, the remainder of the paper examines other contributing factors, including the external economic environment faced by African economies, changes in the financial sector, macroeconomic policies, and other changes in economic or institutional structure (Section 5).

Several papers investigate the great moderation in the US and other advanced economies (AE) along similar lines. [Horan \(2006\)](#) studies the reduction of output volatility in AE, focussing on the competing explanations of better monetary policy, more efficient inventory investment of firms, and lower exposure to global shocks (oil price shocks). He finds that, due to the different onsets

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<sup>11</sup>See the bottom half of Table C7.

of output moderation in AE, only the former two provide credible explanations for the great moderation. [McConnell & Perez-Quiros \(2000\)](#) and [Blanchard & Simon \(2001\)](#) also find evidence that more countercyclical inventory management has contributed to the stabilization of business cycles in the US. [Ahmed et al. \(2004\)](#) attributes to monetary policy a role in bringing down US inflation volatility. [Schmidt-Hebbel \(2009\)](#) discusses causes of the great moderation in emerging markets and developing economies (EMDE), mentioning stronger policies and better institutions (especially property rights, governance and accountability, and central bank independence) as drivers. He documents that the adoption of inflation-targeting monetary policy (IT) in EME was associated with reduced domestic inflation and exchange rate pass-through. Many developing countries also adopted more sustainable fiscal policies. In South Africa, [Burger \(2008\)](#) provides evidence that better monetary policy and a more efficient financial sector brought down volatility in the 90s, but inventories did not. [Du Plessis & Kotzé \(2010\)](#) also note that a less volatile international environment following South African liberalization in the late 80s and the greater political stability during the post-apartheid late 90s enhanced macroeconomic stability in South Africa.

In the bulk of African economies, little is known about inventory management practices, but I have argued against it based on the small contribution of the industrial sector to African moderation. I will also argue against IT as a driver of moderation in Africa. There have, however, been notable changes in the external environment faced by African economies in this time frame, reflected in better terms of trade (ToT), lower external debt burdens, higher inflows of FDI and remittances, as well as lower volatility of merchandise trade, FDI and remittance inflows. There has also been a gradual process of financial deepening, reflected in broad money, credit to the private sector, national savings, and reserve assets. Finally, there have been changes toward a more stable exchange rate policy and an increased adoption of fiscal rules.

## 4.1 External Environment

Reduced volatility may partly result from a more favorable external environment faced by African economies, permitting both stronger growth and more long-term economic planning and investments. It is notable from [Figure 1](#) that growth rates peaked shortly after 2010, which, thanks to the Heavily Indebted Poor Countries (HIPC) Initiative launched in 1996, is also the period when Africa faced the lowest levels of public and external debt (see [Figure C18](#)). African economies also experienced more favorable ToT and higher FDI and remittance inflows after 2010.

[Table C11](#) shows correlations of 10-year rolling averages of these indicators with rolling medians and MADs of per-capita growth and inflation in country-standardized first-differences. ToT and FDI are significantly positively correlated with growth, whereas public and external debt are strongly negatively related to growth. In addition, higher ToT and remittances are associated with lower growth volatility and inflation levels, whereas greater debt stocks correlate with higher volatility and inflation. This indicates that more favorable linkages with the world could have contributed to the increased resilience in African real sectors.

A less volatile external environment may also have directly contributed to less volatile domestic activity. [Figure C19](#) shows that exchange rate, ToT, and merchandise trade volatility have dropped substantially over the sample period, and also FDI and remittance flows became less volatile. Current account volatility also fell after 2010. [Table C12](#) shows corresponding within-country correlations of 10-year rolling volatility measures, indicating that higher exchange rate, ToT, FDI, and remittance volatility are associated with lower growth, higher inflation, and greater macroeconomic volatility. Especially exchange rate volatility is strongly correlated with inflation.

## 4.2 Financial Deepening

Another source of increased resilience in Africa may be domestic financial deepening and increased levels of international reserves to counter external shocks. For example, [Easterly et al. \(2001\)](#) analyze volatility with an emphasis on the financial sector and constate that credit constraints are an important source of volatility in developing countries. [Figure C20](#) indicates that Africa has indeed made some progress in this direction over the past 30 years. Gross National Savings have increased from around 14% of GDP in 1990 to around 18% in 2019, total reserves have risen to

around 100% of external debt or 5.5 months of imports of goods and services, domestic credit to the private sector has risen from 17% to 25% of GDP, broad money from 30% to 40% of GDP, and banks liquid reserves to assets ratio has risen from  $<20\%$  to  $\geq 25\%$ , at least when weighted by GDP or population. Table C13 shows the corresponding correlations in country-standardized first differences, indicating that higher national savings, reserves, domestic credit to the private sector, and broad money correlate positively with economic growth and macroeconomic stability.

### 4.3 Macroeconomic Policies

Improved domestic macroeconomic and financial policies may also have contributed to the African Moderation. I only consider the most important stabilization policies: managing inflation and the exchange rate, macroprudential stringency, and fiscal rules.

#### Inflation Targeting

Africa still has very few inflation targeters. According to the IMF’s Annual Report on Exchange Arrangements and Exchange Restrictions (AREAER) database, only 4 countries currently target inflation: South Africa from 2000, Ghana from 2007, Uganda from 2011, and Seychelles from 2019. Figure C21 shows the inflation rates of these countries, indicating that the IT regimes were adopted when inflation had already stabilized to levels well below 20%. Thus, the adoption of IT did not play a large role in the African Moderation.

#### Exchange Rate Arrangements

To examine the evolution of exchange rate regimes, I take data from Ilzetzi et al. (2019), available for 53 African countries. Figure C22 shows that the share of crawling bands and free-falling/dual markets has declined in Africa since 1992, in favor of crawling peg arrangements. Free floats are also rare, and since 2005, only South Africa has maintained a floating regime.

Table C14 reports 15-year rolling panel fixed-effects regressions of growth and inflation volatility on the exchange regime dummies, using the hard peg as a base category. Results imply that relative to the hard peg, crawling pegs are associated with greater growth stability, whereas more liberal regimes correlate with less stable growth performance. The coefficients on model (3) with country and time fixed effects imply that a crawling peg is associated with a 0.86 percentage point (pp.) decrease in the MAD of real per-capita growth vis-a-vis the hard peg arrangement. For inflation, the hard peg appears to be the most stable regime, but the coefficient on the crawling peg is insignificant, indicating that the inflation cost of switching to a crawling peg is moderate. As elucidated by Bleaney et al. (2016), the choice of exchange rate arrangement is endogenous to macroeconomic conditions and policy priorities, and reduced inflation has made pegging more attractive in recent years. Nevertheless, the shift in exchange rate regimes in Africa since 1990 towards crawling pegs and decline in freely-falling and other volatile regimes, evidenced by a strong decline of exchange rate volatility (Figure C19), has likely contributed to Africa’s moderation.

#### Macroprudential Regulation

Macroprudential policy received increased attention after the 2008/09 global financial crisis. The IMF adopted a new Institutional View in 2012, recognizing the usefulness of macroprudential measures for macroeconomic stability, particularly in economies with less developed financial markets (Arora et al., 2013; IMF, 2017, 2022). Figure C23 shows indices of total, inflow, and outflow controls across 18 African countries, computed by averaging dummies for restrictions in 10 financial markets, from Fernández et al. (2016) (August 2021 update). Macroprudential measures have eased in the 1995-1997 period,<sup>12</sup> but have remained quite stable around 0.5 for inflow measures and 0.625 for outflow measures afterward. It is, therefore, unlikely that aggregate macroeconomic moderation in Africa is much affected by changes in macroprudential policy.

Some continent-level developments emerge when considering restrictions in the 10 different markets separately. Figure C24 shows 10-year MAs of the overall stringency in 18 African economies,

<sup>12</sup>Mainly due to liberalizations in Ethiopia, Nigeria, Uganda, and Ghana.

indicating that bond and guarantee markets, as well as FDI, have become more restricted in recent years, whereas equity, real estate, and commercial credit markets have become less restricted. Table C15 shows 10-year rolling panel-FE regressions of the MADs of GDP per capita growth and inflation on aggregate macroprudential stringency indicators, indicating that macroprudential stringency is negatively associated with both output and inflation volatility. Drawing on the specification with country and time fixed effects, an increase in overall macroprudential stringency by 0.1 is associated with a 0.54 pp. reduction in the MAD of per-capita growth and a 1.22 pp. reduction in the MAD of inflation. Outflow measures have a stronger association with output stability, whereas inflow measures strongly associate with reduced inflation volatility.

## Fiscal Rules

A fourth and important set of stabilization policies are fiscal rules. Global data on fiscal rules adopted since 1985 is available through the IMF Fiscal Rules Dataset (Davoodi et al., 2022b,a). Table 7 compactly summarizes the history of fiscal rules in Africa.<sup>13</sup>

Table 7: A Chronology of Fiscal Rules in Africa

Entity	First Rule	Expenditure (ER)	Revenue (RR)	Budget Balance (BBR)	Debt (DR)
Kenya	1997		1997		1997 (2019)
Cape Verde	1998			1998	1998
WAEMU <sup>a</sup>	2000		2000 (2015)	2000 (2015)	2000 (2015)
Namibia	2001	2010			2001
CEMAC <sup>b</sup>	2002			2002 (2008, 2017)	2002
Botswana	2003	2003 (2006, 2016)		2003	2005
Nigeria	2007			2007	
Mauritius	2008				2008 (2010)
Liberia	2009				2009
EAC <sup>c</sup>	2013			2013	2013
Tanzania	2015	2015		2015	
Uganda	2016			2016	2016
Rwanda	2019			2019	

Data Source: Davoodi et al. (2022b). Rule revisions in parentheses.

<sup>a</sup> Comprising Benin, Burkina Faso, Côte D'Ivoire, Guinea-Bissau, Mali, Niger, Senegal and Togo

<sup>b</sup> Comprising Cameroon, Central African Republic, Chad, Republic of Congo, Equatorial Guinea and Gabon

<sup>c</sup> Comprising Tanzania, Kenya, Rwanda, Uganda, Burundi and South Sudan

Most fiscal rules in Africa can be regarded as weak. Apart from Mauritius and Botswana, no country has instigated a formal enforcement procedure for national rules, and no country has an extra-governmental body to monitor compliance with national rules.

To evaluate the relationship of fiscal rules with macroeconomic stability, Table C16 presents 10-year rolling regressions considering first a dummy indicating the adoption of any fiscal rule, then the total number of rules, and finally a set of dummies for the different types of rules. Adding both country and time-fixed effects lets the within  $R^2$  drop to zero, indicating insufficient time variation in the fiscal rules to control for global events. The models with country-fixed effects, however show a meaningful and significant negative association of fiscal rules with both growth and inflation volatility. When disaggregating the set of rules, only the coefficient on the Budget Balance Rule (BBR) is negative and significant in the growth volatility regression. The coefficient size implies that a BBR is associated with around 1 pp. lower MAD of growth. For inflation, both Revenue Rules and BBRs have large negative coefficients. Debt Rules (DRs) are also negatively related to growth/inflation volatility, with insignificant coefficients of 0.23/0.54.

Table C17 further shows that the existence and number of rules implemented correlate positively with the current account (CAB) and government budget balance (GBB), and negatively with the level of gross government debt (GGD). When disaggregating rules, BBRs are associated with an approx. 4.2 pp. improvement in the CAB (in % of GDP), and a 7 pp. improvement in the GBB. DRs appear to be strongly associated with GGD, at effect sizes up to 70-80 pp. lower debt to GDP.

These coefficients are not to be interpreted as causal since fiscal rules are often a commitment device of governments that already engage in sound macroeconomic practices. They nevertheless

<sup>13</sup>Figure C25 also shows an aggregate timeline of fiscal rules adoption in Africa by type and issuing authority.



suggest that instigating a rule is an effective device for these governments.

Having considered four different types of macroeconomic policies in Africa over the past 30 years, it appears that only the shift towards crawling pegs from crawling bands and freely falling arrangements and the adoption of fiscal rules in an increasing number of countries could have contributed to the large macroeconomic moderation in growth and inflation. Inflation-targeting monetary policy has only been taken up by four countries at a point when their inflation levels were already low and stable, and macroprudential policies, while potentially effective in curbing macroeconomic volatility, show no aggregate trend over most of the period under consideration. This assessment is, of course, incomplete. For example, it is possible that central banks have become more effective in targeting monetary aggregates without shifting to inflation targeting or that many countries have run financial sector, trade, or agricultural policies that contributed to macroeconomic stability. Above all, the issue of policy endogeneity to macroeconomic conditions precludes drawing too wide-ranging conclusions about policy efficacy.

## 5 Structural Factors

An assessment of macroeconomic volatility and moderation would be incomplete without reference to structural characteristics of an economy, such as political and economic institutions, diversification in production and trade, economic openness, the incidence of conflicts and disasters, geography, human capital, etc. Significant literatures in economics have evaluated the effects of these factors in different contexts. For example, [Acemoglu et al. \(2003\)](#) analyze the effects of long-term institutional development on macroeconomic stability and find that countries that inherited more 'extractive' institutions from their colonial past are more likely to experience high volatility and economic crises. They argue that poor institutions cause volatile and distortionary macroeconomic policies, which act as a proximate cause for volatility. [Rodrik \(1999\)](#) relates the lack of persistent growth in developing countries to social conflicts fuelled by inequality, ethnic fractionalization, and weak institutions. [Malik & Temple \(2009\)](#) examine the structural determinants of output volatility in developing countries with Bayesian methods. They find a significant role of market access: remote countries are more likely to have undiversified exports, high levels of export concentration, high ToT volatility, and high output volatility. [Auffret \(2003\)](#) finds positive effects of natural disasters on consumption volatility in the Caribbean region. [Abdullahi & Suardi \(2009\)](#) examine the effects of financial and trade liberalization on output and consumption growth volatility in Africa and show that trade liberalization increases volatility, whereas financial liberalization decreases volatility through greater efficacy of consumption smoothing. They also find that financial depth and institutional quality interact negatively with trade and financial openness.

A significant literature has also evaluated the link between economic and trade diversification and macroeconomic volatility ([Papageorgiou & Spatafora, 2012](#); [Papageorgiou et al., 2015](#); [Moore & Walkes, 2010](#); [Koren & Tenreyro, 2007](#); [Romeu & da Costa Neto, 2011](#); [Farshbaf, 2012](#); [Jansen et al., 2009](#)), reaching a consensus that more diversified economies show lower volatility in variables such as GDP, consumption, investment, and exports, and are more resilient to external shocks. A key channel is that diversification involves LICs shifting resources from sectors where prices are highly volatile and correlated, such as mining and agriculture, to less volatile and correlated sectors, such as manufacturing and services, resulting in greater stability.

The effects of capital flows and transfers have also been heavily studied. [Singh et al. \(2011\)](#) provide a careful macroeconomic study of remittances in Sub-Saharan Africa (SSA), and find that remittances vary counter-cyclically with GDP per capita, consistent with the hypothesis that remittances can help mitigate economic shocks.

### 5.1 Cross-Sectional Analysis

In the following, I present an attempt to rank these factors by relevance for predicting volatility in a cross-section of African economies during the 1990-2019 period. For this, I selected 98 predictors jointly available for 49 African economies (excluding Djibouti, Liberia, Somalia, South Sudan, and Zimbabwe), with a total of 2.5% missing values. These include the vast majority of characteristics studied in the literature referenced above and also the external environment and financial sector



indicators studied in Sections 4.1 and 4.2. I group these 98 indicators into 19 topics, listed in Table 8, and, with statistical details, in Table C18. I then use a Random Forests (RF) machine learning model following Breiman (2001) to predict the volatility of per-capita growth and inflation and determine the importance of different predictors, both individually and at the topic level.<sup>14</sup>

Table 8: Indicator Topics for Cross-Sectional Prediction

#	Topic	Indicators
1	Institutions	9
2	Business Environment	4
3	Production Shares	2
4	Climate & Agriculture	8
5	Trade Intensity and Composition	7
6	Trade Diversification	4
7	Exchange Rate and Terms of Trade	5
8	Financial & Aid Flows	5
9	Financial Sector	6
10	Debt & Reserves	4
11	Population	6
12	Health	5
13	Education	5
14	Natural Disasters & Conflict	6
15	Geography & Accessibility	7
16	Natural Resources	2
17	Poverty & Inequality	3
18	Religion & Ethnicity	4
19	Others	6
SUM		98

*Notes:* 98 indicators, available for a cross-section of 49 African countries (excluding Djibouti, Liberia, Somalia, South Sudan, and Zimbabwe), are classified into 19 topics. See Table C18 for details.

To rank predictors individually, I fit a regression forest of 100,000 highly de-correlated trees, grown to full size, with only 3 out of 98 predictors randomly chosen at each split. I determine each predictor’s importance by randomly permuting that predictor’s observations and measuring the increase in the Out-of-Bag (OOB) Mean Squared Prediction Error (MSE) caused by the permutation in percentage terms. Figure C28 shows the top 30 predictors of the MAD of GDP per capita growth over the 1990-2019 period. Surprisingly, despite the high-dimensional dataset, the model only explains 28% of the OOB variance in the outcome variable. There are 10 predictors whose permutation increases the MSE by more than 2%; among these, there are 3 institutions, 2 business environment, and 2 remittance variables. The other top 10 variables are natural resource rents as a fraction of GDP, the share of industry in GDP, and natural disaster deaths. Among the variables that decrease predictive accuracy by more than 1% are also oil rents, trade with LMICs as a share of GDP, the MAD of FDI, total reserves, the cereal yield, human rights and level of democracy, the MAD of ToT growth, and the trade share of GDP.

Ranking topics (Table 8) is challenging, as topics are multi-dimensional and correlated. A first approach is to use the model underlying Figure C28, permute all predictors within a topic, and measure the decrease in predictive power. A problem with this method is that it does not attain the predictive performance of a model fit without those predictors. Thus, another approach is fitting different models, excluding topics and comparing their performance to the baseline model. This method can, however, also be criticized if different topics are correlated, as predictors in other topics will capture some variation of predictors in the excluded topic. One possibility to limit this is to project all other predictors on the predictors of the excluded group and use the residuals to fit

<sup>14</sup>Initially, the RF model is used to predict the 2.5% missing values in the predictor dataset by an iterative algorithm called ‘MissForest’ developed by Stekhoven & Bühlmann (2012). Most predictors have no missing values (see Table C18), and no predictor has more than 8 missing values.

a new model.<sup>15</sup> In the face of ambiguity, I implement all 3 methods and compute the average rank based on the increase in MSE from permutation/exclusion/partialling out the topical predictors. Table C19 reports the results. Overall, institutions emerge as the most important topic, followed by financial flows, trade intensity and composition, the financial sector, business conditions, natural resource intensity, natural disasters, and conflict.

The exercise is repeated, in Figure C29 and Table C20, with the MAD of CPI inflation. Exchange rate pass-through plays a dominant role in many African economies, followed by indicators of fragility and conflict, and institutions. Table C20 shows that excluding exchange rate variables worsens the model fit by 17.6%, whereas excluding most other topics increases the fit by 1-3%. Apart from the exchange rate, conflict/fragility and institutions, business conditions, population dynamics, trade intensity, trade diversification, and the financial sector are important predictors of inflation volatility.

## 5.2 Time-Variation in Structural Factors

The comparison of changes in these factors with the documented changes in volatility over the 1990-2019 period is of great importance in the scope of this paper but challenging as many indicators are either (nearly) time-invariant or lack historical data to trace them back to 1990. Particularly, survey-based variables measuring the quality of the business environment and financial access lack historical coverage. Figure C27 shows some institutional and business variables over the time period, indicating no positive change in the Worldwide Governance Indicators but significant improvements in business conditions and economic institutions in the recent years since measures became available. Restricting the analysis to variables with the necessary history thus provides an incomplete perspective of changes within African economies in the past 30 years.

Of the 98 variables considered in the cross-section, 70 have some time variation to be considered for analysis of changes.<sup>16</sup> Not included are mainly geography, religion, and ethnicity variables, static agricultural characteristics, and some institutions and business indicators with low time coverage. The analysis is then repeated on a cross-section of first-differences for 49 African economies, obtained by subtracting the median of the 70 indicators over the 1990-2004 period from the 2005-2019 median and relating this to the difference in the MADs of PCGDP growth and CPI inflation. Figure C30 and Table C21 show the results for PCGDP. It turns out that predicting changes in macroeconomic volatility over time is very challenging. The RF model in Figure C30 explains 0% of the variance in the change of the MAD of GDP per capita growth between 1990 and 2019 OOB (the in-sample  $R^2$  is 98%, indicating overfitting). With some hyperparameter tuning, the OOB  $R^2$  can be increased to 4%, but this is still poor. It is nevertheless noteworthy that 2 financial sector variables are among the top 5 predictors that increase the MSE by close to 1%. The other 3 variables are GDP per person employed, life expectancy, and population, which proxy for changes in the labor force and in human capital. Table C21 confirms the importance of the financial sector as well as social characteristics such as population dynamics, health, and education, alongside institutions and 'Others' which includes GDP per person employed, gross national savings, and the Human Development Index.

Overall, the result is a negative one. This could be due to relating changes in the medians to changes in the MAD of volatility, which throws away a lot of potentially useful variation, but, as shown in Appendix D, employing less robust measures such as the standard deviation of growth and time-averages of predictors, does not produce models with higher predictive power. Thus, the results strongly suggest that the bulk of the African Moderation in growth volatility is not due to changes in hard structural factors like institutions, trade intensity, and diversification, conflict intensity, poverty, and inequality, or natural resource rents, which make up the bulk of the predictor space, and thus the variables randomly sampled at each split to build a predictive model. These factors continue to be important in explaining different levels of baseline volatility between African countries (as shown above), but they do not explain the African Moderation. This finding is confirmed by the model selecting financial sector and human development variables as the most

<sup>15</sup>The projection is done using linear regression, e.g.  $Z(Z'Z)^{-1}Z'X$  where  $Z$  is a set of topical predictors and  $X$  the set of remaining predictors. If the set of topical predictors  $Z$  were large, this projection could also be made using an RF model, but with  $<10$  predictors in  $Z$  the RF is not a sensible modeling choice.

<sup>16</sup>The first column in Table C18 in the Appendix shows which variables are included in the panel.

important time-varying predictors of growth moderation in Africa.

Analogous results for inflation are provided in Figure C31 and Tables C22 and C28. The reduction in exchange rate volatility (Figure C19) is the strongest correlate of inflation moderation in Africa, followed, with some distance, by changes in institutions, natural disasters, trade composition, human capital, and external debt. With an OOB  $R^2$  of 2.8%, the overall result is also negative.

These results are broadly robust against choices of outcome variables. Robustness checks using the standard deviation and IQR of per-capita growth and inflation and alternative per-capita growth and inflation series from the World Bank are provided in Appendix D.

## 6 Summary and Conclusion

Macroeconomic data for the past 30 years (1990-2019) show a large, broad-based, and persistent improvement in macroeconomic conditions in African economies, characterized by less volatile real per capita growth and CPI inflation rates, alongside higher average growth and lower inflation levels. The improvement in macroeconomic conditions is such that, apart from inflation, where the ROW median was at  $\sim 2\%$  in 2010-2019 vs.  $\sim 4\%$  in Africa, the median African country has caught up with ROW. The bulk of this "Great African Moderation" took place between 1995 and 2012, during which macroeconomic conditions improved  $\sim 2$  times more rapidly in Africa than in ROW. A particularly large stabilization occurred in African LICs. Disaggregated analysis at the country and sector level reveals that the majority of countries have experienced large declines in the volatility of agricultural VA, and sizeable declines in the volatility of services VA. In parallel, there were more heterogeneous developments in the industrial sector, where several countries like Ghana or Tunisia incurred increases in volatility.

At the regional level, Eastern and Northern Africa experienced the greatest decline in agricultural volatility. This was accompanied, in Eastern Africa, by sizeable declines in services and industrial volatility, while Northern Africa experienced an increase in industrial volatility and a small reduction in services (Table C10). Western and Southern Africa experienced smaller improvements in agriculture and services stability, but both also incurred slight increases in industrial volatility. Overall, Eastern Africa region shows the most remarkable macroeconomic stabilization and is on par with North Africa in terms of macroeconomic stability. The relatively weaker stabilization of Western Africa is an interesting avenue for further research.<sup>17</sup>

Sectoral decompositions of the change in aggregate per-capita growth volatility show that 60-70% is accounted for by changes in the volatility of agriculture and services VA, and around 30% can be explained by changes in the covariance structure of production, with all 3 broad sectors becoming less complimentary to each other. Classical structural change accounts for  $\sim 5\%$  of the aggregate output moderation and works via VA shifting to the less volatile service sector. This is a small effect, but, as noted by Stock & Watson (2002), a large and stable services sector can have stabilizing effects on other sectors through income and demand channels, so the contribution of more broadly conceived structural change may be larger. This also invites further research.

The second part of this paper investigated changes in the external environment, financial deepening, domestic macroeconomic policies, and structural factors. Results suggest that growth and moderation in Africa were likely benefited by lower levels of domestic and external debt, higher FDI and remittance inflows, and improved terms of trade (ToT). Externally induced volatility, such as volatility of the exchange rate, ToT, the merchandise trade balance, FDI, and remittances, also decreased over the period. A gradual deepening of the financial sector, as evidenced by higher levels of reserves held by the central bank as well as by commercial banks, more domestic credit to the private sector and broad money as a share of GDP, and an increase of gross national savings by 4-5% of GDP, likely also played a role.

In terms of macroeconomic policies, several countries stabilized the exchange rate through a crawling peg, such that (crawling) pegs constituted more than 80% of African arrangements in

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<sup>17</sup>This may be associated with specific factors worthwhile investigating, such as larger effects of climate change on agricultural production, greater volatility in crop prices, or greater political instability in the region.

2019, from 25% crawling bands and nearly 20% freely falling (i.e. very volatile) arrangements in 1990. Exchange rate volatility is the most important correlate of inflation volatility in Africa and has more than halved since 1990 (Figure C19). Macroprudential policy, while potentially effective for reducing volatility, shows no aggregate trend since 1998, except within certain financial markets such as bonds and commercial credits. Another potentially important development was the adoption of fiscal rules by a significant number of African countries from 1997 onwards. The adoption of such rules, particularly budget balance and debt rules, has a large and statistically significant negative relationship with macroeconomic volatility. Inflation-targeting monetary policy, on the other hand, has only been adopted by 4 African countries at a time when inflation was already low and is thus an insignificant contributor to the African Moderation.

Examining a broad set of 'structural' characteristics shows that these factors can explain around 30% of the cross-sectional variation of growth volatility between African countries from 1990-2019. The quality of institutions appears to be the most important factor affecting structural per-capita growth volatility, followed by the intensity of financial flows, the characteristics of the financial sector, trade intensity, and composition. The business environment, natural resource extraction, and disaster and conflict incidence were also found to be important. Inflation volatility is heavily influenced by exchange rate volatility, conflict, and the institutional and business environment. This suggests that stabilizing the exchange rate and maintaining a strong institutional environment are important to keeping inflation low. The prediction of differences in volatility over the period with changes in these factors yields that the African Moderation cannot be predicted by them. The results nevertheless suggest a role of financial depth and human capital development for growth stabilization and exchange rate management for inflation stabilization.

Overall, the paper succeeds to a greater extent in showing what did *not* cause the African Moderation; that is, it was not, at large, a byproduct of classical structural change, not caused by reduced volatility in the industrial sector (e.g. via improved inventory management), or by monetary policy shifting to inflation targeting, and also not heavily influenced by other changes in economic structure, diversification, conflict incidence, or institutions. On the positive side, the results provide evidence for a role of changes in the external environment faced by African economies, greater resilience of the financial sector, and macroeconomic policy, particularly exchange rate and fiscal management. The analysis also suggests that improvements in human capital and the business environment played a role, but the evidence presented in this paper is very weak.

These findings provide a basis for further research that investigates in more detail the causes and consequences of macroeconomic moderation in Africa and the role of policy for macroeconomic stabilization. Further significant changes in policies or institutions may have taken place that are not easily measurable. For example, central banks might have become much better over time at targeting macroeconomic aggregates or implementing macroprudential policies. The role of global factors such as US monetary policy, global financial markets, and commodity price volatility for African Moderation could also be investigated in more detail. It is also not clear in which ways improvements in the business environment, as evident in the Doing Business Rankings for Africa and the Logistics Performance Index, interact with broader macroeconomic stabilization and domestic financial deepening.

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## Appendix

The Appendix consists of 4 parts. Part A provides a spectral analysis to examine the qualities of the volatility of the growth rate of a GDP per capita as a proxy for adverse economic volatility. Part B examines GDP composition and volatility from the expenditure side. Part C provides additional tables and figures referred to in the main text of the paper. Part D is provided [separately online](#),<sup>18</sup> and includes a few additional (detailed) tables and figures, and robustness checks for the machine learning analysis of structural factors in Section 5, using alternative outcome measures.

### A. Spectral Analysis

As noted by [Gelb \(1979\)](#), many measures of instability used in economic literature are arbitrary and emphasize volatility at certain frequencies without rigorous justification. [Shumway & Stoffer \(2000\)](#) show that first-differencing amounts to a high-pass filter that gives most weight to volatility at frequencies of 2 years and gradually down weights volatility at lower frequencies. [Gelb \(1979\)](#) suggests considering the full frequency spectrum and devising a weighting scheme emphasizing the relative importance of certain frequencies above others to generate an indicator. This idea is formalized by [Tsui \(1988\)](#), who also shows that various common trend-cycle estimates (including first-differences) can be regarded as special cases of a weighting function  $f(\omega)$  applied to the spectral density. This analysis follows [Tsui \(1988\)](#) and proposes a weighting function based on the empirical relationship of volatility at different frequencies with average growth rates.

In the first step, the spectral density of fluctuations needs to be computed for all country GDP per Capita series, shown in Figure C1 (the IMF series is used). [Gelb \(1979\)](#) notes that in the presence of strong trends, spectral density estimates on the raw series are often highly misleading because no periodic component fits the trend well, so variance from this very low-frequency phenomenon (the trend) "spills over" onto higher frequency components. Therefore all country series are first detrended using a linear trend on the log-level series, i.e. we consider all variation that lets countries depart from growing at a constant rate in per-capita terms. The spectral density can be approximated by the periodogram given by

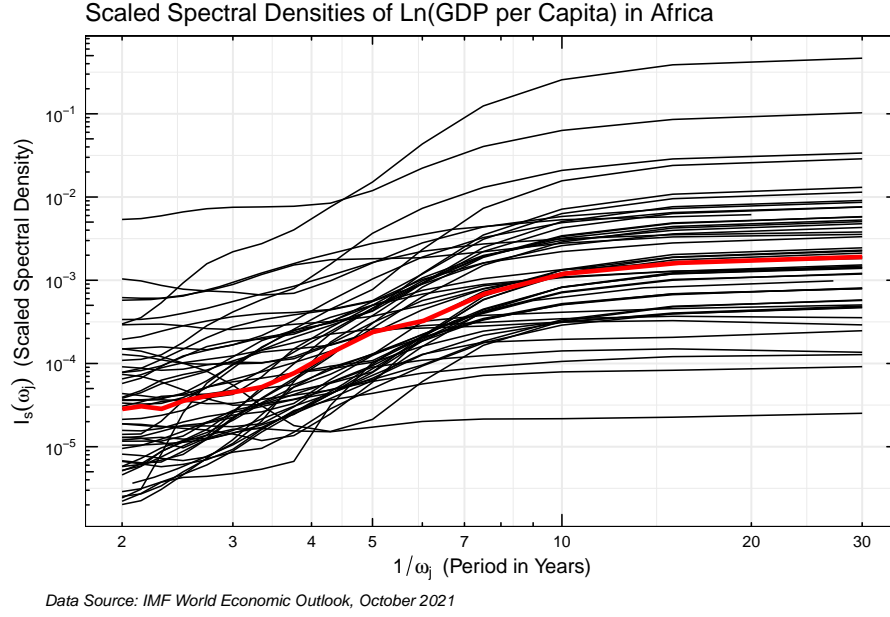
$$I(\omega_j) = |d(\omega_j)|^2 \quad \text{where} \quad d(\omega_j) = \frac{1}{\sqrt{n}} \sum_{t=1}^n x_t e^{-2\pi i \omega_j t} \quad (6)$$

is the complex-valued coefficient of the Discrete Fourier Transform at fundamental frequency  $\omega_j = j/n$  for  $j \in 0, \dots, n-1$  of the series  $x_t$  observed for  $n$  periods. To aid interpretation we consider the scaled periodogram  $I_s(\omega_j) = \frac{4}{n} I(\omega_j)$ , such that the sum of the periodogram ordinates over all frequencies  $\sum_{\omega_j} I_s(\omega_j)$  equals the squared amplitude of the signal  $x_t$ , and furthermore  $\sum_{\omega_j} I_s(\omega_j) = 2 \text{var}(x_t)$ , such that the power of the scaled periodogram at each frequency  $\omega$  can be considered as twice the contribution of that frequency to the overall variance of  $x_t$ .<sup>19</sup> A further issue is that the periodogram is not a consistent estimator of the spectral density. A frequently employed solution is smoothing the periodogram with Daniell smoothers to produce more consistent estimates. Another technique to improve the periodogram as a spectral estimator is tapering, which reduces the effect of frequencies outside the estimated interval. To reach consistent spectral estimates at the country level, I apply a cosine bell taper of 15% and smooth the periodogram with two modified Daniell smoothers of widths 3 and 7 (period-years), which are convolved to produce the final spectral estimates. The scaled densities thus estimated for all countries are shown in Figure A1, where the red line denotes the median across all country spectra.

<sup>18</sup><https://www.dropbox.com/s/57fact7ilsq0upc/Appendix%20D.pdf?dl=0>

<sup>19</sup>It is a property of sine and cosine waves that the squared amplitude equals twice the variance. For details see [Shumway & Stoffer \(2000\)](#).

Figure A1: Estimated Country Spectral Densities and Median Spectral Density



It is evident that the spectra of different countries are quite heterogeneous, with about 3 orders of magnitude lying between the least and most-volatile countries at each frequency, but an overall decrease in spectral power with higher frequencies is common to all countries. The median estimate in Figure A1 shows that on average volatility at low frequencies with periods of 20-years+ is around 2 orders of magnitude larger than year-to-year changes in output (2-year period).

To determine whether volatility at certain frequencies is harmful to growth in African economies, I compute the cross-sectional correlation of the spectral density with median GDP per capita growth in the 1990-2019 period, for each fundamental frequency  $\omega_j$ . Figure A2 reports these correlations in the top half, and the bottom half shows corresponding regression coefficients, which also take into account the differing magnitudes of volatility at different frequencies that Figure A1 made evident.

Figure A2: Correlation of Spectral Density and Median Per-Capita Growth, Africa 1990-2019

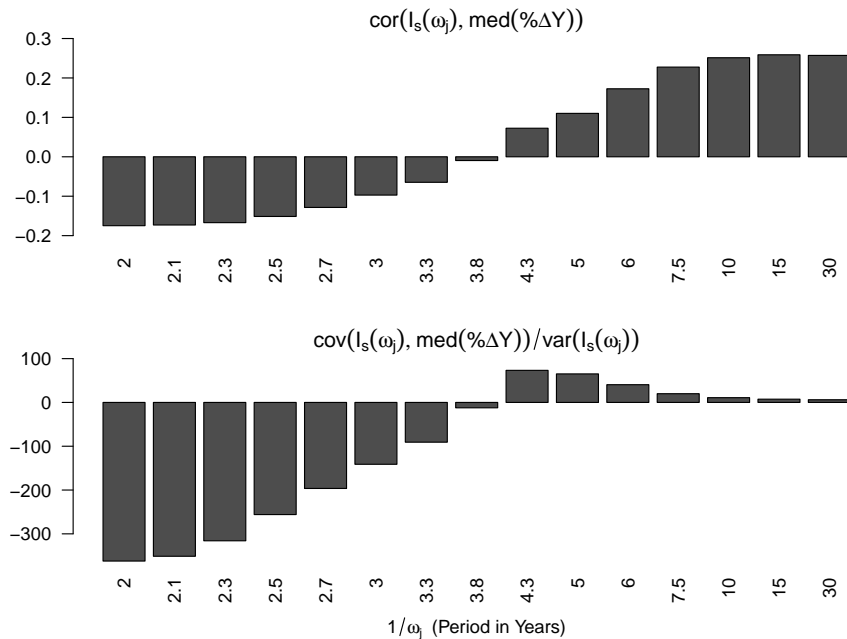


Figure A2 exhibits an astonishingly clear pattern, with a strong negative correlation of about -0.2 between economic growth and volatility at high frequencies of 0.5 (period 2 years), which then gradually tends to zero at frequencies of 0.25 (period 4 years), and turns positive up to about 0.3 for lower frequency variation with 10 to 30-year periods. Thus African data indeed show that short-term volatility with periods of up to 4 years is associated with lower growth, whereas volatility at longer periods is an indication of healthy growth.

This suggests that a high-pass filter like computing the growth rate might do reasonably well to extract fluctuations harmful to growth. I use the regression coefficients in the bottom half of Figure A2 to create an optimal discrete high-pass filter  $f(\omega_j)$  in the spirit of Tsui (1988), that captures volatility harmful for growth. The filter simply consists of the absolute values of all negative regression coefficients on the frequency bands, setting positive coefficients to zero. Multiplying the spectral density estimate for each country with this filter and summing up the weighted spectral ordinates gives the power of the filtered spectrum, which provides a summary statistic of the harmful volatility in each country. Formally, I define a harmful volatility index (HVI) as

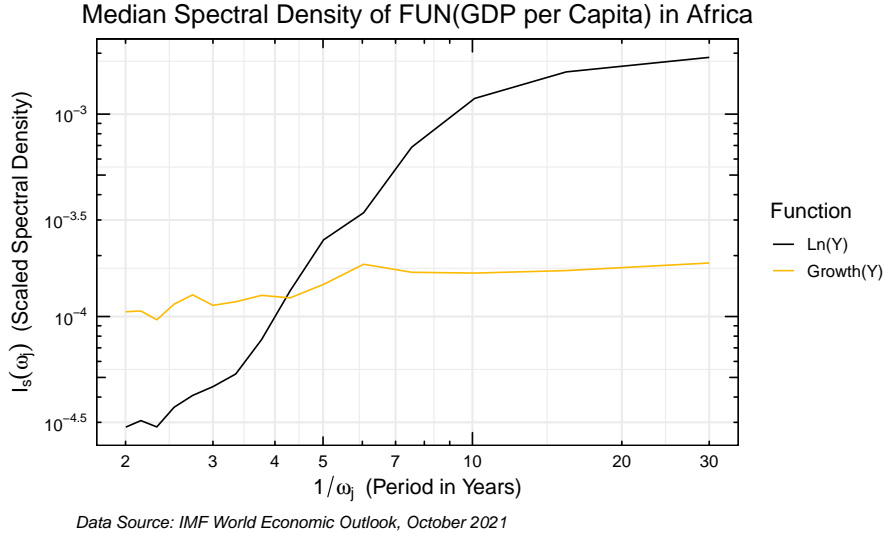
$$\text{HVI} = \sum_j f(\omega_j) \times I_s(\omega_j) \quad \text{where} \quad (7)$$

$$f(\omega_j) = -\beta_{\omega_j} \times 1[\beta_{\omega_j} < 0] \quad \text{and} \quad (8)$$

$$\beta_{\omega_j} = \frac{\text{cov}(I_s(\omega_j), \text{med}(\% \Delta Y))}{\text{var}(I_s(\omega_j))}. \quad (9)$$

Before comparing the HVI to some statistic computed on the growth rate, I wish to determine to what extent computing a growth rate itself resembles the transformation induced by applying  $f(\omega_j)$  to the data. Figure A3 shows that computing the growth rate indeed works like a high-pass filter that, relative to the natural log baseline, accentuates volatility at periods lower than 4.2 years and dampens volatility at higher periods.

Figure A3: Spectral Densities of Growth Rate and Natural Log of GDP per Capita



Dividing the growth spectrum by the log spectrum yields the discrete filter that, if multiplied with the log spectrum, yields the same effect as computing a growth rate (i.e. differencing the log-level series) in the time domain. I call this derived first-difference filter  $f^\Delta(\omega_j)$ . To compare  $f^\Delta(\omega_j)$  to the optimal empirical filter  $f(\omega_j)$  based on regressions against median per capita growth, I scale both filters so that the weights/coefficients on all frequencies  $\omega_j$  sum to 1. Figure A4 shows the outcome.

Figure A4: First-Difference Filter and Regression-Based Filter

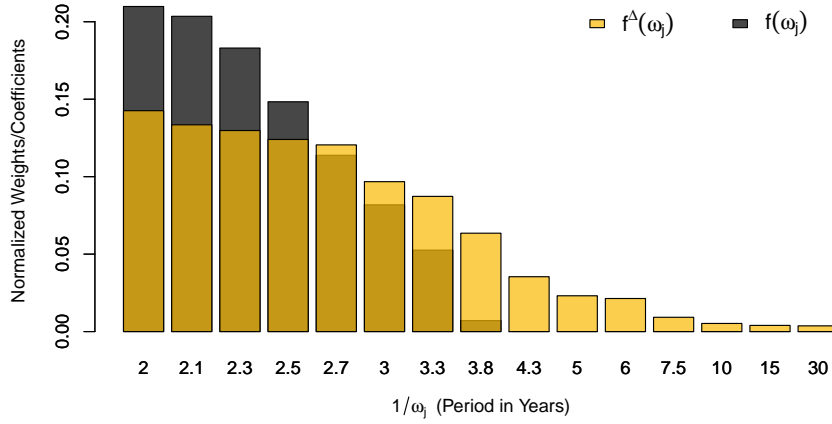
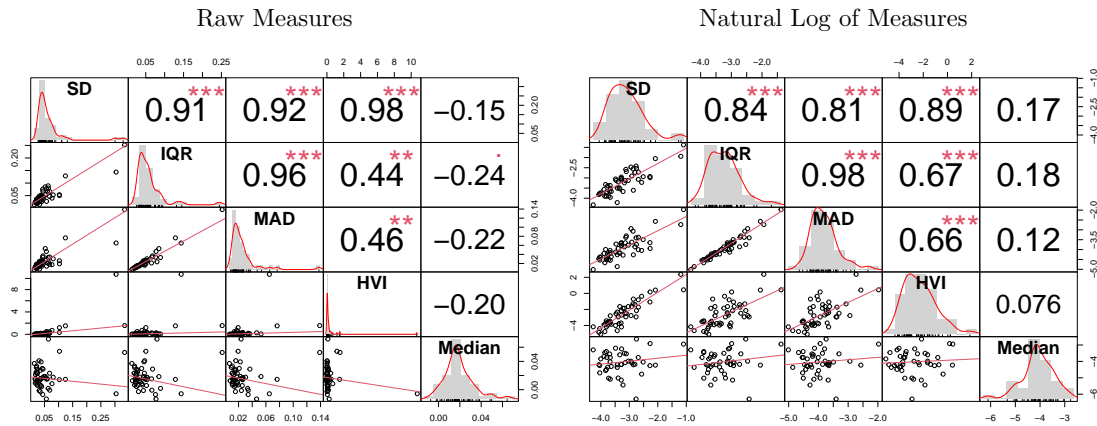


Figure A4 indicates that the first-difference filter  $f^\Delta(\omega_j)$  broadly resembles the optimal empirical filter  $f(\omega_j)$  for extracting volatility harmful to growth. Compared to the latter, first-differencing provides a smoother transformation of the data, that puts less weight on high-frequency volatility, but therefore keeps some of the low-frequency volatility as well. Since finding an optimal filter  $f(\omega_j)$  to extract harmful economic volatility is likely always going to be a complex empirical task, and the resulting filter is prone to be highly dependent on the data and methodology used to estimate it, a simpler methodology such as computing first-differences and then applying some statistic to summarise the volatility in the differenced series is preferable to ensure the transparency and reproducibility of research. Below I consider the 3 summary statistics used in this paper: the standard deviation (SD), interquartile range (IQR), and median absolute deviation (MAD) of the growth rate of GDP per capita, and compare them to the HVI index (Eq. 7) and median per capita growth, computed for each African country using data from 1990 through 2019. The data are correlated, and a regression line is fit, using a robust MM estimator following Yohai (1987) and Koller & Stahel (2011), with a high breakdown point of 0.5, ensuring that outliers don't influence the estimates. Figure A5 shows charts including these robust fits, a robust correlation coefficient derived from the fit, and empirical volatility distributions estimated by a histogram and a gaussian kernel density.

Figure A5: Volatility Measures and Median GDP per Capita of 51 African Economies, 1990-2019



The left side of Figure A5 shows that the HVI is positively correlated with all 3 volatility measures derived from the growth rate, particularly with the SD. All volatility measures are also negatively correlated with the median growth rate. Since a few countries such as Libya, Guinea-Bissau, Eritrea, and Rwanda have very high levels of volatility (due to conflicts during this period), the empirical volatility distributions are right-skewed. As indicated on the left side, the negative

correlation of the IQR and MAD of growth with median growth is stronger compared to the HVI and the SD, which may be the effect of outliers having a stronger effect on the SD and HVI.<sup>20</sup> The right side of Figure A5 therefore also shows a version of the chart where the natural log was applied to all measures. This gives nicer scatterplots and density estimates but also lets the relationship between volatility and median growth turn positive (albeit insignificant), for all measures apart from the HVI where the correlation is zero. This change in the sign of correlations is explicable as some of the countries affected by conflict in 1990-2019, such as Rwanda and Guinea-Bissau, also experienced high average growth throughout this period, and may exert a stronger influence on the MM estimates after taking the log.

To conclude, the discussions in this section highlighted that when dealing with a difficult-to-measure phenomenon such as economic volatility, three things are important: precise measurement of (harmful) volatility, robustness against outliers, and a simple, reproducible, and data-independent methodology. This paper endorsed robust statistics such as the IQR and the MAD, computed on the growth rate of the series, to measure economic volatility. The analysis conducted in this section shows that computing the growth rate provides a decent approximation to an optimal empirical filter, applied to the spectral density to extract volatility harmful to economic development in Africa and that computing the IQR or MAD of the growth rate provides an acceptable and robust summary measure of this volatility, comparable to the power of the optimally filtered spectrum (the HVI). The IQR and MAD of the growth rate thus sufficiently meet the joint aims of precision, robustness, and simplicity. At the country level, the MAD is preferred to the IQR as it is more robust.

## References

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<sup>20</sup>The Fast Fourier Transform underlying the smooth spectral estimates used to produce the HVI is not robust against outliers.



## B. A Brief Look at Expenditure on GDP

Figure B1 provides a detailed breakdown of expenditure shares in GDP, averaged across countries. CINV denotes changes in inventories, SD are statistical deviations, and exports (X) and imports (M) are provided alongside net exports (NX). CINV is very small in the median African country.

Figure B1: GDP Shares: Expenditure Side

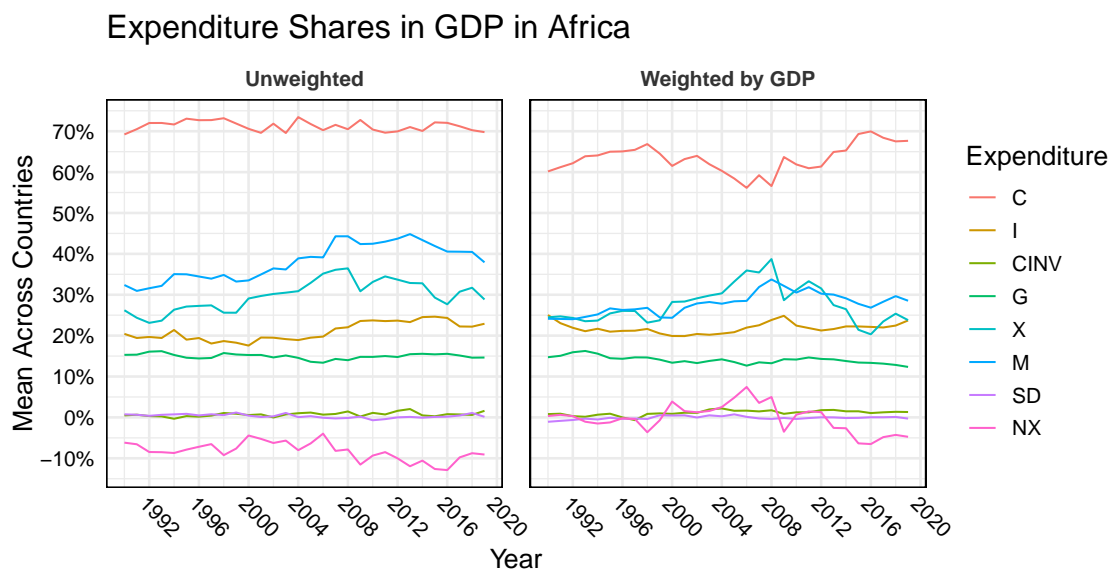
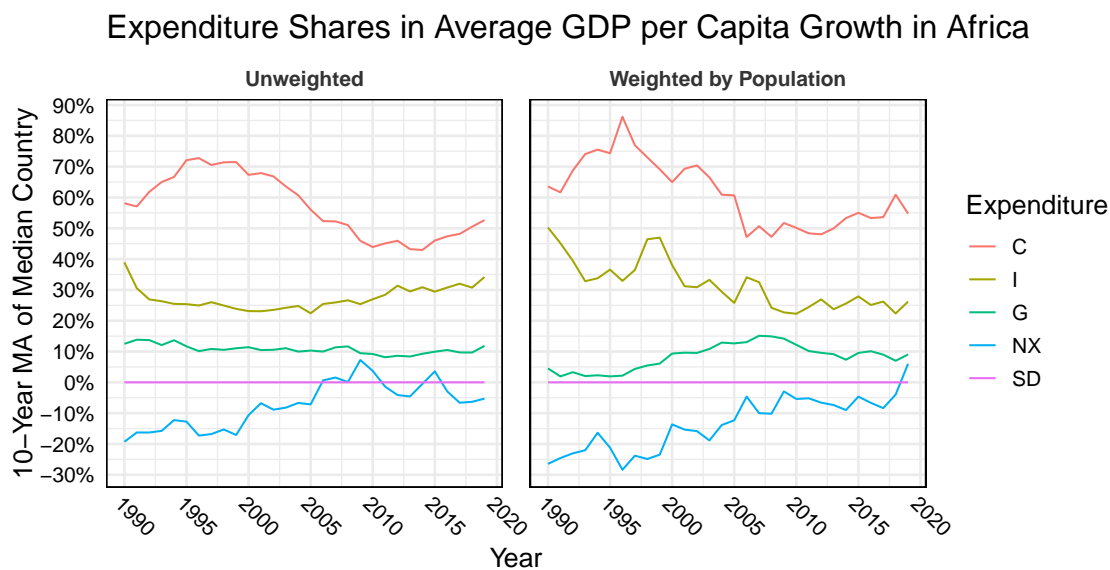


Figure B2 shows smoothed contributions of major expenditure components to GDP per capita growth, analogous to Figure C11 on the production side. It is evident that consumption growth declined in importance until around 2013 and increased a bit again thereafter.

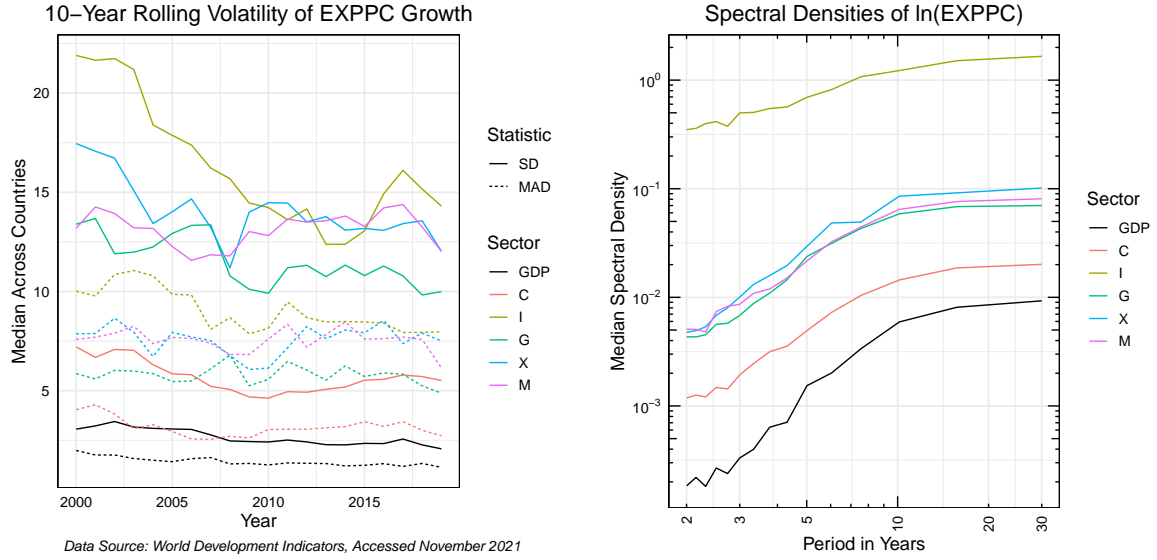
Figure B2: Contributions to GDP Growth: Expenditure Side



Overall the shares are relatively stable. Investment has increased slightly, climbing from ~ 20% in 2005 to ~ 25% in 2012. Exports and imports also both increased gradually until 2012 and then began to fall, with a greater decline in the export share, yielding a higher aggregate trade deficit.

The left panel of Figure B3 shows the aggregate decline in volatility, which, on the expenditure side, is accounted for by declines in the volatility of all components before 2010, with the volatility of trade and investment remaining high thereafter. Particularly investment volatility (which includes CINV in this disaggregation), declined strongly. The right panel of Figure B3 shows that from a frequency domain perspective, investment is the most volatile component at all frequencies (exempting net exports). Consumption is the least volatile component and approaches the volatility of GDP at lower frequencies.

Figure B3: Expenditure Volatility Across Time and Frequency



Notes: The LHS shows 10-year rolling SDs and MADs of the growth rate of GDP per capita at constant 2015 prices and its expenditure components ( $GDP = C + I + G + X - M$ ). For the RHS see the note to Figure 3 and Appendix A.

Table B1 provides a covariance matrix analogous to Table C6. This shows large negative covariances of imports with absorption and exports, indicating the endogeneity of net exports and the difficulties to account aggregate changes in volatility from the expenditure side. Linking production and expenditure side data is also difficult without detailed breakdowns, but the large declines in agriculture and service sector volatility are likely reflected on the expenditure side in the decline in consumption volatility, but also in declining volatility of the merchandise trade balance.

Table B1: Expenditure Volatility and Contribution to Aggregate Volatility, 1990-2019

Data	Sector:	C	I	G	X	M	C	I	G	X	M
GDP Share ( $\bar{\theta}_k$ )		0.701	0.227	0.152	0.336	-0.416	0.698	0.220	0.149	0.338	-0.406
	Cov.:	Classical					Robust (SDE)				
Expenditure	C	52.22					33.69				
Growth	I	-0.93	528.25				1.87	272.76			
( $\Delta VA/VA_{t-1}$ )	G	0.57	11.42	229.63			3.79	26.07	114.99		
	X	-7.82	14.84	-5.95	269.80		-14.96	5.14	-7.61	212.40	
	M	-26.78	-92.13	-16.58	-93.44	242.37	-20.57	-120.07	-29.83	-63.39	166.73
Expenditure	C	22.95					18.23				
Contribution	I	0.27	14.43				0.47	11.57			
( $\Delta VA/GDP_{t-1}$ )	G	0.12	0.56	3.41			-0.05	0.47	2.15		
	X	-1.09	0.79	-0.18	14.21		-2.02	0.56	-0.08	12.88	
	M	-5.36	-6.73	-0.91	-6.76	22.06	-5.08	-5.54	-1.51	-6.95	16.84

Notes: Since sectoral growth rates can be very volatile, I employ both a classical (Pearson) and robust covariance estimator with a high breakdown point (0.5) based on [Stahel \(1981\)](#) and [Donoho \(1982\)](#). The choice of methods was informed by [Maronna et al. \(2018\)](#) and available implementations in various R packages. The Stahel-Donoho robust covariance estimator is implemented by the package *rrcov* ([Todorov & Filzmoser, 2009](#)). Covariance terms are aggregated across countries using the median, whereas sectoral shares are aggregated with the mean. Average shares for each country are computed using all but the first observation following Eq. 3. The shares reported above "Robust" are computed by taking the median share for each country, and aggregating across countries using the mean.

Table B2 shows a decomposition of the reduction in GDP volatility between  $\tau_1 = 1990-2004$  and  $\tau_2 = 2005-2019$ , based on the LHS of Eq. 3, analogous to Table B2 in the paper. Due

to the difficulty with exports accounting, I only report results where shares are computed at the country-level and aggregated across countries using the median. The results imply that the expenditure-side shares in the moderation are roughly consistent with their share in aggregate volatility, reported in Table B1, with consumption, investments and exports having a higher than proportional share, consistent with Figure B3. The results are quite noisy through, even when aggregated across countries using the median; for example the sign of the covariance contribution from the expenditure side is not robust to the choice of covariance estimator.

Table B2: Sectoral Contribution to Moderation in GDP Volatility

CovEst	AggFun	Fit	$\Delta var(\% \Delta Y)_\tau$	C	I	G	X	M	$\sum cov_{jk}$
Pearson	Median	100%	-6.65	48%	16%	3.8%	7.3%	11%	16%
Comedian	Median	55%	-1.14	73%	32%	5.1%	27%	12%	-35%

*Notes:* The 'Fit' column signifies how closely Eq. 3 is satisfied. Columns C-M give the sectoral contribution to the aggregate volatility reduction in percentage terms, and  $\sum cov_{jk}$  gives the combined contribution of all covariance terms. Shares are computed at the country-level, and aggregated using the median.

## C. Additional Tables and Figures

Figure C1: Log10 GDP per Capita for 54 African Economies in Constant USD, 1990-2019

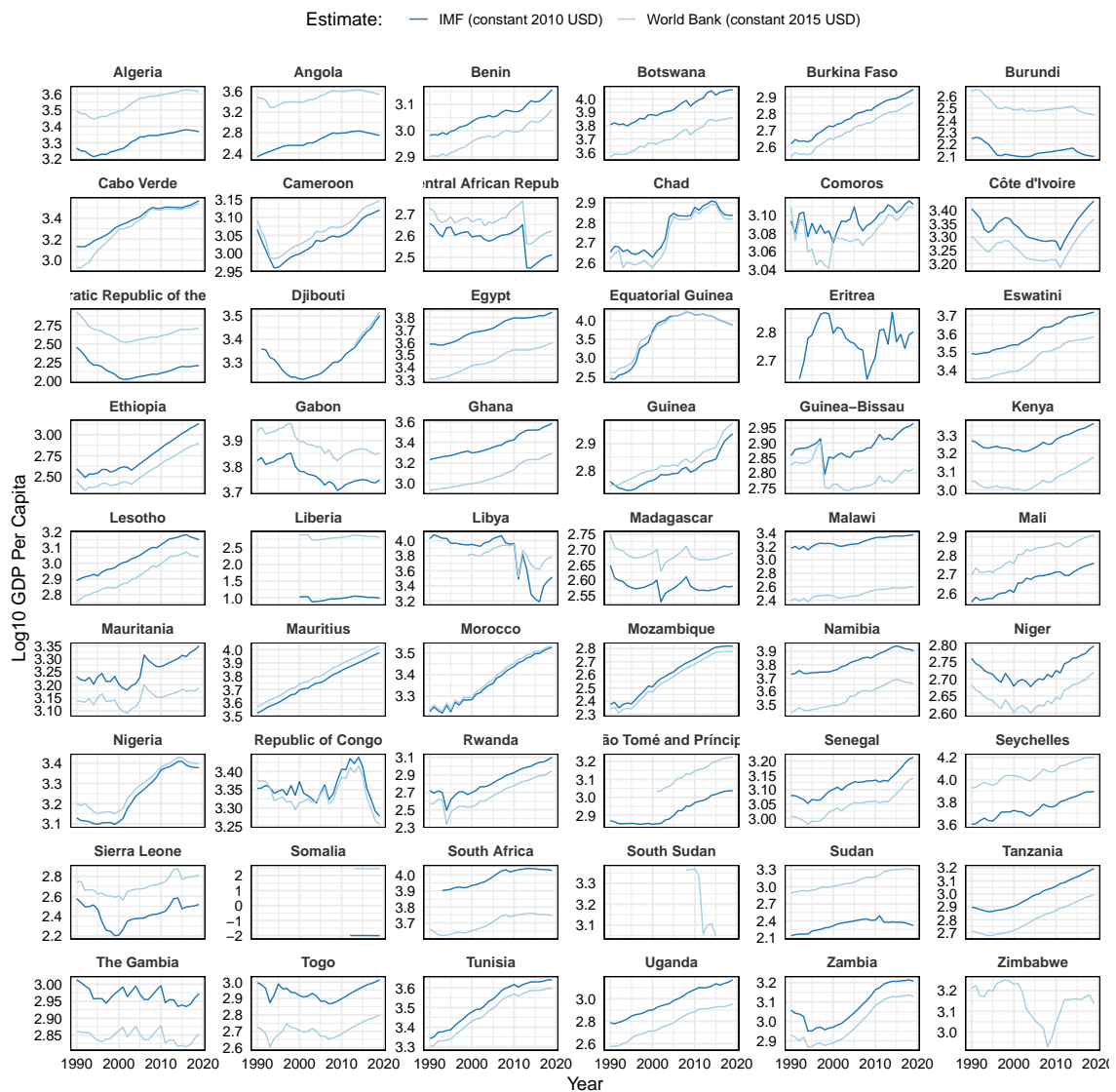
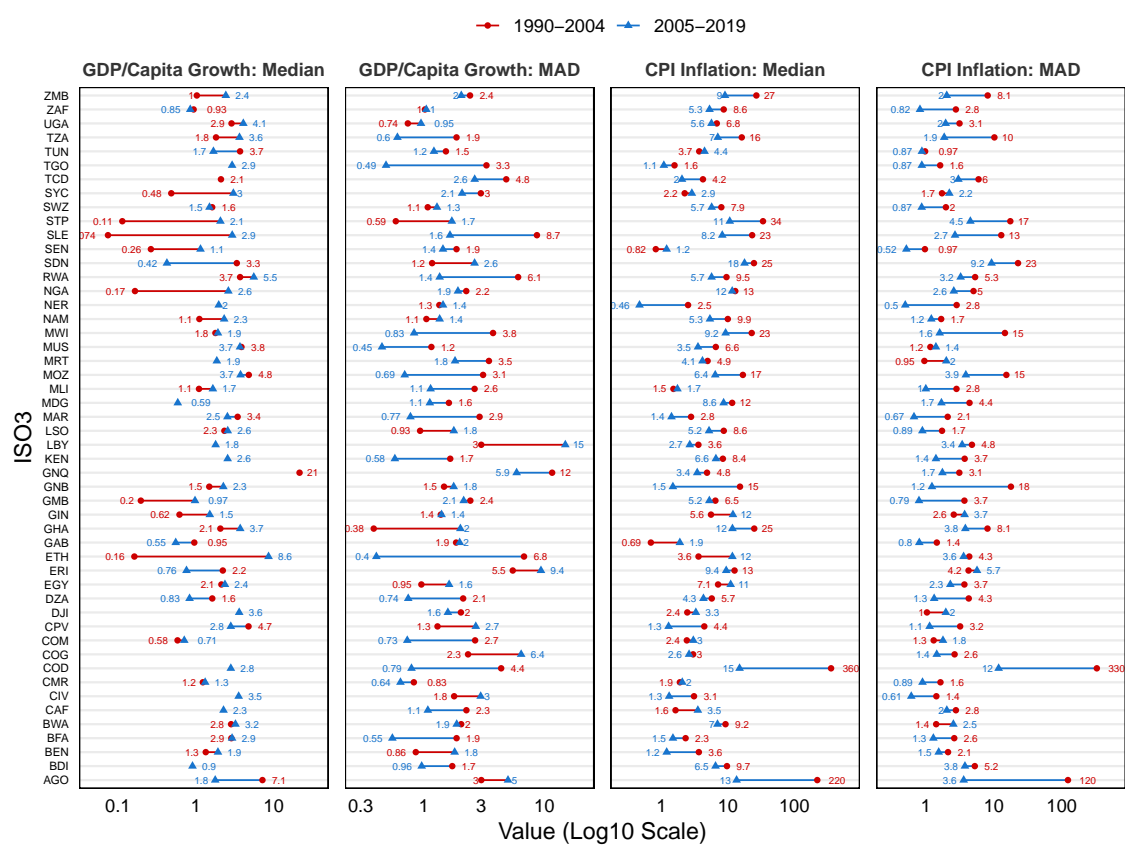


Table C1: Aggregate Volatility of 51 African Countries: 1990-2019

ISO3	Country	Income	GDP Per Capita Growth			CPI Inflation		
			Median	MAD	IQR	Median	MAD	IQR
DZA	Algeria	Upper middle	1.124	1.197	2.359	4.642	1.740	4.925
AGO	Angola	Lower middle	1.851	5.291	8.479	30.269	22.229	190.916
BEN	Benin	Low	1.422	1.246	2.320	2.140	1.766	3.978
BWA	Botswana	Upper middle	3.006	2.100	3.908	8.067	2.109	3.876
BFA	Burkina Faso	Low	2.883	1.476	2.601	1.804	2.025	3.812
BDI	Burundi	Low	-0.274	1.547	3.068	8.294	4.474	8.363
CPV	Cabo Verde	Lower middle	4.092	1.609	4.714	2.944	2.050	4.551
CMR	Cameroon	Lower middle	1.271	0.774	1.481	2.022	0.987	1.988
CAF	Central Afr. Rep.	Low	0.843	1.753	3.991	2.782	1.993	3.787
TCD	Chad	Low	-0.071	3.422	6.621	3.930	4.615	6.987
COM	Comoros	Lower middle	0.618	1.576	2.925	2.704	1.683	3.214
CIV	Côte d'Ivoire	Lower middle	-0.691	3.404	7.570	2.298	1.523	3.067
COD	Dem. Rep. o. Congo	Low	0.185	3.322	8.901	27.230	25.014	326.361
DJI	Djibouti	Lower middle	1.520	2.586	4.819	2.629	1.366	2.887
EGY	Egypt	Lower middle	2.133	1.258	2.389	9.727	3.186	5.367
GNQ	Equatorial Guinea	Upper middle	5.262	13.878	25.209	4.380	2.134	4.118
ERI	Eritrea	Low	1.457	7.647	12.841	10.288	5.501	10.631
SWZ	Eswatini	Lower middle	1.506	1.146	2.197	7.469	1.818	3.302
ETH	Ethiopia	Low	7.154	2.375	7.976	9.024	5.614	11.314
GAB	Gabon	Upper middle	0.664	1.940	4.110	1.448	1.220	2.249
GHA	Ghana	Lower middle	2.333	1.063	1.915	15.291	4.902	13.191
GIN	Guinea	Low	1.345	1.280	2.548	9.592	5.204	11.816
GNB	Guinea-Bissau	Low	1.493	1.402	2.710	3.277	3.886	13.204
KEN	Kenya	Lower middle	1.292	1.464	3.397	7.324	2.230	6.072
LSO	Lesotho	Lower middle	2.326	1.100	2.503	7.043	2.010	3.880
LBY	Libya	Upper middle	-0.577	6.512	14.369	3.122	3.704	7.868
MDG	Madagascar	Low	0.433	1.383	2.551	9.100	2.824	5.332
MWI	Malawi	Low	1.863	2.294	4.394	10.460	2.828	15.386
MLI	Mali	Low	1.493	1.412	3.018	1.563	2.617	5.526
MRT	Mauritania	Lower middle	1.682	2.670	5.467	4.715	1.547	2.772
MUS	Mauritius	Upper middle	3.702	0.666	1.326	5.164	1.936	3.644
MAR	Morocco	Lower middle	2.743	1.542	2.917	1.576	0.939	2.312
MOZ	Mozambique	Low	3.935	2.257	4.526	12.531	8.445	13.257
NAM	Namibia	Upper middle	1.782	1.756	3.442	6.727	2.590	4.673
NER	Niger	Low	-0.120	2.424	4.382	0.952	1.821	2.887
NGA	Nigeria	Lower middle	1.521	2.463	4.909	11.837	3.253	5.849
COG	Republic of Congo	Lower middle	-1.317	4.648	7.723	2.790	1.860	3.586
RWA	Rwanda	Low	5.427	1.942	5.033	6.374	3.907	7.907
SEN	Senegal	Lower middle	1.053	1.842	3.601	1.082	0.894	1.857
SYC	Seychelles	High	2.909	3.665	6.798	2.630	1.846	3.433
SLE	Sierra Leone	Low	1.415	2.604	5.344	13.312	7.259	16.186
ZAF	South Africa	Upper middle	0.911	1.079	2.289	5.980	1.368	3.713
SDN	Sudan	Lower middle	2.325	1.822	4.635	20.161	13.356	38.351
STP	São Tomé & Príncipe	Lower middle	0.658	1.103	2.032	13.830	6.478	23.908
TZA	Tanzania	Low	3.143	0.939	2.023	7.561	3.312	10.897
GMB	The Gambia	Low	0.585	2.546	5.186	5.306	1.743	2.736
TGO	Togo	Low	1.532	2.112	6.524	1.348	1.226	3.446
TUN	Tunisia	Lower middle	2.490	1.505	2.825	4.092	1.104	2.029
UGA	Uganda	Low	3.340	1.094	2.025	5.970	2.446	7.148
ZMB	Zambia	Lower middle	1.696	2.585	4.367	18.147	9.063	17.567
ZWE	Zimbabwe	Lower middle	-0.840	4.289	10.358	0.641	5.470	12.797

Notes: Excluding Liberia, Somalia, and South Sudan. Data Source: IMF WEO October 2021.

Figure C2: The Great Moderation by Country: 50 African Countries

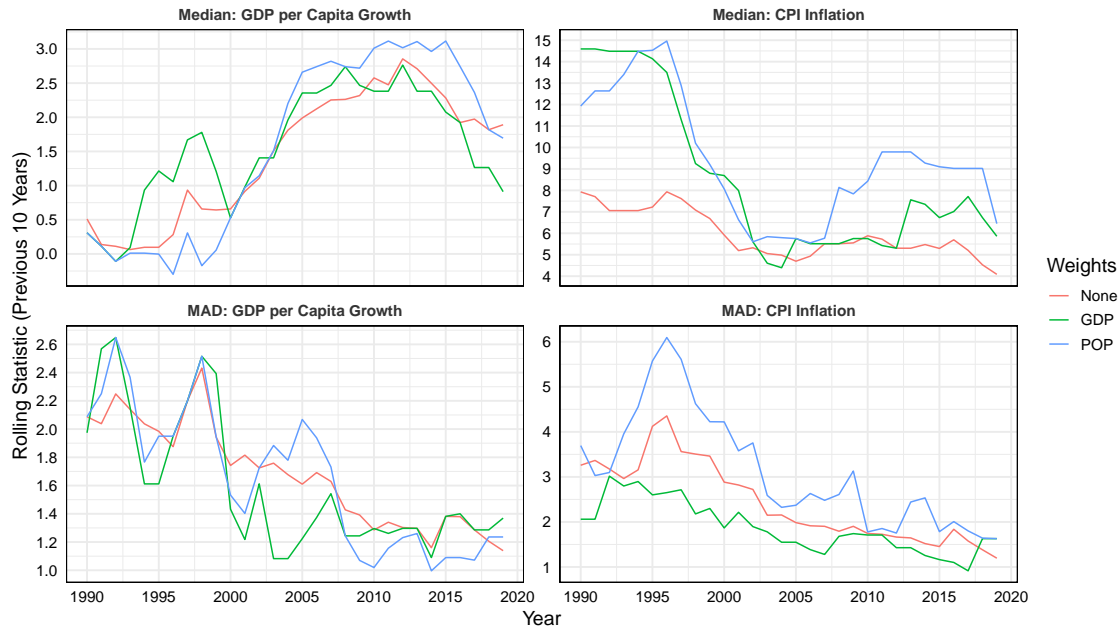




## Section 2: Aggregate Relationships and Trends

Figure C3: Volatility in Africa Over Time

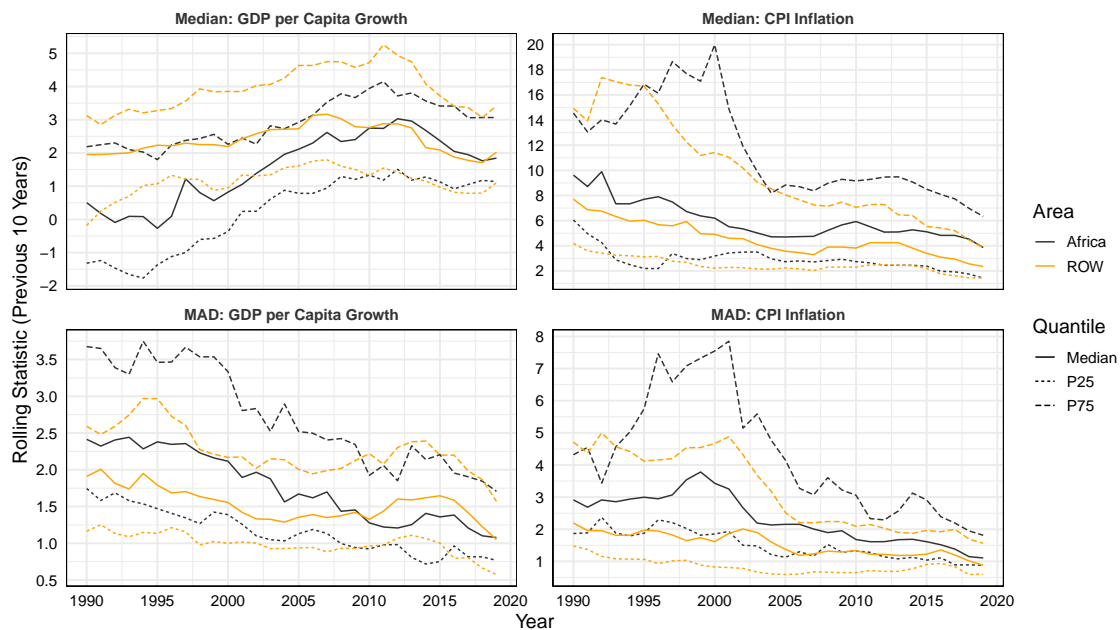
GDP per Capita Growth and CPI Inflation, 10-Year Rolling Statistics, 1990–2019



Data Source: IMF World Economic Outlook, October 2021

Figure C4: Figure 1 with World Bank WDI Data

GDP per Capita Growth and CPI Inflation, 10-Year Rolling Statistics, 1990–2019

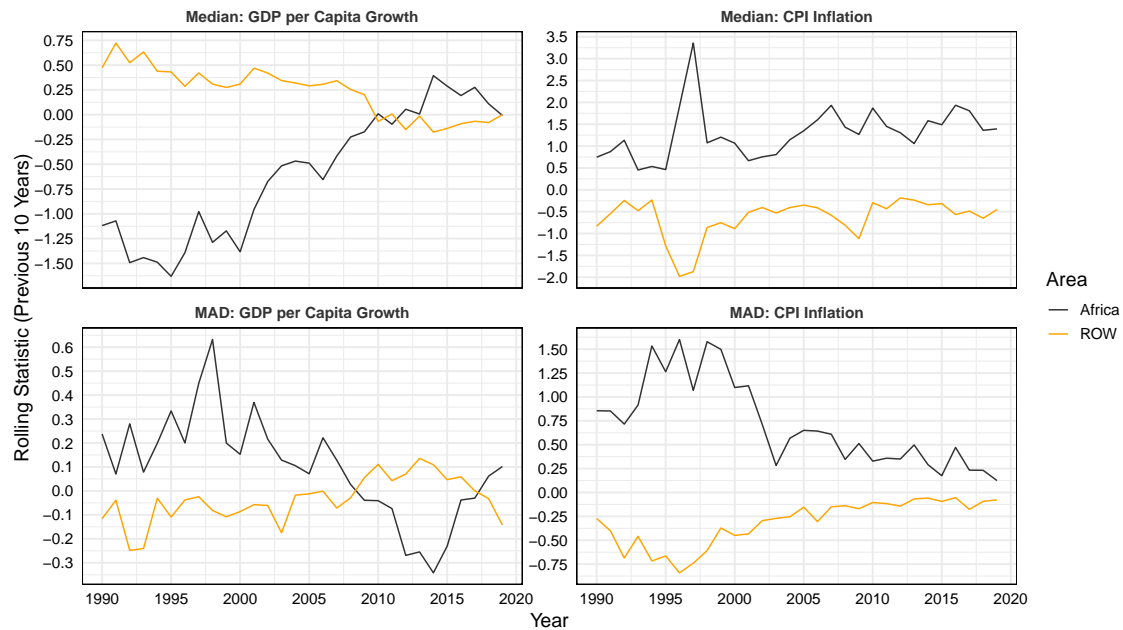


Data Source: World Development Indicators, Accessed November 2021

Figure C5: Figure 1 with Time-Medians Subtracted from Rolling Statistics

IMF WEO Data

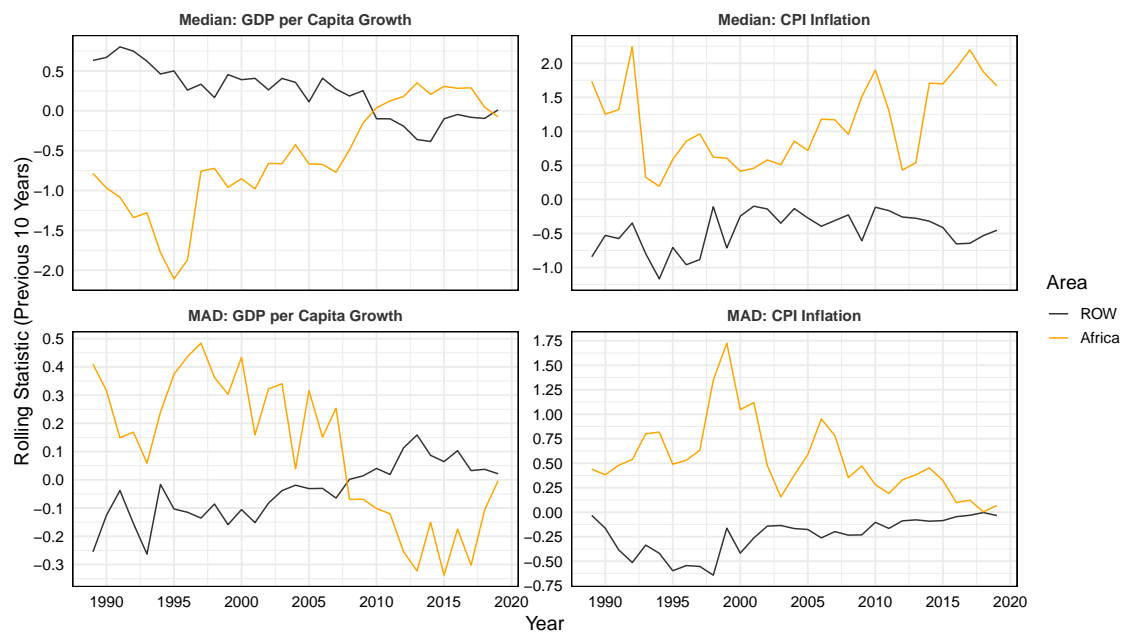
GDP per Capita Growth and CPI Inflation, 10-Year Rolling Statistics, 1990–2019



Data Source: IMF World Economic Outlook, October 2021

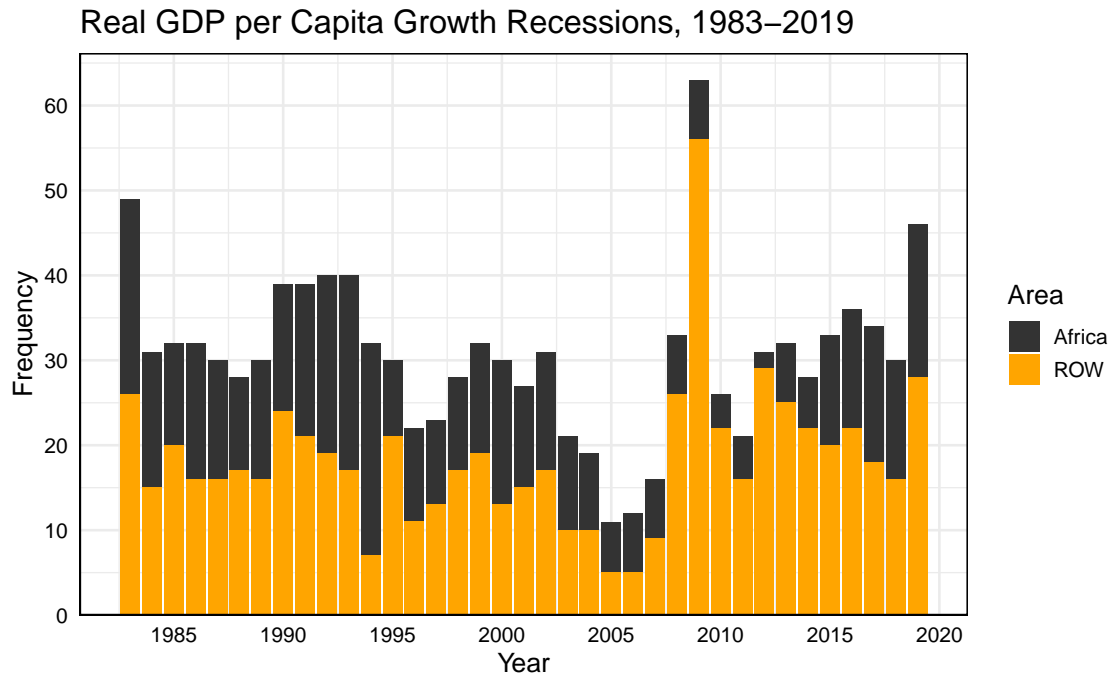
World Bank WDI Data

GDP per Capita Growth and CPI Inflation, 10-Year Rolling Statistics, 1990–2019



Source: World Development Indicators, 2021

Figure C6: Growth Recessions Following [Syed et al. \(2017\)](#)



Data Source: IMF World Economic Outlook, October 2021

Figure C7: AR1 Analysis à la [Blanchard & Simon \(2001\)](#) with World Bank Data

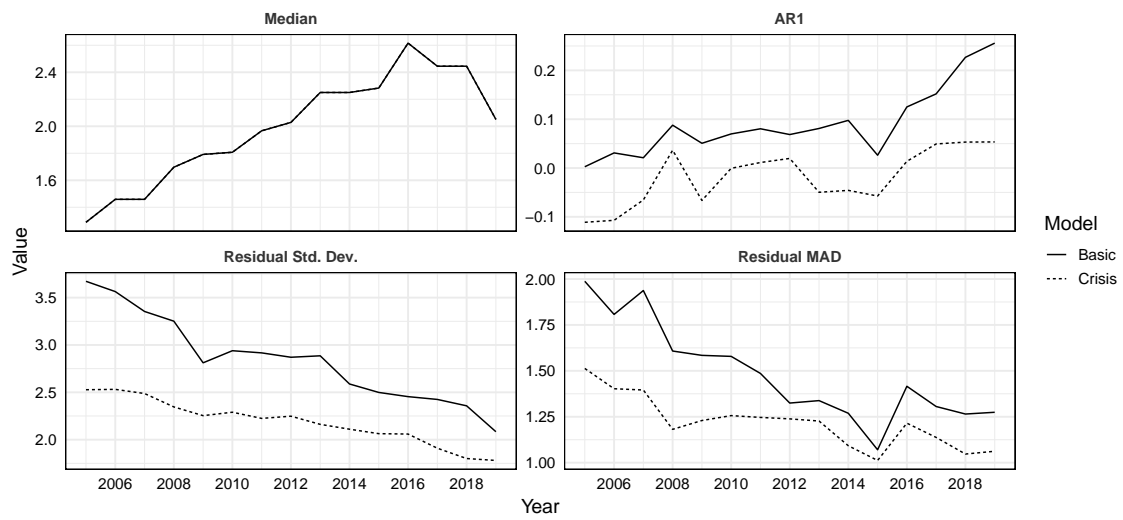


Table C2: Real Per Capita Growth and Inflation Performance in Africa, 1990-2019

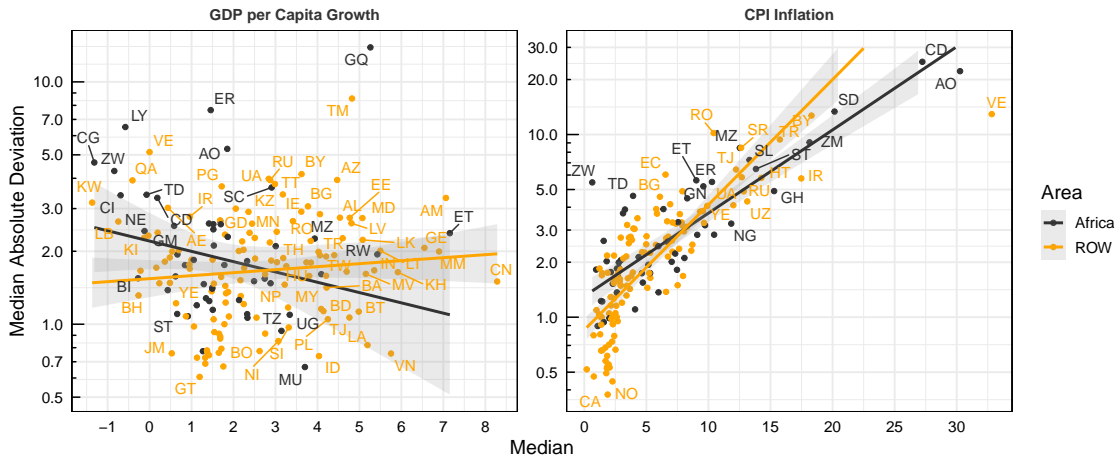
Area	Per Capita Growth				Inflation		
	N	Median	MAD	IQR	Median	MAD	IQR
<b>Africa</b>	<b>51</b>	<b>1.506</b>	<b>1.822</b>	<b>3.991</b>	<b>5.306</b>	<b>2.230</b>	<b>4.925</b>
Low income	21	1.457	1.942	4.382	6.374	3.312	7.907
Lower middle income	21	1.521	1.609	3.601	4.715	2.010	3.880
Upper middle income	8	1.453	1.848	3.675	4.903	2.023	3.997
High income (SYC)	1	2.909	3.665	6.798	2.630	1.846	3.433
<b>ROW</b>	<b>124</b>	<b>2.370</b>	<b>1.724</b>	<b>3.532</b>	<b>3.549</b>	<b>1.754</b>	<b>4.318</b>
Low income	5	2.755	1.172	2.642	12.007	4.102	10.610
Lower middle income	24	2.985	1.654	3.085	6.996	2.733	5.856
Upper middle income	43	2.752	2.173	4.207	5.015	2.581	6.057
High income	52	1.758	1.616	3.178	2.285	1.024	2.112

*Data Source:* IMF WEO, October 2021. Real GDP per capita growth is calculated using the constant national currency series (NGDPRPC), and inflation is based on average national consumer price indices (PCPIPCH).

*Notes:* Statistics are calculated at the country-level, and aggregated across countries using the median. Countries with < 20 obs. for growth or inflation in 1990-2019 were excluded - in Africa Liberia, Somalia and South Sudan.

Figure C8: Empirical Relationship Between Levels and Volatilities

Real GDP per Capita Growth and CPI Inflation, 1990–2019



*Data Source:* IMF World Economic Outlook, October 2021

Table C3: Output and Inflation Volatility

Area	N	GDP/Capita			Inflation		
		$\beta$	$P(\beta \neq 0)$	$R^2$	$\beta$	$P(\beta \neq 0)$	$R^2$
<b>Africa</b>	<b>51</b>	<b>-0.187</b>	<b>0.035</b>	<b>0.083</b>	<b>0.375</b>	<b>&lt;0.001</b>	<b>0.596</b>
Low income	21	-0.048	0.596	0.016	0.396	<0.001	0.608
Lower middle income	21	-0.569	0.002	0.389	0.252	<0.001	0.810
Upper middle income	8	-0.837	0.130	0.370	0.058	0.689	0.026
<b>ROW</b>	<b>124</b>	<b>0.043</b>	<b>0.322</b>	<b>0.008</b>	<b>0.361</b>	<b>&lt;0.001</b>	<b>0.820</b>
Low income	5	-0.076	0.228	0.444	0.365	0.246	0.427
Lower middle income	24	-0.105	0.341	0.041	0.252	<0.001	0.632
Upper middle income	43	0.068	0.343	0.022	0.383	<0.001	0.800
High income	52	0.125	0.055	0.066	0.427	<0.001	0.478

*Data Source:* IMF WEO, October 2021. See also footnote to Table C2.

*Note:* A regression of the medians on the MADs of the country-series is run using a robust MM estimator following Koller & Stahl (2011). Available in R package *robustbase* (Maechler et al., 2021).

Figure C9: Empirical Relationship Between Levels and Volatilities in Africa

Whole Period: 1990-2019

Half-Period Difference: 2005-19 – 1990-04

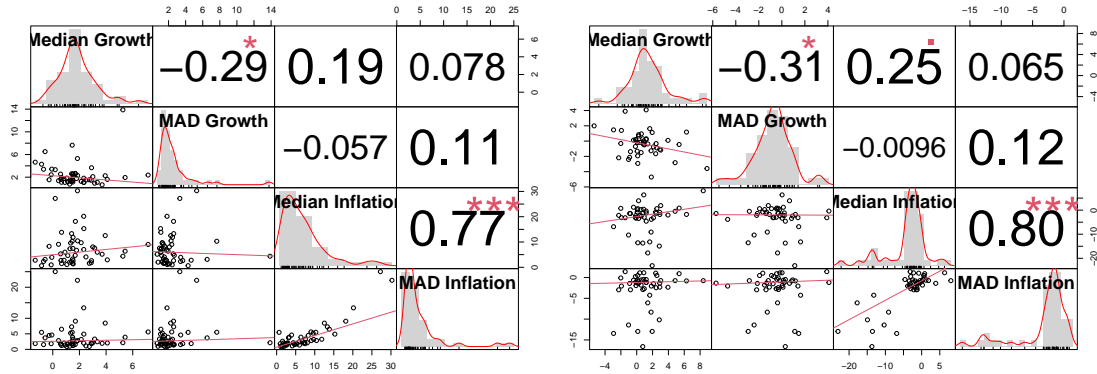


Table C4: Variation (MAD) Between Countries Over Time by Income Group

Area	Period	N	Per Capita Growth			Inflation		
			Median	MAD	IQR	Median	MAD	IQR
Africa	1990-04	50	1.166	0.834	2.122	3.868	1.568	3.272
	2005-19	50	0.806	0.586	0.986	3.175	0.876	1.590
Low income	1990-04	21	1.119	1.049	2.069	4.783	1.612	3.024
	2005-19	21	0.742	0.427	0.549	3.639	1.051	2.983
Lower middle income	1990-04	20	1.342	0.670	1.605	3.405	1.340	2.359
	2005-19	20	0.564	0.492	1.138	3.457	0.733	1.313
Upper middle income	1990-04	8	0.948	0.845	1.402	2.522	0.843	0.950
	2005-19	8	0.878	0.719	1.997	1.307	0.465	0.669
ROW	1990-04	118	1.141	0.585	1.233	3.245	1.245	2.792
	2005-19	119	1.144	0.683	1.235	1.375	0.511	1.074
Low income	1990-04	4	0.691	0.675	1.137	5.708	2.747	16.987
	2005-19	4	1.941	0.551	0.849	1.244	1.212	2.249
Lower middle income	1990-04	23	1.247	0.401	1.043	2.105	2.237	4.146
	2005-19	23	1.921	0.426	1.203	1.421	0.581	1.188
Upper middle income	1990-04	39	1.382	0.783	1.708	5.367	2.796	10.957
	2005-19	40	1.535	0.618	0.986	1.642	0.580	1.269
High income	1990-04	52	0.866	0.402	0.928	0.869	0.386	0.735
	2005-19	52	0.914	0.613	1.344	0.530	0.329	0.617

Data Source: IMF WEO, October 2021. Real GDP per capita growth is calculated using the constant national currency series (NGDPRPC), and inflation is based on average national consumer price indices (PCPIPCH).

Notes: Statistics calculated at country-level and aggregated across countries using the MAD. Countries with < 9 obs. for growth or inflation in 1990-04 or 2005-19 were excluded, in Africa Liberia, Somalia, South Sudan, and Zimbabwe.

Table C5: International Synchronization of Growth/Inflation Rates: World Bank Data

Period	Per Capita Growth				Inflation			
	Africa	ROW	World	Corr	Africa	ROW	World	Corr
1990-2004	0.199	0.221	0.202	0.245	0.386	0.404	0.364	0.327
2005-2019	0.252	0.388	0.321	0.275	0.415	0.516	0.476	0.400
Overall (1990-2019)	0.162	0.234	0.191	0.189	0.374	0.395	0.356	0.298

Data Source: IMF WEO, October 2021. See also note to Table 1.

Notes: The numbers under 'Africa', 'ROW' and 'World' are the share of the first eigenvalue in the sum of eigenvalues, computed from a pairwise Pearson's correlation matrix of the country-series. They estimate the share of an international business cycle in the joint variance of the data. The 'Corr' column reports the average absolute correlation between African and ROW countries series and measures alignment between Africa and ROW.

### Section 3: Decomposing Output Volatility

Figure C10: Production side GDP Shares

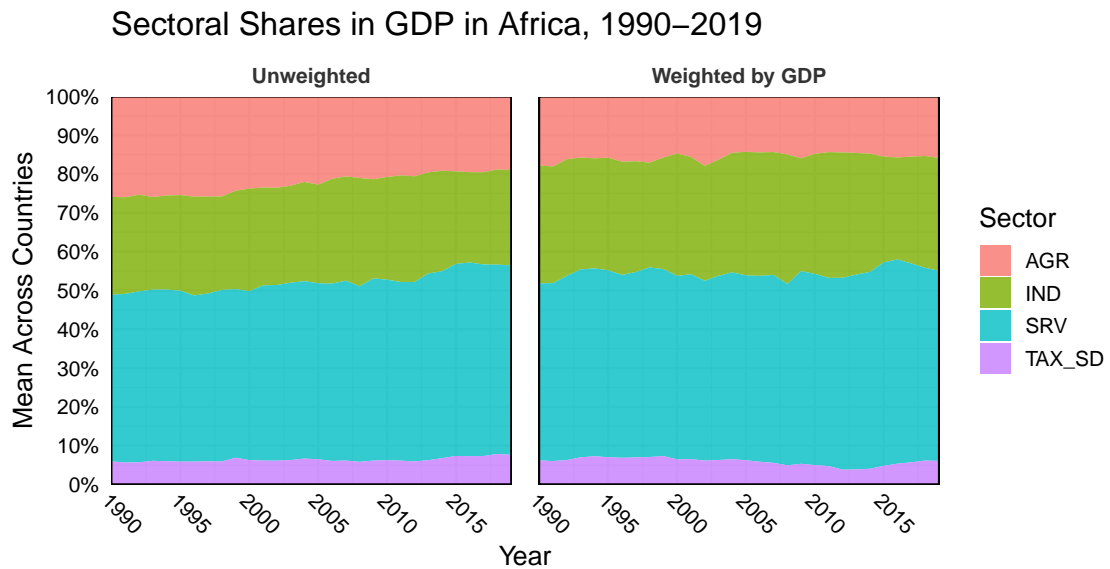


Figure C11: Production side GDP Growth Shares

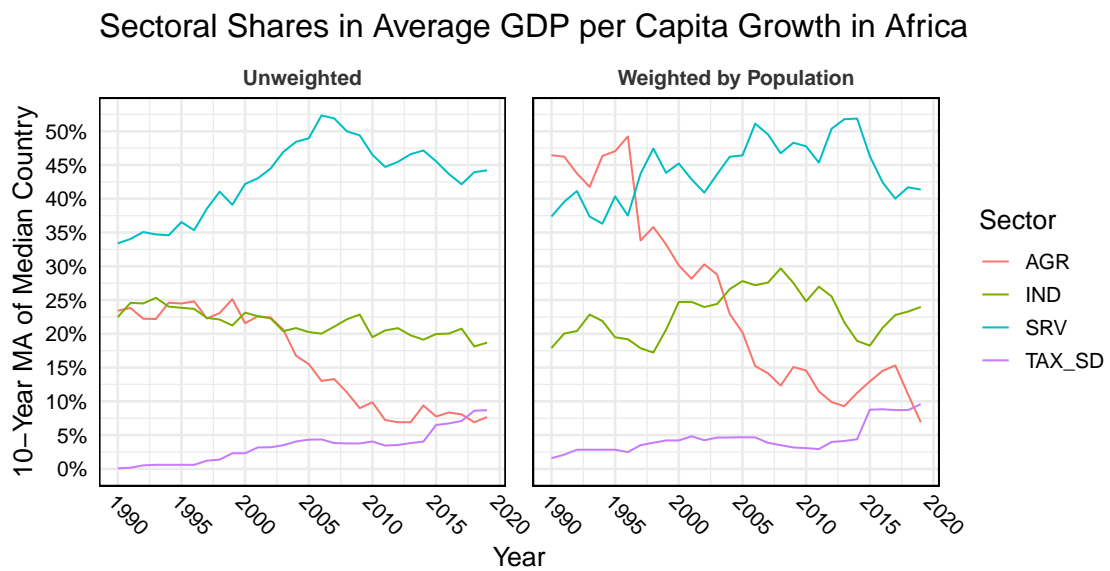




Table C6: Sectoral Volatility and Contribution to Aggregate Volatility, 1990-2019

<i>Data</i>	<i>Sector:</i>	AGR	IND	SRV	AGR	IND	SRV
Sector Share ( $\bar{\theta}_k$ ):		0.232	0.276	0.492	0.226	0.276	0.494
	<i>Covariance:</i>	<b>Classical</b>			<b>Robust (SDE)</b>		
Sector	AGR	126.95			69.01		
Growth	IND	-12.77	124.60		-5.67	64.73	
( $\Delta VA/VA_{t-1}$ )	SRV	-2.64	-9.86	52.93	-1.34	-1.78	25.90
Sector	AGR	6.40			2.14		
Contribution	IND	-0.50	5.79		-0.30	2.85	
( $\Delta VA/GDP_{t-1}$ )	SRV	-0.21	-0.66	8.44	-0.06	-0.38	5.39

*Notes:* Since sectoral growth rates can be very volatile, I employ both a classical (Pearson) and robust covariance estimator with a high breakdown point (0.5) based on [Stahel \(1981\)](#) and [Donoho \(1982\)](#). The choice of methods was informed by [Maronna et al. \(2018\)](#) and available implementations in various R packages. The Stahel-Donoho robust covariance estimator is implemented by the package *rrcov* ([Todorov & Filzmoser, 2009](#)). Covariance terms are aggregated across countries using the median, whereas sectoral shares are aggregated with the mean. Average shares for each country are computed using all but the first observation following Eq. 3. The shares reported above "Robust" are computed by taking the median share for each country, and aggregating across countries using the mean.

Figure C12: Rolling Covariances of Sectoral Growth Rates/Contribution

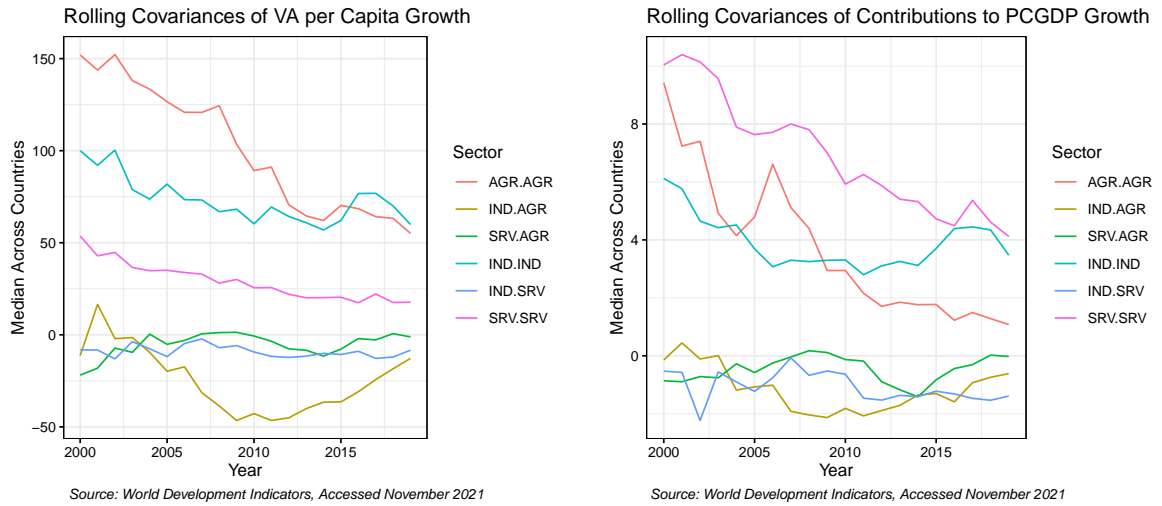


Figure C13: Production side GDP Shares: ETD Data

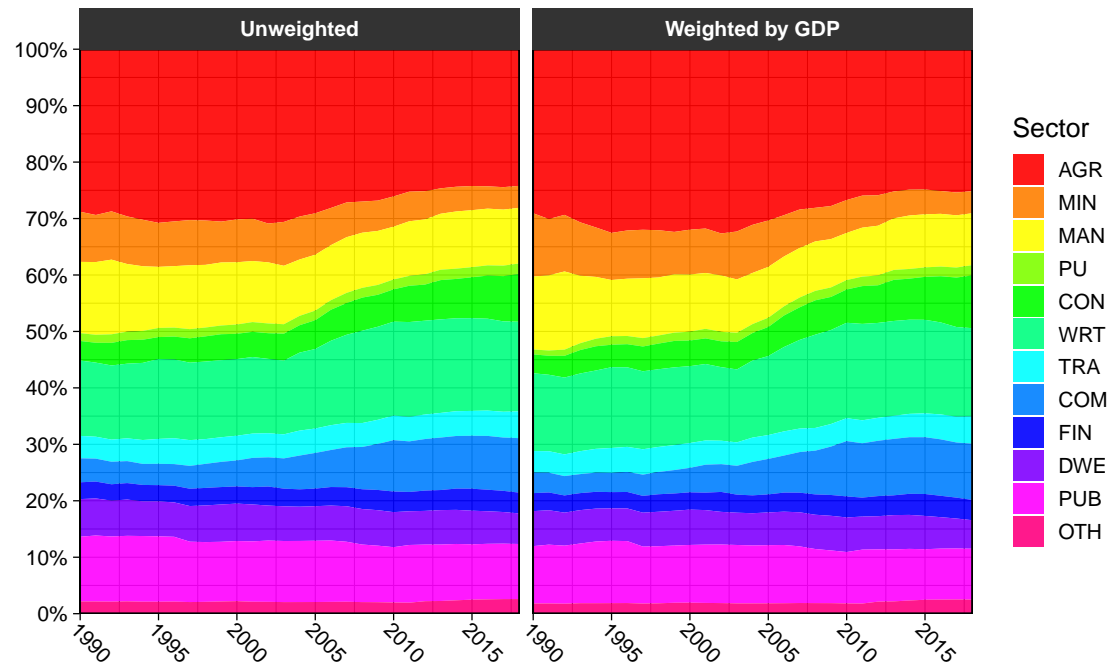


Figure C14: Sector Volatility and Contribution to Aggregate Volatility

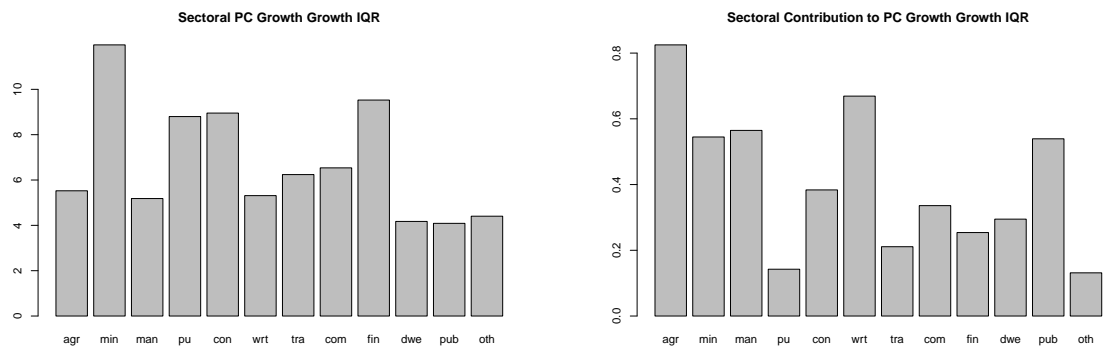


Figure C15: Rolling MADs of Sectoral Growth Rates/Contribution

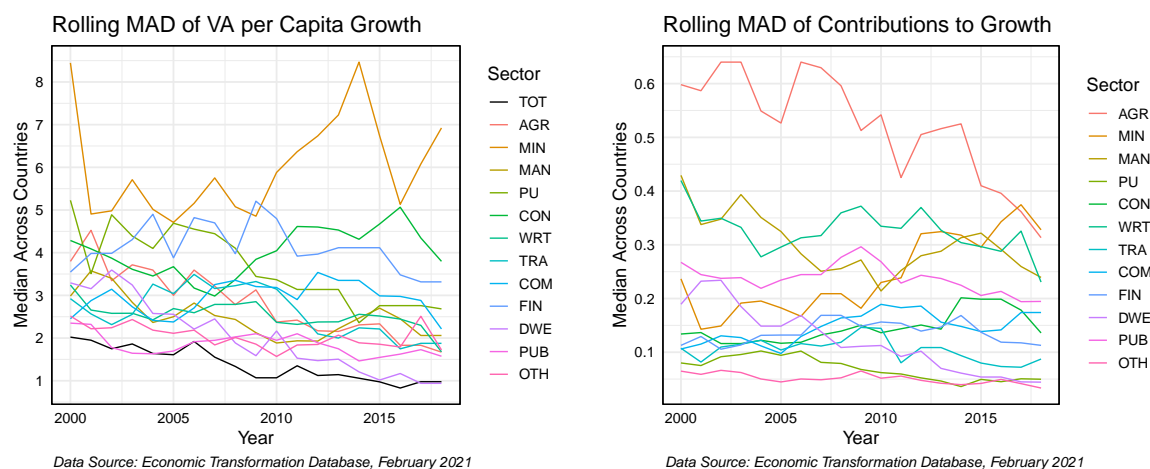


Table C7: Country Classification by Largest Sectoral Volatility

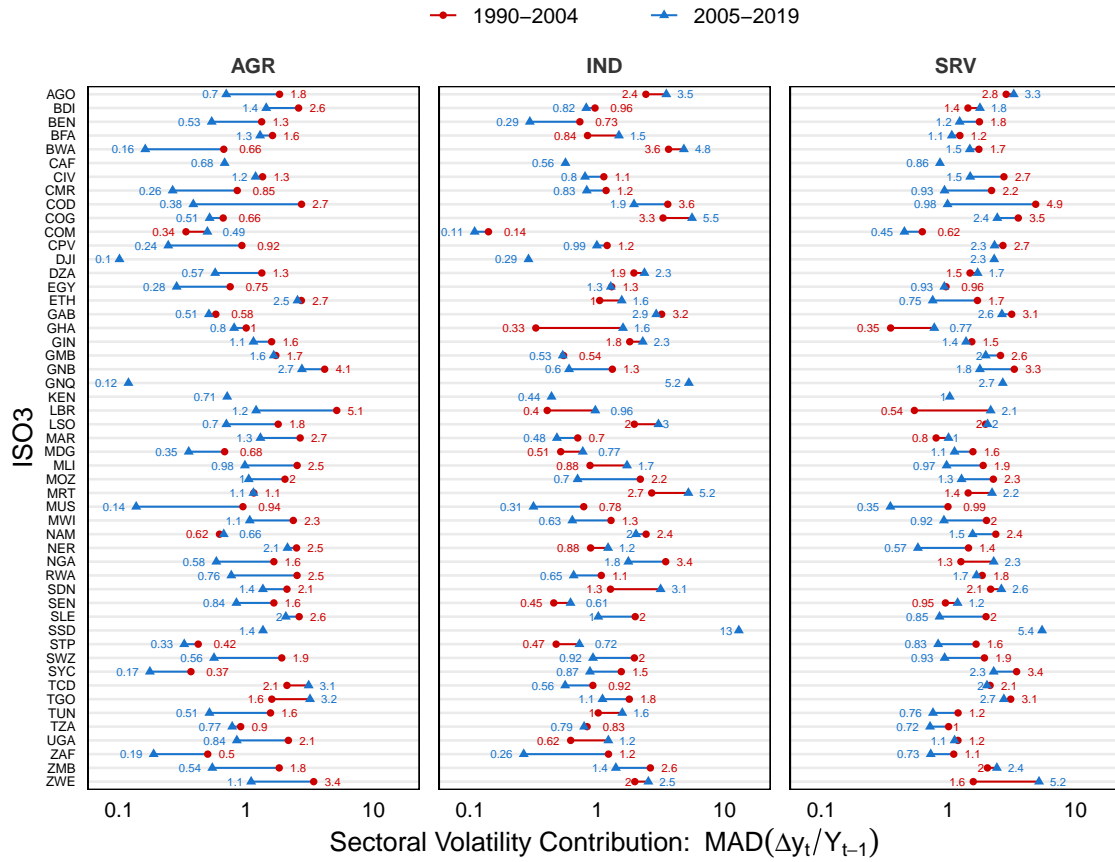
Metric	AGR (13)	IND (17)	SRV (21)
Sectoral Volatility	BDI, BFA, ETH, GNB, LBR, MAR, MLI, NER,	AGO, BWA, COD, COG, DZA, EGY, GAB, GIN, GNQ, LSO,	BEN, CAF, CIV, CMR, COM, CPV, DJI, GHA,
Contribution: MAD( $\Delta y_t/Y_{t-1}$ )	SEN, SLE, TCD, UGA, ZWE	MRT, MUS, NGA, SSD, SWZ, TUN, TZA	GMB, KEN, MDG, MOZ, MWI, NAM, RWA, SDN, STP, SYC, TGO, ZAF, ZMB
Metric	AGR (22)	IND (28)	SRV (1)
Sector Growth Volatility: MAD( $\% \Delta y_t$ )	AGO, BFA, CAF, CMR, COM, CPV, DJI, DZA, GHA, GIN, GMB, GNB, KEN, MAR, MUS, SEN, SWZ, SYC, TUN, ZAF, ZMB, ZWE	BDI, BEN, BWA, CIV, COD, COG, EGY, ETH, GNQ, LBR, LSO, MDG, MLI, MOZ, MRT, MWI, NAM, NER, NGA, RWA, SDN, SLE, SSD, STP, TCD, TGO, TZA, UGA	GAB

Table C8: Aggregate Sectoral Growth Stabilization

Period:	1990-2019			1990-2004			2005-2019		
Sector:	AGR	IND	SRV	AGR	IND	SRV	AGR	IND	SRV
<i>Statistic: Median Across Countries (and Periods)</i>									
MAD( $\Delta y_t/Y_{t-1}$ )	1.06	1.17	1.57	1.63	1.21	1.74	0.71	1.02	1.38
MAD( $\% \Delta y_t$ )	5.69	5.46	3.14	6.56	5.74	3.95	5.05	4.75	2.65
<i>Share of Countries Above the 1990-2019 Cross-Country-Period Median</i>									
MAD( $\Delta y_t/Y_{t-1}$ )	0.57	0.49	0.51	0.61	0.47	0.51	0.33	0.47	0.43
MAD( $\% \Delta y_t$ )	0.47	0.47	0.61	0.49	0.51	0.57	0.45	0.43	0.37

Note: The 1990-2019 statistics are medians across country-level MADs for both the 1990-2004 and 2005-2019 periods. This more accurately reflects the median volatility between these two periods, since country-level MADs calculated over the entire 1990-2019 period are much closer to the 2005-2019 MADs.

Figure C16: Sectoral Volatility Contribution by Country

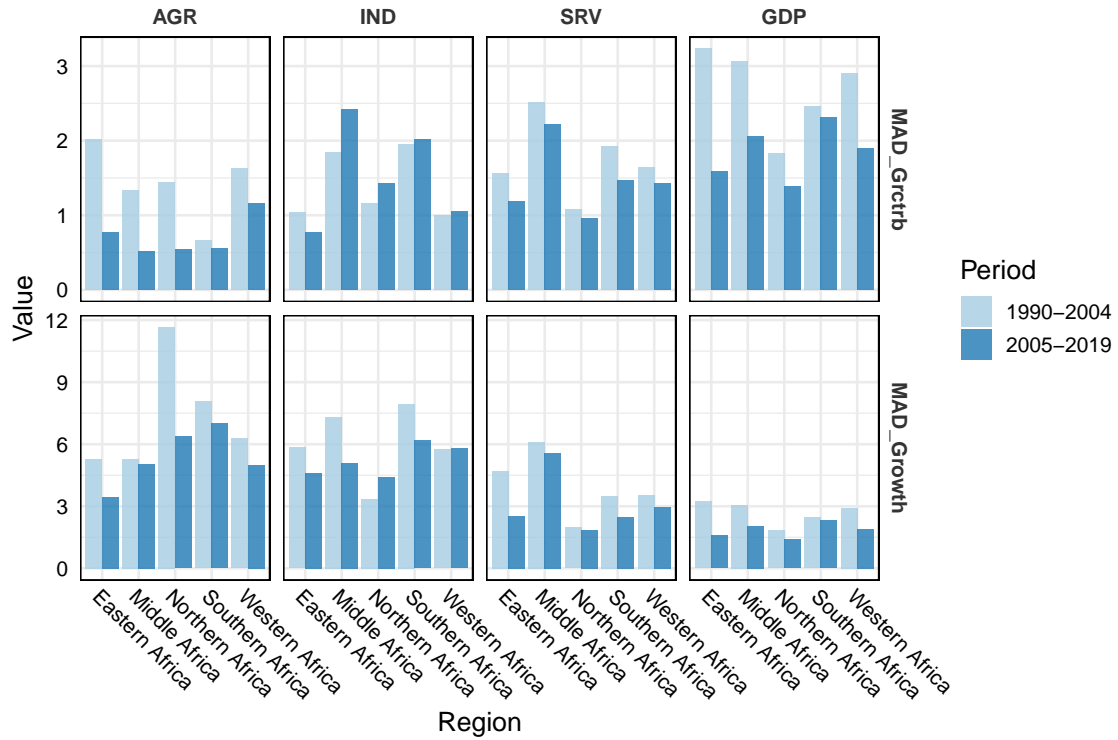


Data Source: World Development Indicators, Accessed November 2021

Table C9: Regions in Africa (51 Countries with Sectoral Data)

Region	Countries ISO3
Eastern Africa	BDI, COM, DJI, ETH, KEN, MDG, MOZ, MUS, MWI, RWA, SSD, SYC, TZA, UGA, ZMB, ZWE
Middle Africa	AGO, CAF, CMR, COD, COG, GAB, GNQ, SDN, STP, TCD
Northern Africa	DZA, EGY, MAR, TUN
Southern Africa	BWA, LSO, NAM, SWZ, ZAF
Western Africa	BEN, BFA, CIV, CPV, GHA, GIN, GMB, GNB, LBR, MLI, MRT, NER, NG, SEN, SLE, TGO

Figure C17: Sectoral Growth Risk by Region



Data Source: World Development Indicators, Accessed November 2021

Table C10: Sectoral Growth Stabilization By Region

Region	Period	N	(1) $MAD(\Delta y_t / Y_{t-1})$			(2) $MAD(\% \Delta y_t)$		
			AGR	IND	SRV	AGR	IND	SRV
Eastern	1990-2004	13	2.01	1.04	1.57	5.28	5.84	4.69
Eastern	2005-2019	16	0.77	0.78	1.19	3.45	4.62	2.54
Middle	1990-2004	8	1.34	1.84	2.51	5.28	7.30	6.12
Middle	2005-2019	10	0.51	2.42	2.21	5.04	5.11	5.57
Northern	1990-2004	4	1.44	1.15	1.07	11.65	3.36	1.98
Northern	2005-2019	4	0.54	1.42	0.96	6.37	4.40	1.85
Southern	1990-2004	5	0.66	1.95	1.92	8.06	7.94	3.50
Southern	2005-2019	5	0.56	2.01	1.47	7.00	6.18	2.48
Western	1990-2004	16	1.63	1.00	1.64	6.28	5.74	3.55
Western	2005-2019	16	1.16	1.06	1.43	5.01	5.80	2.98

Note: Statistics were aggregated across countries using the median.

## Section 4: External, Financial, and Policy Factors

Figure C18: External Environment: Selected Indicators

Terms of Trade, FDI, Remittances and Debt in Africa, 1990–2019

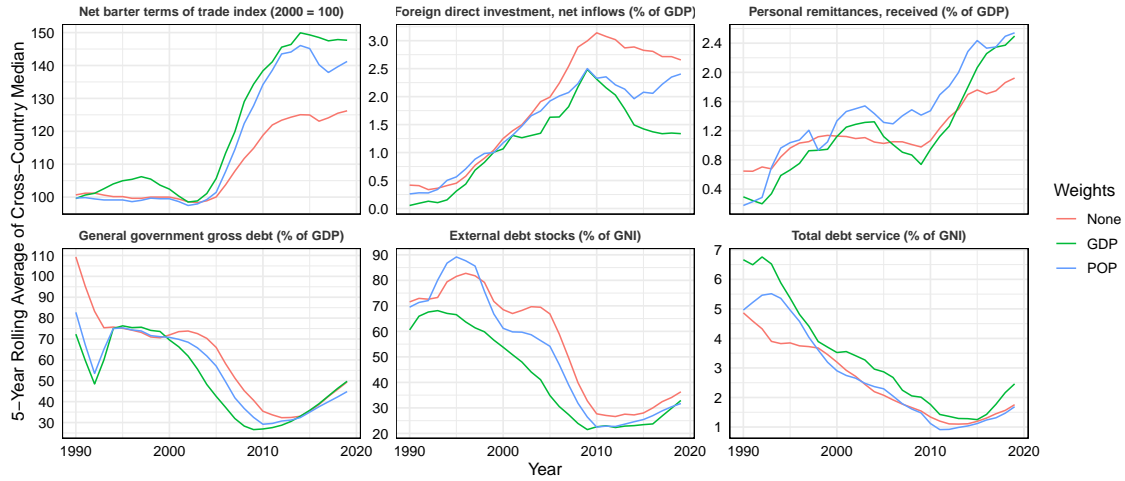


Table C11: Correlations with External Environment Indicators

Mean:	ToT	FDI	REM	GGDT	EDT	EDS
Median PC Growth	.065*	.177*	.053	-.271*	-.208*	-.045
MAD PC Growth	-.116*	-.052	-.074*	.091*	.104*	.039
Median Inflation	-.057*	-.039	-.083*	.117*	.187*	.084*
MAD Inflation	-.077*	-.031	-.017	.098*	.067*	.035

Notes: A 10-year MA with data from 1981 is used to smooth the variables shown in Figure C18 (in % of GDP/GNI terms), and 10-year rolling medians and MADs for per-capita growth and inflation. These rolling series are then standardized within each country, and first-differenced. Pairwise Pearson's correlations are computed on these first differences across all countries. A star denotes significance at the 5% level.

Figure C19: External Environment Volatility: Selected Indicators

Volatility of the Growth Rate of Selected External Variables in Africa, 1990–2019

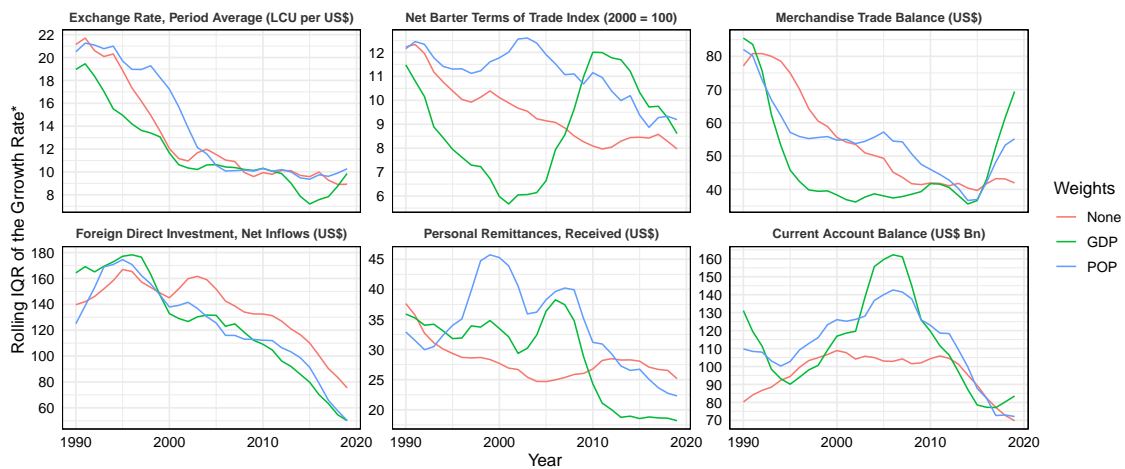


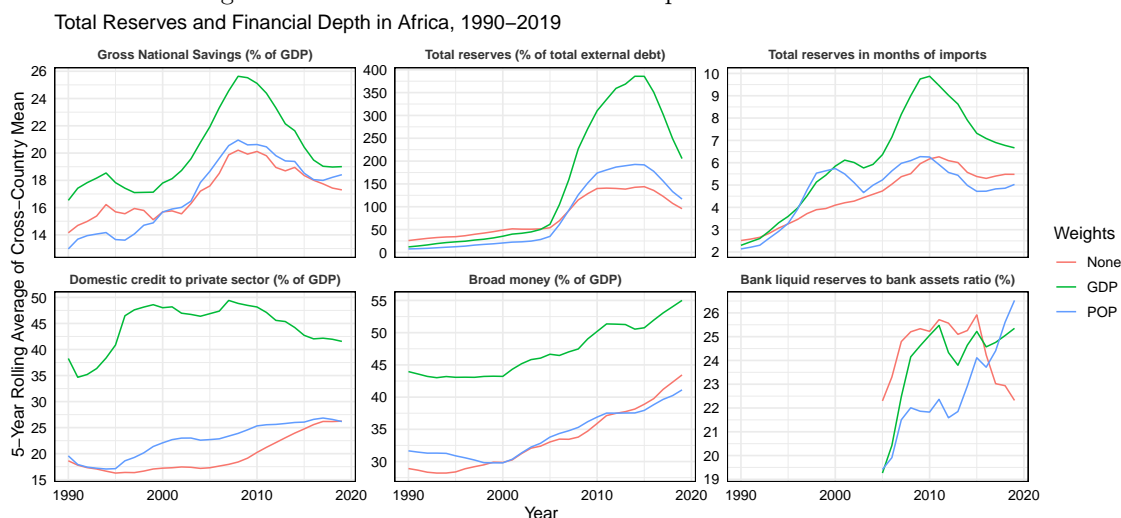


Table C12: Correlations with External Environment Volatility Indicators

MAD:	E_PA	ToT	TB	FDI	REM	CAB
Median PC Growth	-.173*	-.202*	-.116*	-.034	-.115*	.000
MAD PC Growth	.043	.263*	.093*	.206*	.265*	.153*
Median Inflation	.911*	.299*	.058	.134*	.243*	.048
MAD Inflation	.915*	.295*	.032	.132*	.321*	.060*

Notes: 10-year rolling medians and MADs of the growth rates of the data from 1981 are computed for each country and related through pairwise Pearson's correlations across all countries. A star denotes significance at the 5% level.

Figure C20: Reserves and Financial Depth: Selected Indicators



Data Source: IMF and World Bank. Accessed through the africamonitor API.

Table C13: Correlations with Financial Indicators

Mean:	GNS	TR_EDT	TR_MIM	PSC	BM	BLR_A
Median PC Growth	.073*	.249*	.093*	.086*	.072*	-.017
MAD PC Growth	-.024	-.077*	.060	-.106*	-.078*	.035
Median Inflation	-.056*	-.160*	-.050	-.098*	-.090*	-.011
MAD Inflation	-.004	-.035	.006	-.074*	-.078*	-.126*

Notes: A 10-year MA with data from 1981 is used to smooth the variables shown in Figure C20, and 10-year rolling medians and MADs for per-capita growth and inflation. These rolling series are then standardized within each country, and first-differenced. Pairwise Pearson's correlations are computed on these first differences across all countries. A star denotes significance at the 5% level.

Figure C21: Inflation Targeting in Africa

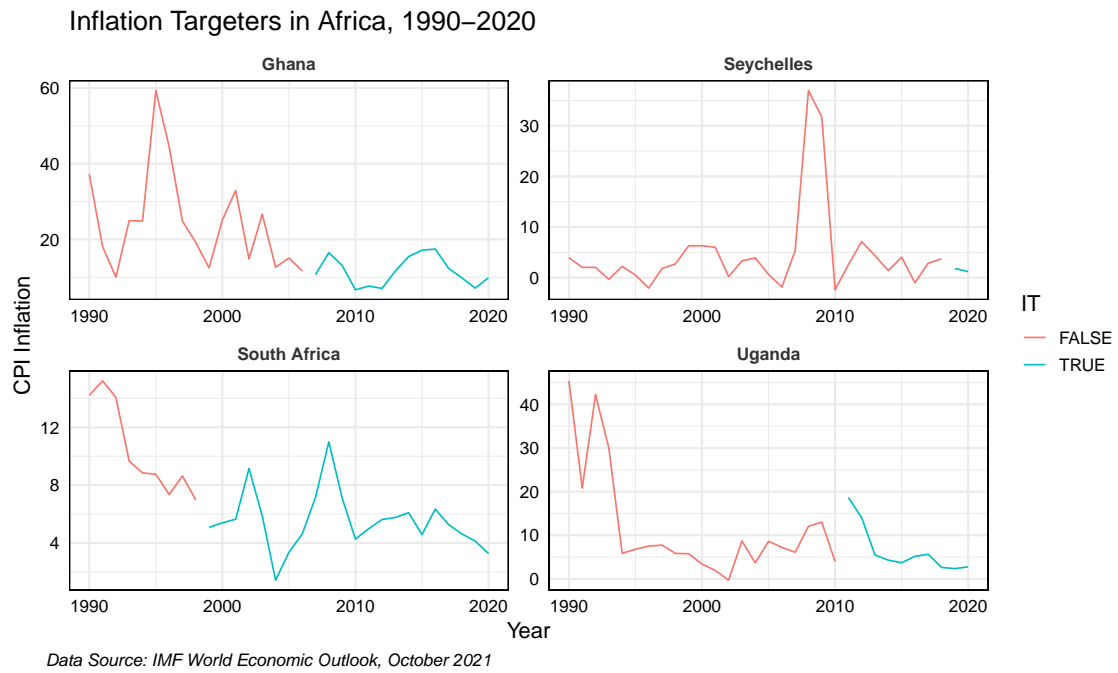
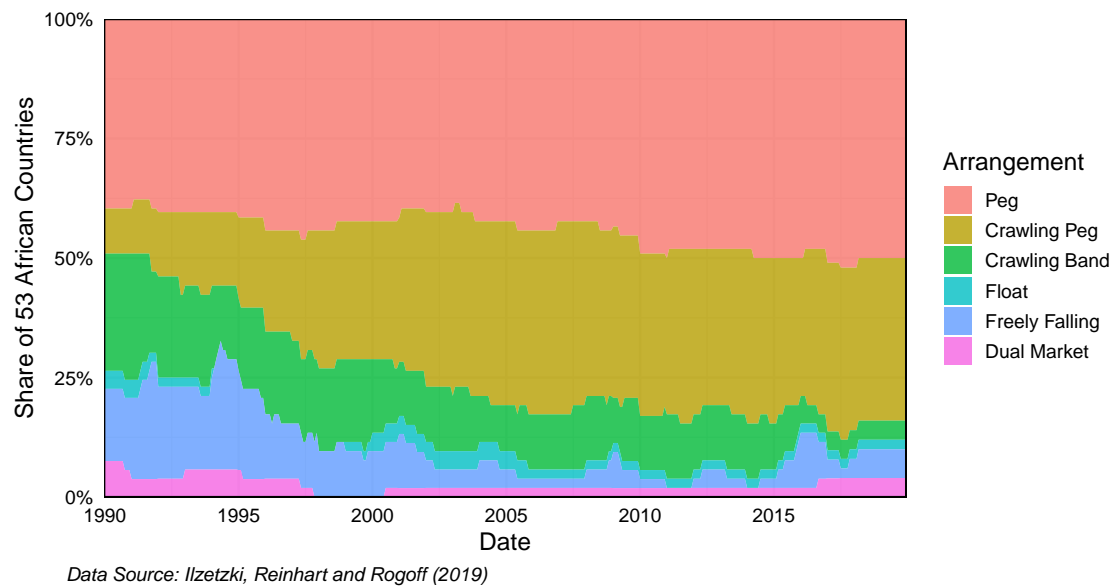


Figure C22: Exchange Rate Regimes in Africa, 1990-2019



Notes: The figure shows the 'coarse' exchange rate regime classification from Ilzetzki et al. (2019) with 6 categories. The share of 53 African economies (excl. South Sudan) with different regimes is computed for each year from 1990-2019.

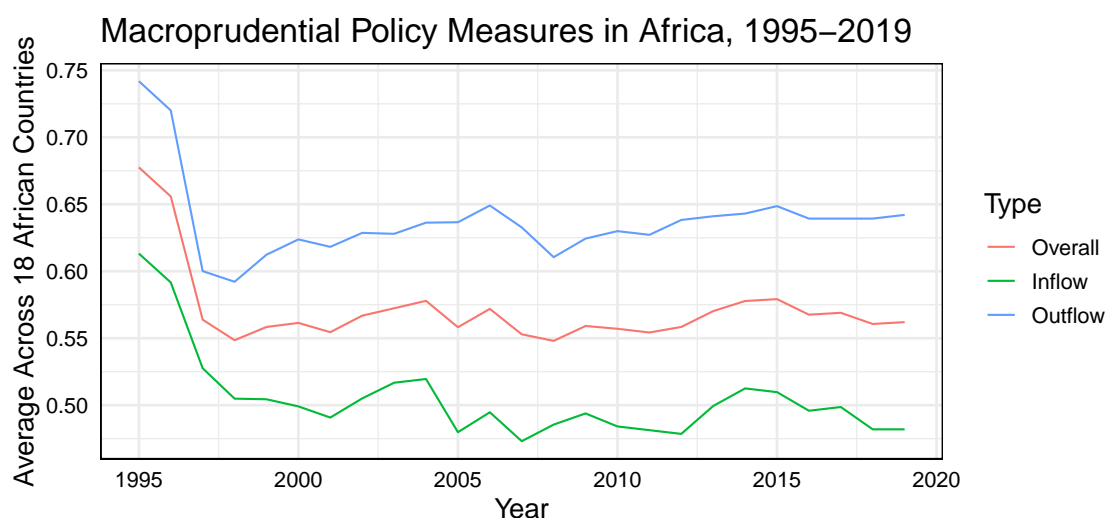
Table C14: Exchange Rate 15-Year Rolling Panel-Dummy-Regressions, 1990-2019

Dependent Variable:	MAD Real GDP/Capita Growth (%)			MAD Inflation (%)		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
<i>Variables</i>						
Crawling Peg	-0.5017*** (0.1213)	-1.030** (0.4212)	-0.8594* (0.4743)	-0.2853 (0.4360)	5.676 (10.57)	6.576 (10.68)
Crawling Band	-0.7126** (0.2486)	0.2733 (0.6678)	-0.0654 (0.5721)	-0.5408 (2.155)	19.72** (8.871)	18.62* (9.523)
Float	-1.227*** (0.1489)	1.325 (1.067)	0.7436 (0.7344)	-1.756 (1.161)	46.70* (22.06)	46.38* (21.93)
FF + DM	0.3907*** (0.1044)	1.288*** (0.3280)	0.4496 (0.2781)	46.42** (17.21)	117.5*** (26.13)	114.7*** (27.07)
<i>Fixed-effects</i>						
Country	—	52	52	—	52	52
Year	—	—	15	—	—	15
<i>Fit statistics</i>						
Observations	751	751	751	759	759	759
R <sup>2</sup>	0.026	0.733	0.743	0.198	0.474	0.477
Within R <sup>2</sup>		0.030	0.010		0.254	0.220

Driscoll & Kraay (1998) (L=1) standard-errors in parentheses Signif. Codes: \*\*\*, 0.01, \*\*, 0.05, \*, 0.1  
Avg. Country Group Sizes: Peg: 22.8, Crawling Peg: 17, Crawling Band: 6.4, Float: 1, FF: 2.9, DM: 0.9

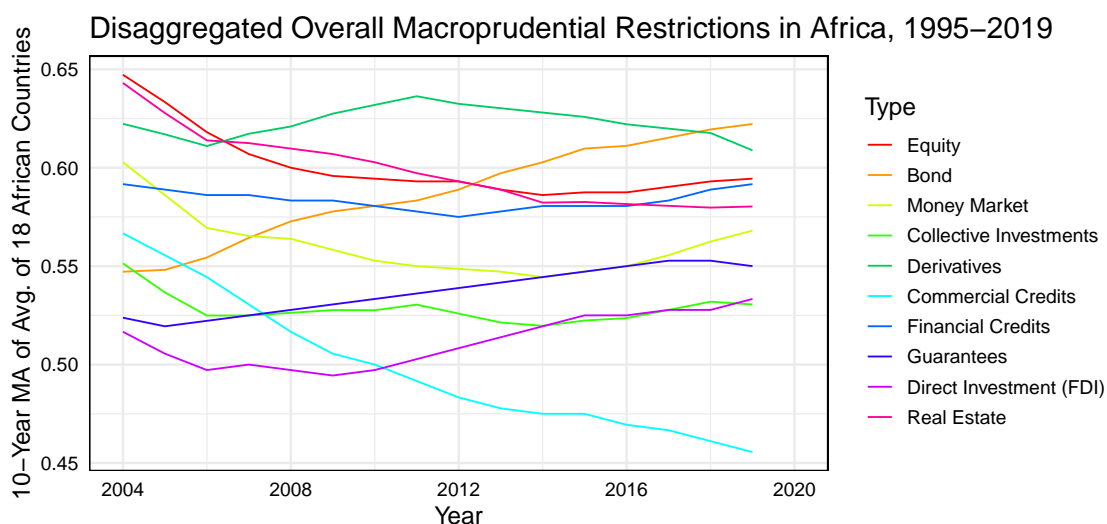
Notes: 15-year MAs of the exchange regime dummies on data from 1990-2019 (retaining 15 observations per country) are regressed onto 15-year rolling MADs of GDP per capita growth and CPI inflation. Data from WEO, Oct. 21.

Figure C23: Macroprudential Measures in Africa



Data Source: Fernandez, Klein, Rebucci, Schindler and Uribe (2016, 2021)

Figure C24: Disaggregated Macroprudential Measures in Africa



Data Source: Fernandez, Klein, Rebucci, Schindler and Uribe (2016, 2021)

Table C15: Macroprudential Policy: 10-Year Rolling Panel-Regressions, 1995-2019

Dependent Variables:	MAD Real GDP/Capita Growth (%)			MAD Inflation (%)		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
<i>Variables</i>						
Overall Measures	0.1724 (0.1264)	-5.095*** (0.7261)	-5.368*** (0.7969)	2.497 (1.966)	-10.23* (4.871)	-12.17*** (3.644)
R <sup>2</sup>	0.004	0.512	0.602	0.007	0.344	0.388
Within R <sup>2</sup>		0.153	0.196		0.004	0.007
Inflow Measures	0.3058*** (0.0654)	-0.5994 (0.7604)	-2.215*** (0.5578)	9.942* (5.142)	-7.188*** (2.314)	-21.25*** (2.018)
Outflow Measures	-0.0717 (0.1187)	-4.096*** (1.034)	-3.050*** (0.9308)	-5.008** (1.978)	-3.473 (3.277)	5.768 (4.398)
R <sup>2</sup>	0.006	0.520	0.603	0.035	0.344	0.392
Within R <sup>2</sup>		0.167	0.197		0.004	0.013
<i>Fixed-effects</i>						
Country	—	18	18	—	18	18
Year	—	—	16	—	—	16
Observations	288	288	288	287	287	287

Driscoll &amp; Kraay (1998) (L=2) standard-errors in parentheses

Signif. Codes: \*\*\*: 0.01, \*\*: 0.05, \*: 0.1

Notes: 10-year rolling MADs of GDP per capita growth and CPI Inflation from the WEO Oct. 21 are regressed onto 10-year MAs of overall, inflow and outflow measures taken from the macroprudential database of Fernández et al. (2016) (August 2021 update) and available for 18 African economies: Algeria, Angola, Burkina Faso, Cote d'Ivoire, Egypt, Ethiopia, Ghana, Kenya, Kingdom of Eswatini, Mauritius, Morocco, Nigeria, South Africa, Tanzania, Togo, Tunisia, Uganda, and Zambia.

Figure C25: The Adoption of Fiscal Rules in Africa

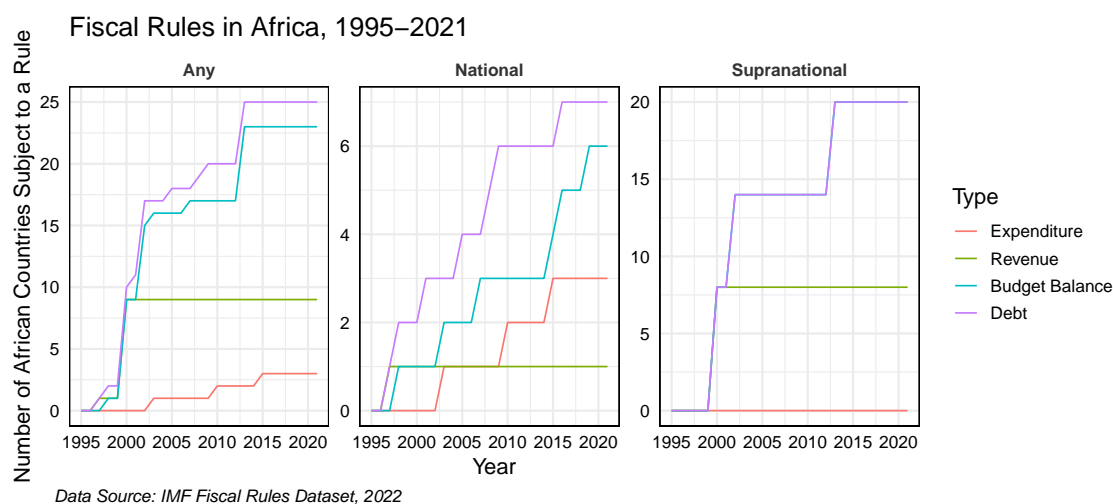


Figure C26: Important Macroeconomic and Fiscal Aggregates, 1990-2019

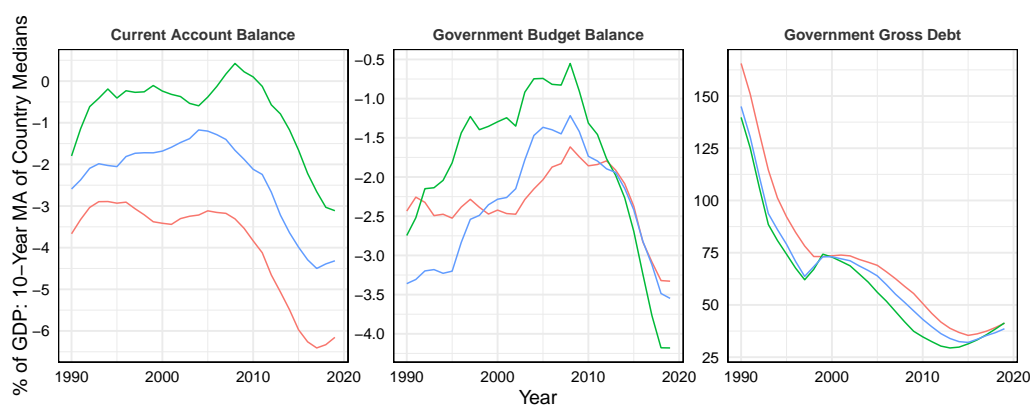


Table C16: Fiscal Rules: 10-Year Rolling Panel-Regressions with Data from 1990-2019

Dependent Variables: Model:	MAD Real GDP/Capita Growth (%) (1)	(2)	(3)	MAD Inflation (%) (4)	(5)	(6)
Any Rule	-0.4450 (0.3045)	-0.8644*** (0.1213)	0.7599* (0.3743)	-1.832*** (0.2925)	-1.886*** (0.2921)	0.5127 (0.4207)
R <sup>2</sup> Within R <sup>2</sup>	0.008	0.710 0.070	0.732 0.011	0.148	0.448 0.163	0.504 0.003
N. Rules	-0.2174** (0.0998)	-0.3574*** (0.0463)	0.2266** (0.0831)	-0.6190*** (0.1196)	-0.8204*** (0.1126)	-0.0546 (0.1158)
R <sup>2</sup> Within R <sup>2</sup>	0.015	0.710 0.070	0.731 0.007	0.123	0.461 0.184	0.503 < 0.001
<i>Rule Dummies</i>						
ER	-1.012*** (0.0984)	0.3297* (0.1843)	0.4739** (0.2173)	-0.8629*** (0.2966)	0.2318 (0.1978)	0.4147 (0.2470)
RR	-1.115*** (0.0951)	0.4285** (0.1581)	0.5313*** (0.1674)	0.0267 (0.1617)	-1.890*** (0.1814)	-1.559*** (0.1607)
BBR	0.6600*** (0.1413)	-0.9849*** (0.1603)	-0.4113** (0.1843)	-0.2630 (0.1701)	-0.7664** (0.3150)	-0.1291 (0.3817)
DR	-0.2568 (0.2932)	-0.2262 (0.2273)	0.6215* (0.3534)	-1.497*** (0.2762)	-0.5366 (0.4100)	1.158* (0.5931)
R <sup>2</sup> Within R <sup>2</sup>	0.050	0.716 0.088	0.733 0.016	0.145	0.474 0.203	0.524 0.042
<i>Fixed-effects</i>						
Country	—	25	25	—	25	25
Year	—	—	21	—	—	21
Observations	512	512	512	509	509	509

Driscoll &amp; Kraay (1998) (L=2) standard-errors in parentheses

Signif. Codes: \*\*\*, 0.01, \*\*, 0.05, \*, 0.1

Notes: 10-year rolling MADs of GDP per capita growth and CPI Inflation from the WEO Oct. 21, are regressed onto 10-year MAs of fiscal rule dummies from Davoodi et al. (2022b). 26 African countries are recorded to have introduced fiscal rules since 1990 (see Table 7). 3 sets of regressions are run: with an 'Any Rule' dummy indicating the presence of a fiscal rule, an ordinal 'N. Rules' variable, obtained as the sum of dummies for 4 different types of rules, and with the 4 dummies: expenditure (ER), revenue (RR), budget balance (BBR), and debt (DR).

Table C17: Fiscal Rules: Panel-Regression in 30-Year Panel with Data from 1990-2015

Dependent Variables: Model:	Current Account Balance (1) (2) (3)			Government Budget Balance (4) (5) (6)			Government Gross Debt (7) (8) (9)		
Any Rule	0.3748 (1.011)	0.1935 (1.078)	1.155 (1.558)	7.645* (4.415)	8.740* (5.080)	3.671 (3.112)	-32.86*** (9.081)	-37.18*** (7.913)	-38.99*** (9.958)
R <sup>2</sup> Within R <sup>2</sup>	0.0003 < 0.001	0.260 < 0.001	0.306 0.001	0.013	0.143 0.016	0.201 0.001	0.057	0.434 0.089	0.506 0.046
N. Rules	0.0977 (0.2358)	0.0135 (0.3457)	0.1347 (0.3715)	2.478 (1.529)	2.800 (1.749)	-0.5224 (0.9959)	-10.02*** (2.554)	-9.074*** (2.256)	-2.196 (1.959)
R <sup>2</sup> Within R <sup>2</sup>	<0.001	0.260 < 0.001	0.306 <0.001	0.010	0.138 0.010	0.200 <0.001	0.039	0.396 0.029	0.483 <0.001
ER	4.603*** (1.078)	-6.162*** (2.061)	-5.470** (2.118)	-0.5070 (1.492)	-13.63** (6.335)	-11.48* (6.287)	-26.55*** (5.545)	43.71*** (7.603)	51.35*** (6.510)
RR	-0.2078 (1.662)	-3.274 (2.140)	-4.546* (2.283)	-1.307 (0.9910)	-17.77* (9.362)	-25.20** (11.35)	-1.093 (3.214)	28.14*** (9.968)	8.131 (4.862)
BBR	3.246** (1.577)	3.576*** (1.142)	4.238*** (1.270)	2.788** (1.291)	7.615 (5.273)	7.374 (4.772)	-7.840 (4.624)	45.23*** (9.988)	51.17*** (9.414)
DR	-3.138 (2.140)	-0.9916 (1.437)	0.1215 (1.592)	5.647 (3.375)	10.22* (5.305)	7.303* (3.979)	-18.55* (10.28)	-83.44*** (12.17)	-71.83*** (11.66)
R <sup>2</sup> Within R <sup>2</sup>	0.014	0.274 0.018	0.322 0.024	0.013	0.160 0.035	0.225 0.032	0.049	0.469 0.145	0.542 0.115
<i>Fixed-effects</i>									
Country	—	26	30	—	26	30	—	26	30
Year	—	—	26	—	—	26	—	—	26
Observations	749	749	749	673	673	673	586	586	586

Driscoll &amp; Kraay (1998) (L=2) standard-errors in parentheses, dependent variables in % of GDP.

Signif. Codes: \*\*\*, 0.01, \*\*, 0.05, \*, 0.1

## Section 5: Structural Factors

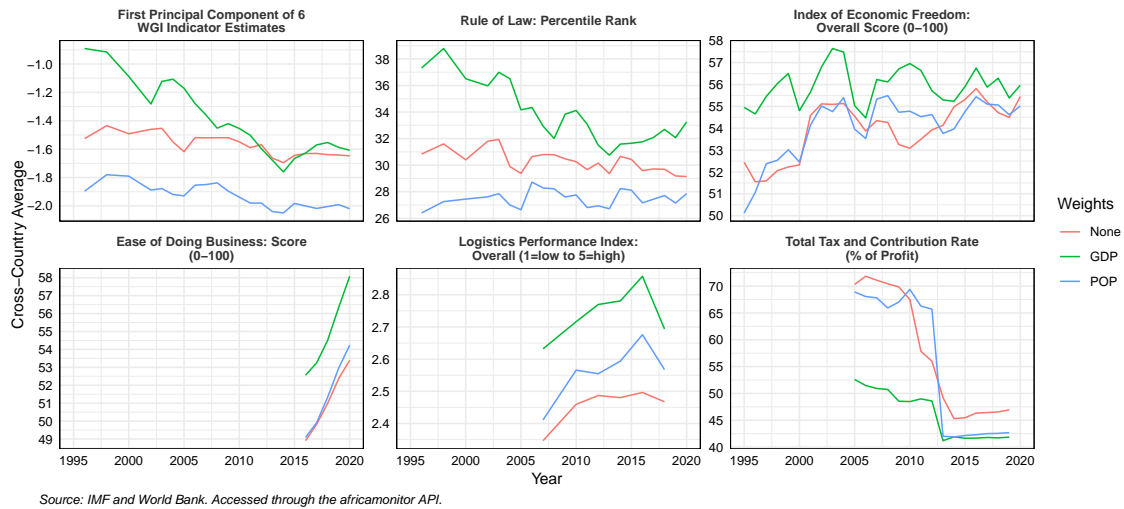
Table C18: Summary Statistics of Predictors in Cross-Sectional and Panel Analysis

Panel	Topic / Variables	N	Ndist	Mean	Median	SD	Min	Max
<i>Institutions</i>								
	Overall Governance	49	49	49.67	48.57	12	26.35	78.06
X	Worldwide Governance Indicators: PC1	49	49	-1.47	-1.49	1.39	-3.97	1.88
	Human Rights and Rule of Law	49	49	7	7.17	1.53	3.76	9.79
X	Level of Democracy (Freedom House)	49	37	5.27	5	2.64	0.75	10
	50-Year Average Freedom House Ratings	48	29	2.44	2.5	0.5	1	3
X	Regime Durability	47	45	12.51	10.28	9.77	2	39
	Colonial Origin: British	49	2	0.39	0	0.49	0	1
	Colonial Origin: French	49	2	0.39	0	0.49	0	1
	Corruption Perceptions Index	48	44	33.77	32.69	11.35	17	62.25
<i>Business Environment</i>								
	Ease of Doing Business Score (0-100)	49	47	50.71	50.25	10.99	21.15	77.70
	Logistics Performance Index (1-5)	46	40	2.48	2.47	0.24	2.03	3.50
X	Index of Economic Freedom (0-100)	49	46	53.76	54.80	7.30	34.60	73
X	The Property Right Protection Index	49	49	49.79	50.00	2.12	46.49	54.38
<i>Production Shares</i>								
X	Agriculture, Forestry & Fishing VA (% of GDP)	49	49	20.89	22.11	13.18	1.33	51.19
X	Industry & Construction VA (% of GDP)	49	49	26.72	22.84	14.73	11.52	77.54
<i>Climate &amp; Agriculture</i>								
X	Permanent Cropland (% of Land Area)	49	49	4.01	0.74	7.66	0.002	40.62
X	Ln(Cereal Yield, Kg/Ha)	47	47	7.03	7.08	0.61	5.45	8.88
X	Annual Average Rainfall	49	49	82.27	82.98	52.86	2.78	206.82
X	Annual Average Temperature	49	49	24.31	24.48	3.34	12.67	28.87
	% 1995 Pop. in Tropics (Af+Am+Aw)	44	28	46.39	43.04	42.42	0	100
X	% of Cropland Equipped for Irrigation	47	46	7.75	2.11	15.79	0.05	99.81
	Irrigation Suitability 1 (%)	44	44	4.12	3.64	2.81	0.16	13.41
	Soil Suitability 1 (%)	44	44	9.37	7.43	7.79	0.15	32.01
<i>Trade Intensity and Composition</i>								
X	Merchandise Trade (% of GDP)	49	49	52.39	46.59	25.36	19.22	128.68
X	Agricultural Raw Materials Exports (% of GDP)	47	47	0.96	0.34	1.43	0	7.01
X	Manufactures Exports (% of GDP)	47	47	5.78	1.37	9.08	0.001	35.54
X	Ores and Metals Exports (% of GDP)	47	47	2.49	0.21	4.92	0.0003	22.52
X	Merchandise Exports to HICs (% of GDP)	49	49	13.59	9.90	12.18	0.61	53.02
X	Merch. EX to LMICs Outside Region (% of GDP)	49	49	3.02	1.94	3.87	0.05	17.34
X	Merchandise Imports from HICs (% of GDP)	49	49	15.07	12.76	9.23	3.69	53.41
<i>Trade Diversification</i>								
X	Herfindahl Index of Bilateral Trade (X+M)	48	48	0.13	0.09	0.10	0.04	0.47
X	Theil Index of Bilateral Trade (X+M)	48	48	2.03	1.87	0.45	1.39	3.29
X	Herfindahl Index of Exports by Product	47	47	0.30	0.27	0.24	0.03	0.92
X	Theil Index of Exports by Product	47	47	3.41	3.32	0.94	1.43	5.46
<i>Exchange Rate and Terms of Trade</i>								
X	Exchange Rate Growth (%)	49	35	5.32	2.90	7.37	-0.01	44.28
X	MAD Nominal Exchange Rate Depreciation (%)	49	37	10.36	7.94	9.17	0.91	63.23
X	Net Barter Terms of Trade Index (2000 = 100)	49	49	113.10	110.16	20.36	65.92	162.62
X	Terms of Trade Growth (%)	49	46	0.44	0	2.12	-4.37	9.00
X	MAD Terms of Trade Growth (%)	49	49	9.14	7.45	5.70	0.84	24.36
<i>Financial &amp; Aid Flows</i>								
X	Net FDI Inflows (% of GDP)	49	49	2.52	2.05	2.15	0.04	9.69
X	MAD Diff(FDI in % of GDP)	49	49	1.98	1.29	2.26	0.07	12.88
X	Personal Remittances, Received (% of GDP)	49	45	2.98	1.14	6.04	0	39.72
X	MAD Diff(Remittances in % of GDP)	49	45	0.46	0.21	0.75	0	4.77
X	Net ODA Received (% of GNI)	49	49	7.79	6.73	6.47	0.20	23.07
<i>Financial Sector</i>								
X	Broad Money (% of GDP)	49	49	33.79	23.17	25.87	10.11	132.60
X	Broad Money Growth (%)	49	49	8.05	8.05	3.46	-0.03	17.16
X	MAD Broad Money Growth (%)	49	49	14.36	13.26	5.47	2.90	33.26
X	Domestic Credit to Private Sector (% of GDP)	49	49	20.87	13.13	22.95	2.37	118.17
X	Bank Liquid Reserves to Bank Assets Ratio (%)	46	46	21.70	18.83	14.46	3.50	59.29
	Bank/MM Account (% of Population Ages 15+)	42	42	30.47	28.44	19.75	6.71	82.21



Panel	Topic / Variables	N	Ndist	Mean	Median	SD	Min	Max
<i>Debt &amp; Reserves</i>								
X	General Government Gross Debt (% of GDP)	48	48	56.24	52.95	31.71	12.92	198.71
X	External Debt Stocks (% of GNI)	45	45	62.83	55.79	35.70	12.71	196.62
X	Total Debt Service (% of GNI)	45	45	2.85	2.08	2.34	0.62	12.54
X	Total Reserves in Months of Imports	41	41	4.62	2.99	6.03	0.07	28.19
<i>Population</i>								
X	Ln(Population)	49	49	15.76	16.11	1.62	11.33	18.74
X	Population Growth (Annual %)	49	49	2.39	2.57	0.78	0.61	4.10
X	Urban Population (% of Total Population)	49	49	39.38	38.02	16.88	9.26	82.12
X	Ln(Population Density, People/Km2)	49	49	3.68	3.88	1.33	0.85	6.40
X	Age Dependency Ratio (% of Work. Age Pop.)	49	49	83.26	87.86	15.71	45.86	106.47
X	International Migrant Stock (% of Population)	49	49	3.13	2.26	3.46	0.15	15.55
<i>Health</i>								
X	Life Expectancy at Birth, Total (Years)	49	49	57.22	55.66	7.81	43.98	74.13
X	Infant Mortality Rate (per 1000 Live Births)	49	49	63.75	67.15	26.01	12.20	125.65
X	% of People using Basic Sanitation Services	49	49	38.27	31.45	26.67	5.81	98.17
	% Pop. at Risk of Malaria, 2005	44	14	75.21	100	40.01	0	100
	Malaria Ecology (Sachs, 2003)	47	47	10.16	7.51	8.53	0	31.55
<i>Education</i>								
X	Human Capital Index	49	49	0.53	0.55	0.17	0.16	0.82
X	Mean Years of Schooling	49	36	4.37	4.30	1.93	1.30	8.90
X	Expected Years of Schooling	49	39	9.12	9	2.60	3.70	15.40
X	Adult Literacy (% of People Ages 15+)	49	49	62.83	67.09	19.91	23.00	93.00
	% of Pop. Speaking Major European Language	48	11	3.37	0	12.88	0	70.00
<i>Natural Disasters &amp; Conflict</i>								
X	Natural Disasters: Ln(N. Homeless)	49	45	9.39	10.91	3.81	0	13.83
X	Natural Disasters: Ln(N. Deaths)	49	49	6.84	7.27	2.12	1.39	10.13
X	Natural Disasters: Ln(Damage in USD)	49	39	8.69	10.34	5.27	0	15.69
X	Ln(ACLED Fatalities, 1997-2019)	44	44	7.49	7.60	2.50	1.39	11.88
	Societal Violence Scale Index (1-5)	48	13	3.44	3.58	0.92	1.50	5
X	State Fragility Index	47	43	14.36	15.04	4.88	1.33	23.33
<i>Geography &amp; Accessibility</i>								
	Geogr. Predicted Trade (FR 1999)	48	48	-3.07	-3.08	0.50	-3.98	-2.16
	% Area 100km from Coast/Sea-Nav. River	44	32	20.61	12.09	26.19	0	100
	Sub-Saharan Africa Dummy	49	2	0.90	1	0.31	0	1
	Landlocked Dummy	48	2	0.27	0	0.45	0	1
	Internal Distance Based on Area	48	48	232.83	205.27	159.59	8.02	595.40
	Latitude in Degrees	48	47	2.52	4.85	17.41	-33.93	36.83
	Longitude in Degrees	48	47	15.08	14.12	20.75	-23.50	57.50
<i>Natural Resources</i>								
X	Total Natural Resources Rents (% of GDP)	49	49	10.88	7.37	10.58	0.01	42.04
X	Oil Rents (% of GDP)	49	20	4.48	0	10.16	0	40.52
<i>Poverty &amp; Inequality</i>								
X	% Poor at \$1.90 a Day (2011 PPP)	46	44	39.11	41	23.95	0.40	85.75
X	Poverty Gap at \$1.90 a Day (2011 PPP) (%)	46	45	15.96	15.03	12.46	0.10	51.70
X	Gini Index	46	44	43.37	41.68	7.87	31.45	63
<i>Religion &amp; Ethnicity</i>								
	Religion: Muslim, 1980	45	38	32.82	16.20	36.80	0	99.40
	Religion: Protestant, 1980	45	35	11.52	4.90	13.25	0	50
	Religion Fractionalization, 2000	49	49	0.47	0.58	0.27	0.003	0.86
	Ethnic Fractionalization, 2000	48	47	0.62	0.71	0.25	0	0.93
<i>Others</i>								
X	Index of Globalization	49	49	44.31	43.29	8.33	28.37	62.70
X	Human Development Index	49	49	0.49	0.48	0.12	0.30	0.76
	Ln(GDP per Capita 1960)	42	41	6.57	6.51	0.54	5.52	7.94
X	Ln(GDP per Person Employed)	47	47	9.16	8.96	1.04	7.51	11.16
X	Access to Electricity (% of Population)	49	49	41.00	34.75	29.66	5.05	99.40
X	Gross National Savings (% of GDP)	48	48	17.38	15.81	9.14	2.31	37.98

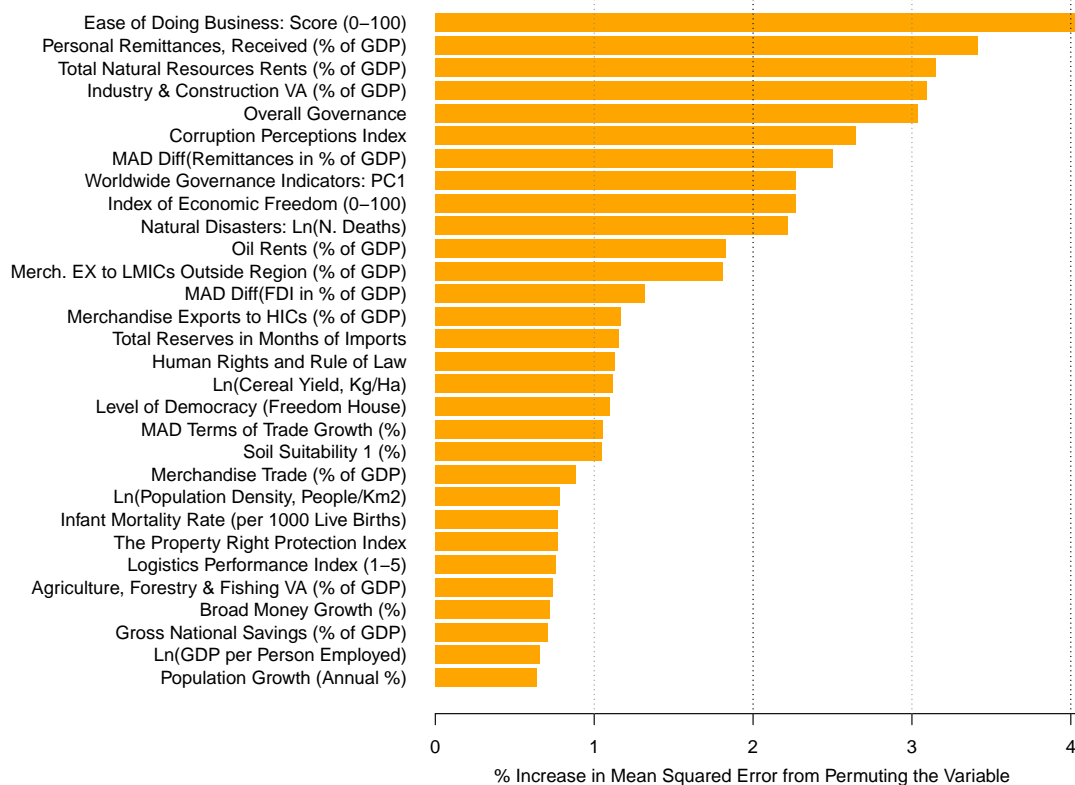
Figure C27: Institutions and Business Environment: Selected Indicators  
Selected Institutions and Business Indicators in Africa, 1990–2020



## Cross-Sectional Results

Figure C28: RF Predicting the MAD of PCGDP Growth of 49 African Economies in 1990–2019

Top 30 Predictors from a RF Model with 98 Variables, 100k Trees and 3 Variables per Split. OOB  $R^2$ -Squared = 27.9%.



Notes: The Random Forest model is fit following Breiman (2001), using the *ranger* R package (Wright & Ziegler, 2017). Each tree is fit on a bootstrap sample of the data, randomly choosing 3 variables at each split. The Out-of-Bag (OOB)  $R^2$  is computed using each tree to predict only the data excluded from the bootstrap sample used to grow the tree, and averaging the predictions from all trees, yielding an OOB fit used to compute the  $R^2$ . Table C18 summarises the variables. 2.5% missing values were imputed beforehand following Stekhoven & Bühlmann (2012) with R package *missRanger*.

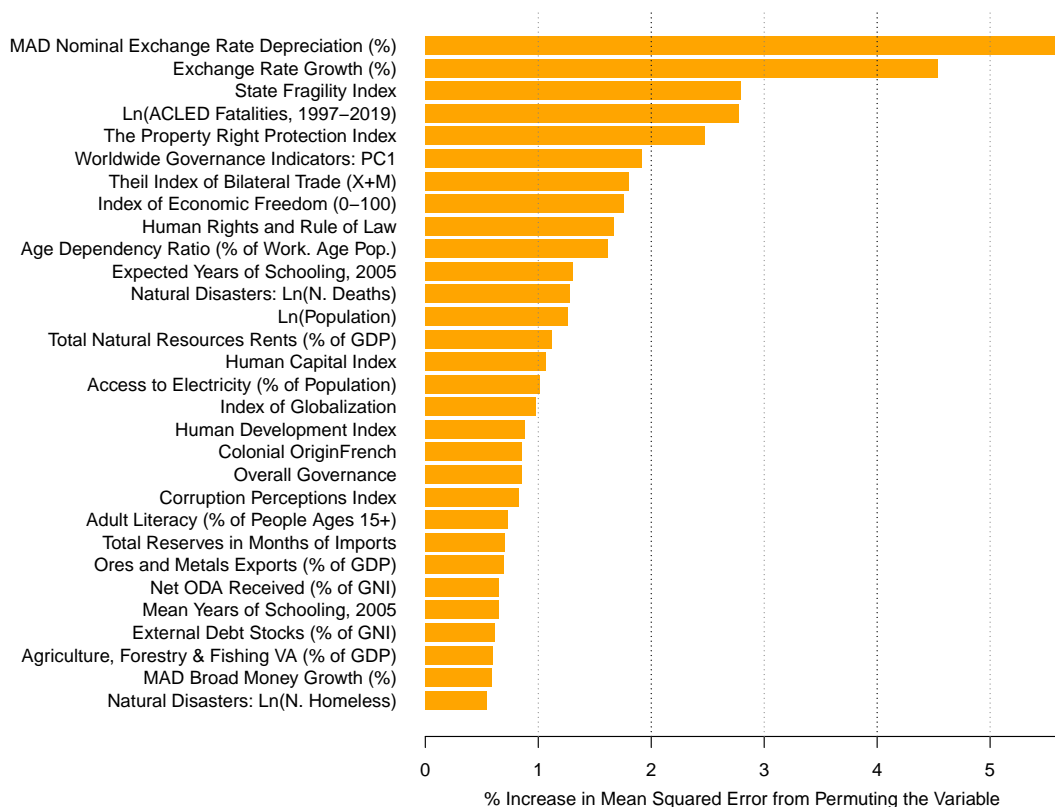
Table C19: RF Ranking of Indicator Topics: Predicting MAD PCGDP Growth, 1990-2019

Method: Topic	Permutation		Exclusion		Residual Fit		Combined Avg. Rank
	% $\Delta$ MSE	Rank	% $\Delta$ MSE	Rank	% $\Delta$ MSE	Rank	
Institutions	88.03	1	6.38	1	40.89	4	2.00
Financial & Aid Flows	73.47	2	4.29	2	43.69	3	2.33
Trade Intensity and Composition	57.63	4	1.90	7	53.93	1	4.00
Financial Sector	65.98	3	0.93	11	47.45	2	5.33
Business Environment	50.67	5	2.83	4	22.43	10	6.33
Natural Resources	28.81	12	3.20	3	34.28	5	6.67
Natural Disasters & Conflict	29.17	11	1.91	6	23.23	9	8.67
Production Shares	31.11	9	2.22	5	16.64	14	9.33
Population	31.17	8	0.75	12	27.72	8	9.33
Exchange Rate and ToT	29.18	10	0.39	14	29.41	7	10.33
Climate & Agriculture	45.07	6	-0.02	15	14.52	15	12.00
Health	16.62	16	1.47	8	20.49	12	12.00
Others	28.06	13	-0.21	18	31.10	6	12.33
Geography & Accessibility	20.78	14	-0.06	16	22.34	11	13.67
Trade Diversification	20.78	15	-0.12	17	18.50	13	15.00
Debt & Reserves	32.33	7	-0.57	19	5.39	19	15.00
Education	13.00	17	1.38	10	11.14	18	15.00
Poverty & Inequality	7.27	19	1.41	9	13.07	17	15.00
Religion & Ethnicity	10.90	18	0.55	13	14.12	16	15.67

Notes: The reports 3 methods to rank topics of predictors using Random Forests. *Permutation* permutes all predictors in a topic and calculates the percent increase in the Out-Of-Bag (OOB) MSE. *Exclusion* excludes all predictors from the topic, fits a new model, and obtains the percent increase in MSE to the full model. *Residual Fit* is like *Exclusion*, but additionally partials out the predictors from a topic using multivariate linear regression, and fits a new model using the residual predictors from all other topics.

Figure C29: RF Predicting the MAD of CPI Inflation of 49 African Economies in 1990-2019

Top 30 Predictors from a RF Model with 98 Variables, 100k Trees and 3 Variables per Split. OOB R-Squared = 21.1%.



Notes: See notes to Figure C28. The variables are summarised in Table C18.

Table C20: RF Ranking of Indicator Topics: Predicting MAD CPI Inflation, 1990-2019

Method: Topic	Permutation		Exclusion		Residual Fit		Combined Avg. Rank
	% $\Delta$ MSE	Rank	% $\Delta$ MSE	Rank	% $\Delta$ MSE	Rank	
Exchange Rate and ToT	86.54	1	17.56	1	45.13	1	1.00
Natural Disasters & Conflict	72.25	2	5.16	2	32.71	2	2.00
Institutions	63.26	3	0.72	5	25.78	5	4.33
Business Environment	58.39	4	1.04	4	19.61	8	5.33
Population	44.53	5	-1.23	8	31.67	3	5.33
Trade Intensity and Composition	43.54	6	-2.22	13	29.10	4	7.67
Trade Diversification	38.31	9	1.20	3	-4.44	16	9.33
Financial Sector	43.36	7	-4.69	19	19.74	6	10.67
Education	12.74	17	-0.91	6	17.57	9	10.67
Geography & Accessibility	33.51	10	-1.43	10	16.25	12	10.67
Others	38.37	8	-2.75	18	19.68	7	11.00
Poverty & Inequality	23.94	13	-2.31	15	16.40	10	12.67
Health	20.53	15	-2.31	14	16.37	11	13.33
Natural Resources	18.40	16	-1.57	11	12.33	13	13.33
Debt & Reserves	26.00	12	-1.98	12	-13.25	18	14.00
Religion & Ethnicity	12.42	18	-1.39	9	-1.98	15	14.00
Production Shares	9.84	19	-0.97	7	-5.80	17	14.33
Financial & Aid Flows	22.82	14	-2.72	17	6.88	14	15.00
Climate & Agriculture	26.20	11	-2.51	16	-16.88	19	15.33

Notes: See notes for Table C19 and explanations provided in the text.

## Results on Cross-Section of Differences

Figure C30: RF Predicting the MAD-Difference of PCGDP Growth of 49 African Economies

Top 30 Predictors from a RF Model with 70 Variables, 100k Trees and 3 Variables per Split. OOB R-Squared = -2.1%.

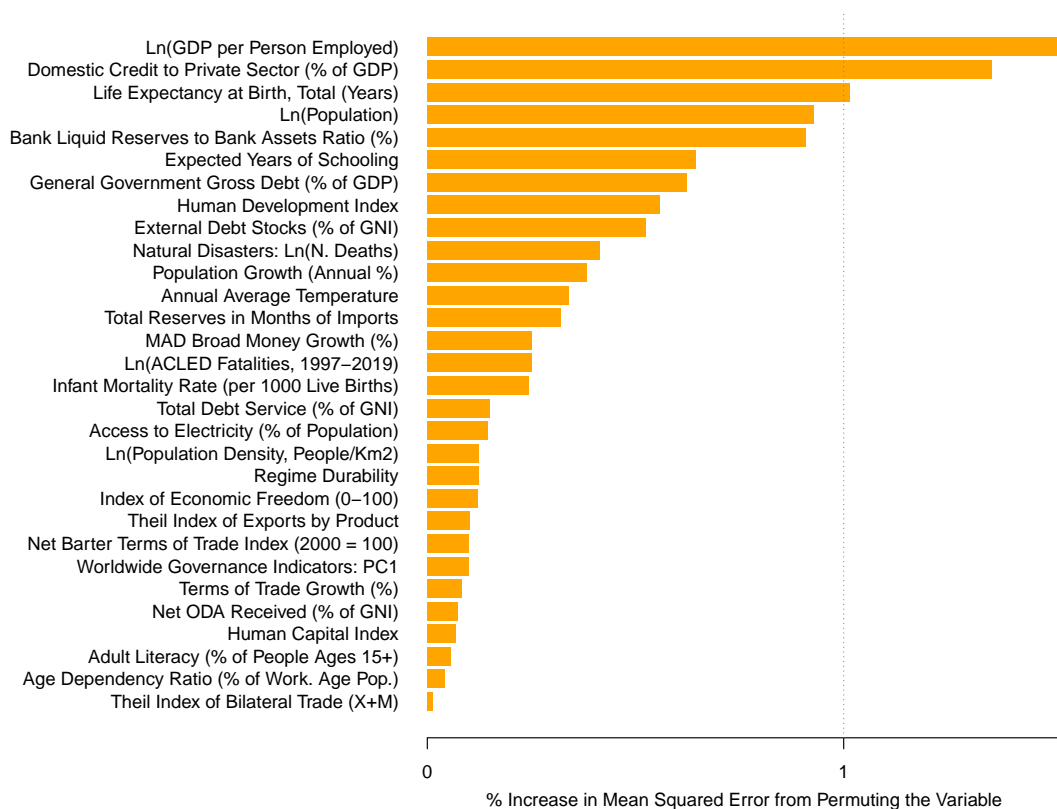


Table C21: RF Ranking of Indicator Topics: Predicting the MAD-Difference of PCGDP Growth

Method: Topic	Permutation		Exclusion		Residual Fit		Combined Avg. Rank
	% $\Delta$ MSE	Rank	% $\Delta$ MSE	Rank	% $\Delta$ MSE	Rank	
Others	63.47	3	2.29	2	16.29	1	2.00
Financial Sector	68.48	2	7.05	1	7.84	7	3.33
Population	44.62	4	0.37	6	8.83	4	4.67
Health	34.72	6	0.37	5	1.21	11	7.33
Institutions	23.60	14	0.47	3	8.65	6	7.67
Education	24.29	13	0.30	7	13.37	3	7.67
Trade Intensity and Composition	74.42	1	-1.25	15	5.06	8	8.00
Climate & Agriculture	30.06	8	-0.28	12	8.75	5	8.33
Debt & Reserves	28.69	9	-1.38	16	13.44	2	9.00
Trade Diversification	33.82	7	-0.89	13	1.53	10	10.00
Natural Disasters & Conflict	39.17	5	-0.09	10	-3.17	17	10.67
Exchange Rate and ToT	27.29	10	-0.05	9	-0.87	15	11.33
Financial & Aid Flows	24.47	12	-0.15	11	0.78	12	11.67
Poverty & Inequality	16.19	16	0.42	4	-2.98	16	12.00
Natural Resources	25.97	11	-1.52	17	3.30	9	12.33
Business Environment	11.88	17	0.26	8	0.07	13	12.67
Production Shares	16.27	15	-0.92	14	-0.01	14	14.33

Figure C31: RF Predicting the MAD-Difference of CPI Inflation of 49 African Economies

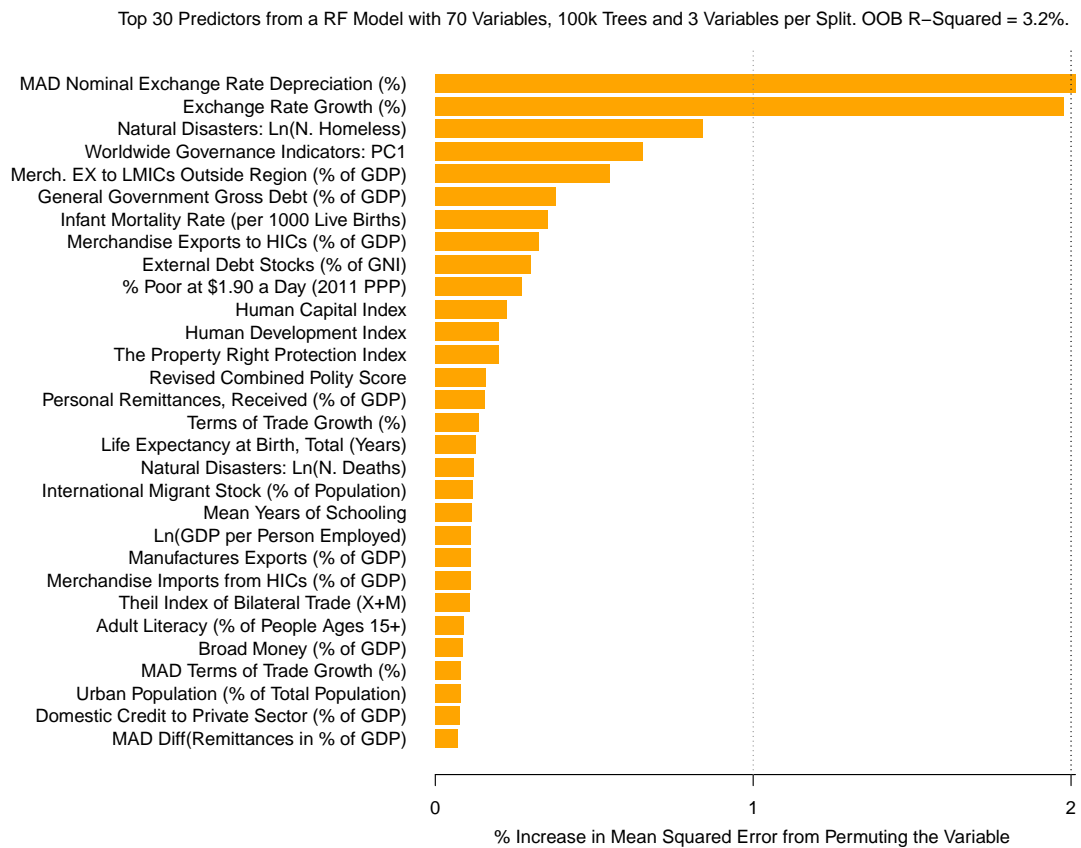


Table C22: RF Ranking of Indicator Topics: Predicting the MAD-Difference of CPI Inflation

<i>Method:</i> Topic	Permutation		Exclusion		Residual Fit		Combined Avg. Rank
	% $\Delta$ MSE	Rank	% $\Delta$ MSE	Rank	% $\Delta$ MSE	Rank	
Exchange Rate and ToT	62.34	2	7.87	1	36.45	1	1.33
Population	68.14	1	-0.01	7	2.10	3	3.67
Debt & Reserves	61.76	3	-1.12	15	2.89	2	6.67
Institutions	22.22	13	0.55	2	1.35	6	7.00
Natural Disasters & Conflict	37.33	9	0.26	4	0.79	9	7.33
Trade Intensity and Composition	39.68	7	0.29	3	-1.69	13	7.67
Production Shares	38.81	8	0.05	6	0.41	10	8.00
Education	45.36	4	-0.03	8	-1.80	15	9.00
Natural Resources	4.70	17	0.18	5	1.43	5	9.00
Climate & Agriculture	32.01	10	-0.84	14	1.25	7	10.33
Financial Sector	42.28	5	-0.05	9	-5.75	17	10.33
Health	25.41	11	-0.37	10	-0.32	11	10.67
Poverty & Inequality	19.66	14	-1.28	16	1.61	4	11.33
Trade Diversification	23.90	12	-0.56	12	-1.20	12	12.00
Business Environment	5.95	16	-0.67	13	1.23	8	12.33
Financial & Aid Flows	42.13	6	-1.29	17	-2.60	16	13.00
Others	13.40	15	-0.42	11	-1.72	14	13.33

**Cross-Sectional Prediction: With First 2 Principal Components for Each Topic**

Table C23: Percent Variance Explained by First 2 Principal Components

Topic	N	% Variance Explained		
		PC1	PC2	Total
Institutions (excl. Colonial Origin)	7	66.86	16.29	83.16
Business Environment	4	76.24	13.38	89.62
Production Shares	2	82.30	17.70	100.00
Climate & Agriculture	8	34.76	21.51	56.27
Trade Intensity and Composition	7	35.04	20.03	55.07
Trade Diversification	4	51.14	27.62	78.75
Exchange Rate and ToT	5	42.81	34.21	77.02
Financial & Aid Flows	5	40.12	34.34	74.46
Financial Sector	6	40.30	24.56	64.86
Debt & Reserves	4	38.84	27.70	66.54
Population	6	39.68	24.03	63.71
Health	5	73.36	12.26	85.63
Education	5	73.77	18.01	91.79
Natural Disasters & Conflict	6	52.65	18.79	71.44
Geography & Accessibility	7	37.78	28.31	66.09
Natural Resources	2	93.18	6.82	100.00
Poverty & Inequality	3	68.30	30.29	98.59
Religion & Ethnicity	4	60.32	24.71	85.04
Others	6	69.91	11.03	80.94
Average	5.05	56.70	21.66	78.37



Table C24: RF Ranking of Indicator Topics: PC12 Predicting MAD PCGDP Growth, 1990-2019

<i>Method:</i> Topic	Permutation		Exclusion		Residual Fit		Combined
	% $\Delta$ MSE	Rank	% $\Delta$ MSE	Rank	% $\Delta$ MSE	Rank	Avg. Rank
Financial Sector	114.50	1	2.48	3	34.07	3	2.33
Production Shares	61.84	4	4.47	1	29.96	5	3.33
Institutions	35.02	6	2.84	2	31.12	4	4.00
Financial & Aid Flows	102.31	2	1.65	4	29.21	6	4.00
Natural Resources	30.86	7	0.88	6	38.82	2	5.00
Trade Intensity and Composition	68.14	3	-1.36	14	48.70	1	6.00
Population	19.52	10	0.88	5	12.82	8	7.67
Trade Diversification	13.92	12	-0.42	8	1.57	14	11.33
Natural Disasters & Conflict	35.68	5	-1.10	13	0.78	16	11.33
Business Environment	23.65	9	-2.32	17	11.53	10	12.00
Exchange Rate and ToT	12.02	13	-1.87	16	19.43	7	12.00
Debt & Reserves	17.17	11	-2.60	18	12.00	9	12.67
Climate & Agriculture	11.98	14	-1.37	15	9.50	11	13.33
Geography & Accessibility	9.80	15	-0.38	7	-10.29	19	13.67
Poverty & Inequality	3.57	19	-0.72	10	2.19	12	13.67
Education	8.60	16	-0.45	9	-2.46	17	14.00
Religion & Ethnicity	5.53	18	-0.91	11	1.63	13	14.00
Health	6.07	17	-1.02	12	0.94	15	14.67
Others	25.18	8	-3.33	19	-3.09	18	15.00

Table C25: RF Ranking of Indicator Topics: PC12 Predicting MAD CPI Inflation, 1990-2019

<i>Method:</i> Topic	Permutation		Exclusion		Residual Fit		Combined
	% $\Delta$ MSE	Rank	% $\Delta$ MSE	Rank	% $\Delta$ MSE	Rank	Avg. Rank
Exchange Rate and ToT	225.75	1	19.91	1	42.39	1	1.00
Institutions	58.74	4	1.30	2	23.53	3	3.00
Natural Disasters & Conflict	61.13	2	0.61	3	22.97	4	3.00
Business Environment	43.39	6	-0.01	5	11.64	7	6.00
Population	15.61	12	-0.01	4	26.71	2	6.00
Geography & Accessibility	19.32	9	-0.79	9	16.46	6	8.00
Natural Resources	59.37	3	-4.29	18	17.97	5	8.67
Others	20.09	8	-1.99	14	11.49	8	10.00
Financial Sector	17.26	11	-0.73	8	0.26	14	11.00
Trade Diversification	10.41	14	-0.22	6	0.16	15	11.67
Poverty & Inequality	44.91	5	-4.60	19	7.90	12	12.00
Health	11.58	13	-2.06	15	8.44	10	12.67
Climate & Agriculture	5.27	19	-0.30	7	3.23	13	13.00
Education	5.58	18	-0.86	10	8.21	11	13.00
Financial & Aid Flows	17.57	10	-1.54	12	-11.58	18	13.33
Religion & Ethnicity	9.38	15	-3.13	17	8.96	9	13.67
Debt & Reserves	38.12	7	-2.63	16	-19.02	19	14.00
Trade Intensity and Composition	9.08	17	-1.44	11	-0.28	16	14.67
Production Shares	9.08	16	-1.97	13	-1.67	17	15.33

### Panel Prediction: With First 2 Principal Components for Each Topic

Table C26: Percent Variance Explained by First 2 Principal Components

Topic	N	% Variance Explained		
		PC1	PC2	Total
Institutions	3	47.87	40.35	88.22
Business Environment	2	61.01	38.99	100.00
Production Shares	2	73.69	26.31	100.00
Climate & Agriculture	5	35.72	21.57	57.29
Trade Intensity and Composition	7	38.79	23.46	62.26
Trade Diversification	4	43.20	22.48	65.69
Exchange Rate and ToT	5	40.17	28.43	68.61
Financial & Aid Flows	5	39.57	33.53	73.10
Financial Sector	5	36.74	27.05	63.79
Debt & Reserves	4	46.07	28.98	75.05
Population	6	44.68	22.30	66.98
Health	3	58.92	32.95	91.87
Education	4	40.36	28.70	69.06
Natural Disasters & Conflict	5	31.21	20.61	51.82
Natural Resources	2	80.75	19.25	100.00
Poverty & Inequality	3	68.51	27.15	95.66
Others	5	29.37	23.56	52.93
Average	4.12	48.04	27.39	75.43

Table C27: RF Ranking of Indicator Topics: PC12 Predicting MAD-Difference of PCGDP Growth

Method: Topic	Permutation		Exclusion		Residual Fit		Combined Avg. Rank
	% $\Delta$ MSE	Rank	% $\Delta$ MSE	Rank	% $\Delta$ MSE	Rank	
Others	83.95	1	1.98	3	11.13	1	1.67
Exchange Rate and ToT	45.31	4	4.34	1	3.39	6	3.67
Financial Sector	35.92	7	2.24	2	4.56	3	4.00
Natural Resources	63.17	3	0.55	7	5.68	2	4.00
Institutions	44.60	5	1.21	5	4.00	4	4.67
Natural Disasters & Conflict	76.57	2	1.47	4	-5.28	17	7.67
Financial & Aid Flows	12.61	15	0.72	6	2.36	7	9.33
Health	25.13	9	-1.76	16	3.97	5	10.00
Debt & Reserves	26.06	8	-0.91	15	1.72	8	10.33
Trade Intensity and Composition	36.89	6	-0.87	14	-2.50	12	10.67
Population	19.11	10	-0.24	11	-1.43	11	10.67
Business Environment	13.99	13	-0.07	9	-3.23	13	11.67
Climate & Agriculture	7.50	17	-0.13	10	0.89	9	12.00
Production Shares	17.46	12	-0.70	13	-3.26	14	13.00
Trade Diversification	17.49	11	-0.67	12	-4.90	16	13.00
Poverty & Inequality	11.56	16	0.09	8	-3.68	15	13.00
Education	13.49	14	-1.91	17	0.43	10	13.67

Table C28: RF Ranking of Indicator Topics: PC12 Predicting MAD-Difference of CPI Inflation

<i>Method:</i> Topic	Permutation		Exclusion		Residual Fit		Combined
	% $\Delta$ MSE	Rank	% $\Delta$ MSE	Rank	% $\Delta$ MSE	Rank	Avg. Rank
Exchange Rate and ToT	106.41	1	8.15	1	25.13	1	1.00
Debt & Reserves	43.52	5	0.15	6	5.97	2	4.33
Production Shares	96.40	2	1.52	2	0.86	12	5.33
Poverty & Inequality	6.23	13	0.25	4	2.58	6	7.67
Climate & Agriculture	38.44	6	-0.15	8	0.97	11	8.33
Natural Resources	8.82	12	-0.20	10	3.66	3	8.33
Health	72.33	3	-0.68	15	1.28	8	8.67
Education	46.45	4	-1.51	17	2.98	5	8.67
Population	36.27	7	1.11	3	-2.30	17	9.00
Natural Disasters & Conflict	11.64	11	0.02	7	1.22	9	9.00
Institutions	13.15	10	-0.64	14	2.33	7	10.33
Financial Sector	24.62	8	-0.48	12	0.42	13	11.00
Business Environment	5.09	15	-1.01	16	3.55	4	11.67
Trade Diversification	13.46	9	-0.64	13	0.13	14	12.00
Financial & Aid Flows	4.99	16	-0.40	11	0.98	10	12.33
Trade Intensity and Composition	5.93	14	-0.19	9	-0.73	15	12.67
Others	2.60	17	0.25	5	-0.91	16	12.67