A simple time-insensitive index of instability as a proxy for the "Africa dummy" variable – A Note

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REEPS

2 October 2019

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Abstract: This paper suggests calculating a simple time-insensitive index of instability using discrete series of events. The calculation of the index does not require complex statistical analysis of event series, discrete-event systems analysis, or categorical analysis. It uses a simple, single-equation regression to estimate the effects of instability on Africa's per capita GDP over the 1961-2018 period. The results are mixed, with some showing that instability has constrained Africa's performance and others implying it has helped. The findings are not quite econometrically pure, but reasonable given that many relevant variables are missing from the regression. Hence, I resist the temptation to comment further until at least conventional factors like capital are included in this regression, while I insist that the index itself is sound.

Keywords: Index of instability, Africa dummy, economic performance, single-equation regression

JEL Code: O47, O55, Z00

1. Introduction

The use of 0-1 dummy variables is of significant value where key data is either unreliable or completely missing. However, because it so widely and frequently employed, the so-called Africa dummy variable raises not only econometric issues such as "dummy variable traps," but also economic issues including proper interpretations. The idea of this paper is very simple: To suggest a time-insensitive instability index as a proxy for the "Africa dummy" that is data economical. As most readers of this paper already know, Barro (1991) kicked off the hornets' nest of research on the significance of the so-called "Africa dummy" variable as a key determinant of economic performance. Amavilah (2019) and Jerven (2011) have listed many other papers on this subject. Englebert (2000), for example, argues that most of the research has attempted to reduce the effect of the "Africa dummy" by introducing separate 0-1 dummy variables for landlockedness, ethno-fractionalization, polity, and, more recently, for governance indicators as placeholders for various institutions. These attempts are clearly improvements, but just as clearly inadequate. First, for some the results are not easy to interpret in natural ways. Second, for others the results are not quite policy intuitive, because nothing can really be done about such things as landlockedness. This paper constructs a time-invariant generalized index of instability, calibrates it on African data, and uses it in a single equation regression to estimate its effect on the performance of per capita GDP for Sub- Saharan Africa during the 1961-2018 years.

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2. Constructing the index

I designate the index as $x_i^*(t)$ -- an unweighted and weighted average of six components. I calculate it as follows:

$$x_i^*(t) = \frac{1}{m}[\sum_{i=1}^{n_1=22} \frac{1}{n_1} x_1(t) + \sum_{i=23}^{n_2=29} \frac{1}{n_2} x_2(t) + \sum_{i=30}^{n_3=36} \frac{1}{n_3} x_3(t)$$

$$+ \sum_{i=37}^{n_4=44} \frac{1}{n_4} x_4(t) + \sum_{i=45}^{n_5=59} \frac{1}{n_5} x_5(t) + \sum_{i=60}^{n_6=66} \frac{1}{n_6} x_6(t)] \qquad (1)$$

Equation (1) simplifies to:

$$x_i^*(t) = \frac{1}{m}\left[\sum_{i}^{n_i} \frac{1}{n_i} x_i(t)\right] = \alpha\left[\sum_i^{n_i} w_i x_i(t)\right], \qquad (2)$$

where $\alpha = 1/m$, m = 1, 2, 3, …, 6, $w_i = 1/n_i$, $n_i < N$ are observations on specific events, running as $n_1 = 1, 2, 3, \dots, 22\ for\ x_1; n_2 = 23, 24, 25, \dots, 29\ for\ x_2; n_3 = 30, 31, 32, \dots, 36\ for\ x_3; n_4 = 37, 38, 39, \dots, 44\ for\ x_4; n_5 = 45, 46, 47, \dots, 59\ for\ x_5; and\ n_6 = 60, 61, 62, \dots, 66\ for\ x_6$.

3. Data

I construct the index using data from Wikipedia's "List of wars and anthropogenic disasters by death toll," which I designate as x_i, where i = 1, 2, 3, …, 66 are the following 11 fuzzy, but largely exclusive, components of instability:

- Wars and armed conflicts with death toll in excess of 100,000 persons (x_1): Observations 1-22.
- Genocides, ethnic cleansing, and mass ethnic/religious persecutions (x_2): Observations 23-29.
- Forced labor/slavery, abuse of workers, and slave trade (x_3): Observations 30-36.
- War crimes, massacres, and ancient war atrocities (x_4): Observations 37-44.
- Death toll by political leader (x_5): Observations 45-59.
- Anthropogenically induced famine and disease outbreaks, and riots and political unrests (x_6): Observations 60-66.
- Political purges and repressions or politicides ($x_7 = 0$, or no data available for Africa).
- Human sacrifice and ritual suicide ($x_8 = 0$, or no data available for Africa).
- Prisons, concentration, and extermination camps ($x_9 = 0$, or no data available for Africa).
- Anthropogenically induced floods and landslides ($x_{10} =$ 0, or no data available for Africa.

The data appears in Table 1 below. The first column lists N = 1, 2, 3, …, 66 observations on x_i. The second column displays the events that caused the deaths, followed by when they happened, how long they lasted (duration), and the number of casualties they caused in the third, fourth, fifth, and sixth columns, respectively. The last column shows causalities per year. Over this time span, Africa has experienced just under 1,900 anthropogenically-induced events that killed nearly 79 million people, an average of 4.6 million a year. These are huge amounts although not in historical terms.

Using (2),

$$x^*(t) = \sum_{i=1}^{N} \frac{x_i(t)}{N},\ N = n_1 + n_2 + n_3 + n_4 + n_5 + n_6 \text{ -- unweighted} \quad (3a)$$

$$x^*(t) = \frac{1}{m}\left(\sum_{i=1}^{N} \frac{x_i(t)}{N}\right),\ m = 6 \text{ -- weighted} \quad (3b)$$

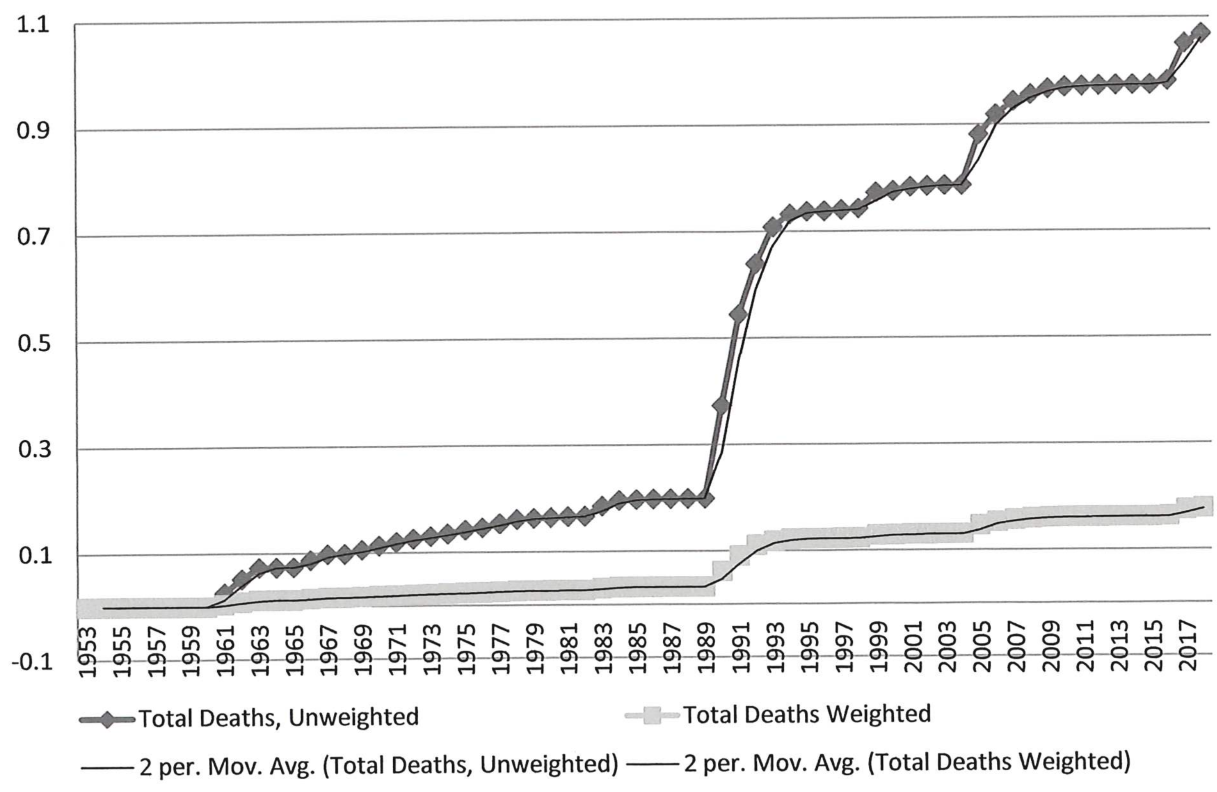
Table 1: Instabilities and their sources in Africa, 1400-2016*

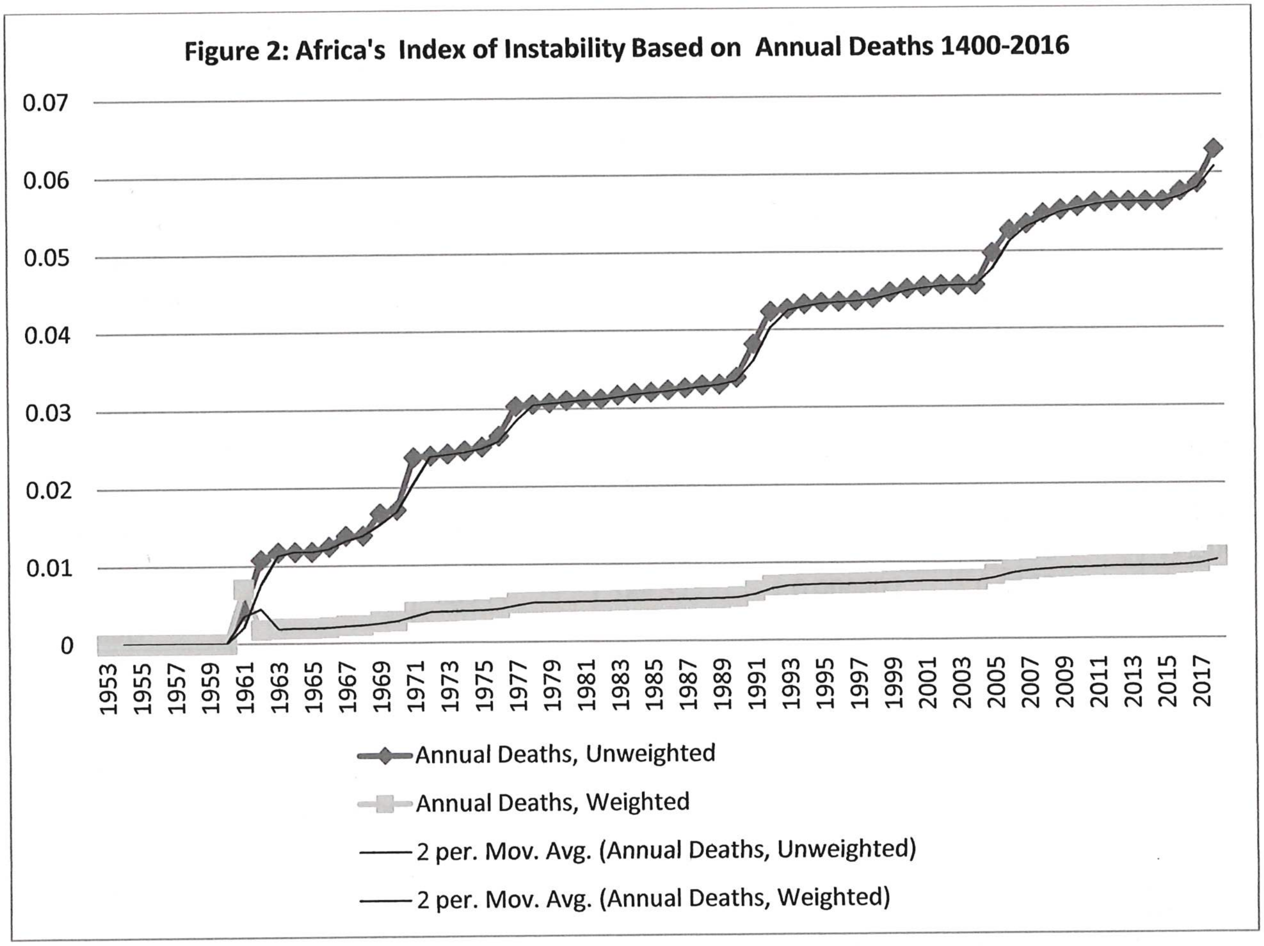
Observation	Event	When	Duration (years)	Total Casualties (millions)	Annual Casualties (millions)
1	WWII	1939-1945	7	1.6800	0.2400
2	Nigerian Civil War	1966-1970	5	1.7300	0.3460
3	Sudanese 2nd Civil War	1983-2005	23	1.4100	0.0613
4	Seven Year War	1756-1763	8	0.0220	0.0028
5	French Revolution	1792-1802	11	0.0200	0.0018
6	Ethiopian Civil War	1971-1991	21	0.8660	0.0412
7	Algerian War	1954-1962	9	0.7240	0.0805
8	War on Terrorism	2001-2013	13	0.0120	0.0010
9	Angolan Civil War	1975-2002	28	0.5042	0.0180
10	Sudanese 1st Civil War	1955-1972	18	0.5000	0.0278
11	1st Congolese War	1996-1997	2	0.4470	0.2235
12	Somali Civil War	1986-	33	0.3870	0.0117
13	French Conquest Of Algeria	1829-1847	19	0.3000	0.0158
14	Burundi Civil War	1993-2005	13	0.3000	0.0231
15	Darfur Conflict	2003-	16	0.4620	0.0289
16	2nd Ethiopian War	1935-1938	4	0.2780	0.0695
17	Uganda Bush War	1981-1986	3	0.5000	0.1667
18	Lord's Resistance War	1987-	32	0.5000	0.0156
19	Sierra Leone Civil War	1991-2002	12	0.1230	0.0103
20	Congo Crisis	1960-1965	6	0.1000	0.0167
21	Kivu Conflict	2004-	15	0.1000	0.0067
22	Angolan War of Independence	1961-1974	14	0.0420	0.0030
23	Rwanda-Burundi War	1959-1997	39	1.2340	0.0316
24	French –Algerian War	1827-1875	49	0.7070	0.0144
25	Italo-Libyan War	1923-1932	10	0.0800	0.0080
26	Rwanda Revolution	1959-1962	4	0.0500	0.0125
27	2nd Boer War	1900-1902	3	0.0330	0.0110
28	Rwandan Massacre	1988-1988	2	0.0250	0.0125
29	Zanzibar Massacre	1964-1964	2	0.0060	0.0030
30	Atlantic Slavery	1500-1700	201	11.5000	0.0572
31	Ottoman Slavery	1400-1800	401	11.3000	0.0282
32	King Leopold's Atrocities	1885-1908	24	6.3000	0.2625
33	Arab Slavery	1500-1700	201	4.5000	0.0224
34	French Slavery	1900-1940	41	1.6120	0.0393
35	Portuguese Slavery	1900-1925	26	0.3250	0.0125
36	Suez Canal	1859-1868	11	0.0670	0.0061
37	Islamist War	2001-	21	0.1640	0.0078
38	WWII Crimes	1939-1945	7	0.1250	0.0179
39	Sudanese 2nd Civil War	1956-2005	50	2.0000	0.0400
40	Italo-Ethiopian War	1935-1941	7	0.1730	0.0247
41	Angolan Civil War	1975-2002	28	0.5000	0.0179
42	2nd Italo-Senushi War	1923-1932	10	0.1000	0.0100
43	National Islam?	1964-1999	36	0.1000	0.00278
44	Algerian Conflict	1991-2002	12	0.0010	0.0001
45	Leopold II	1885-1908	24	6.2500	0.2604

46	Ranavodana	1829-1842	14	2.5000	0.1786
47	Omar el Bashir	1989-2019	31	1.6200	0.0523
48	Mengistu	1977-1987	11	0.8680	0.0789
49	Frelimo	1975-1999	23	0.7000	0.0304
50	Idi Amin	1971-1979	9	0.2240	0.0249
51	Siad Barre	1988-1991	4	0.1000	0.0250
52	Nguema	1968-1979	12	0.0630	0.0058
53	Habre	1982-1990	9	0.0400	0.0044
54	Apartheid	1948-1994	47	0.0190	0.0005
55	Korona	1997-1998	3	0.0060	0.002
56	WWII	1939-1945	7	0.4884	0.0700
57	Smoking	1930-1999	70	4.6200	0.0660
58	WWI	1914-1918	5	1.1600	0.2320
59	2nd Congo War	1998-2004	7	4.5300	0.6329
60	Biafra	1967-1970	4	2.5000	0.625
61	Ethiopian Conflict	1983-1985	3	0.6330	0.2110
62	Sudan	1998-1998	2	0.0700	0.0350
63	Riots, South Africa	1960-2016	57	0.0003	0.0001
64	Riots, Kenya	2008-2009	2	0.0010	0.001
65	Riots, Muhammad Cartoon	2005-2006	2	0.0001	0.0001
66	Riots, Egypt	2012-2013	2	0.0001	0.0001
Total			1845	78.3021	4.5907

*Data source: https://en.wikipedia.org/wiki/List_of_wars_and_anthropogenic_disasters_by_death_toll. Accessed on July 7/7/2019.

Figure 1: Africa's Index of Instability Based on Total Deaths, 1400-2016





The results of the calculation are in Figures 1 and 2. Figure 1 portrays the index based on total deaths, while Figure 2 shows the index based on annual deaths, both unweighted (Eq. 3a) and weighted (Eq. 3b). Annual deaths are an arithmetic average of the deaths caused by one event divided by the duration of the event. For example, the Angolan Civil War (1975-2002) killed 504,200 people and lasted 28 years, which amounts to 18,007 people killed per year.

An important word of caution: Although the figures present these indices as time-series, *they are not!* They are a series of real events that took place in real time, but they are not ordered sequentially in calendar time – the figures are. In other words, the variable "t" is a *real time* dummy -- not a calendar time – it is real time because the events under consideration did happen during the 1400-2016 period, but here they are not considered in terms of history. This is an Einsteinian conception in which time has meaning only because of the events that happened in it, not necessarily over it (Einstein, 1954[1952]).[2] The implication is that the index is calendar time insensitive, allowing us to estimate the total effects of instability that include distant events like slavery and the slave trade. This is a much simpler way of

[2] Einstein is cited by relativitybook.com to have said, "Time has no independent existence apart from the order of events by which we measure it." I take this to mean that instability is a function of events irrespective of the time in which such events happens.

where $y(t) = \log\left(\frac{Y(t)}{Population}\right)$, $z(t) = \log\left(\frac{Z(t)}{Population}\right)$.

In this paper I assume β is well-estimated in the previous literature – that there are few or no arguments there, which permits us to focus on λ and estimate (5) as

$$y(t) = a_0 + \lambda x^*(t). \tag{7}$$

Eq. (7) assumes that $\beta z(t) = 0,\ or\ \beta z(t)$ is an element of a_0. Now assume that $z(t)$ represents all conventional determinants of per capita GDP growth and their total effect can be captured by the historical growth in GDP per capita (y(t-1)). We can then estimate (7) as

$$y(t) = a_0 + \beta y(t-1) + \lambda x^*(t) + error \tag{8}$$

The reader may have noticed already that $x^*(t) \equiv x^*(t-8)$, but that is a minor issue since in my conception $t \neq calendar\ time$. The results and discussion are next. However, it should still be remembered that this is a measurement paper; its principal objective is to construct a time-invariant index of instability based on events in Africa. What the effects of the index on economic performance are is of secondary emphasis. Hence, in what follows the econometrics of the paper are less important than economics.

5. Results and Discussion

The Ordinary least squares (OLS) estimations in Table 3 found the effects instability on per capita GDP to be positive and statistically significant. However, instability explains a mere 7.1% of all variations in per capita GDP at the aggregate level. At the annual level the adjusted R-squared rises to 9.6%. Both adjusted R-squared are too low. This is not surprising because important variables like physical and human capital and so on are missing from these regressions.

Because the goal of the paper is not economic performance, I did not seek to include the missing variables. Even so, OLS results motivated the inclusion of GDP lagged by one period, which does two advantageous things: (a) y(t-1) was produced using all factors of production, and (b) y(t-1) helps us to deal with serial correlation, although no attempt was made to determine the optimality of the time lag. The results in Table 4 were corrected for autocorrelation, where Table 4.1 considered the unweighted (Eq. 3a) and weighted (Eq. 3b) index of instability. The results clearly show that a 10% increase in y(t-1) led to about a 6% increase in current GDP per capita – implying growth led to growth. The total effects of instability ranged from 0.25 to 1.5. Similar effects at the annual level lie between 5.6 and 34.2. In both cases the adjusted R-squared says that only 35% of variations in GDP per capita are a result of the included variables. These are big improvements on OLS results. Still the instability variables are incorrectly signed. Even if one assumes the possibility of a Bastiat's "broken window parable," the positive effects of instability on economic performance are still not expected results. One might argue that there is always increased economic activity after every major disaster. However, much of that would just be replacement activities and not constitute economic growth precisely defined.

Table 3.1: OLS Models of Performance and Instability Based on Total Deaths
(Dependent variable log GDP per capita; Parenthesis = T-tatio at 5% Significance Level)

Variable	Parameter Symbol	Unweighted Estimate	Weighted Estimate
Constant	a_0	0.7159(5.2506)	0.7159(5.2506)
$x^*(t)$	λ	0.5834(0.2926)	3.5007(2.4479)
Inferential Statistics	Adj. R-squared Sigma-squared Log-Likelihood Function	0.0713 0.5425 -72.4547	0.0713 0.5425 -72.4547

Table 3.2: OLS Models of Performance and Instability Based on Annual Deaths
(Dependent variable log GDP per capita; Parenthesis = T-tatio at 5% Significance Level)

Variable	Parameter Symbol	Unweighted Estimate	Weighted Estimate
Constant	a_0	0.5299(2.9622)	0.5299(2.9622)
$x^*(t)$	λ	13.577(2.8100)	81.463(2.8100)
Inferential Statistics	Adj. R-squared Sigma-squared Log-Likelihood Function	0.0959 0.52817 -71.5691	0.0959 0.52817 -71.5691

Table 4.1: Autocorrelation Models of Performance and Instability Based on Total Deaths
(Dependent variable log GDP per capita; Parenthesis = T-tatio at 5% Significance Level)

Variable	Parameter Symbol	Unweighted Estimate	Weighted Estimate
Constant	a_0	0.3359(2.4866)	0.3359(2.4866)
y(t-1)	β	0.55126(5.3036)	0.55126(5.3036)
$x^*(t)$	λ	0.24464(1.1662)	1.4678(1.1622)
Inferential Statistics	Adj. R-squared Sigma-squared Log-Likelihood Function	0.3484 0.38069 -60.2445	0.3484 0.38069 -60.2445

Table 4.2: Autocorrelation Models of Performance and Instability Based on Annual Deaths
(Dependent variable log GDP per capita; Parenthesis = T-tatio at 5% Significance Level)

Variable	Parameter Symbol	Unweighted Estimate	Weighted Estimate
Constant	a_0	0.29016(1.7604)	0.29016(1.7604)
y(t-1)	β	0.51653(4.7697)	0.51653(4.7697)
$x^*(t)$	λ	5.6992(1.2526)	34.195(1.2526)
Inferential Statistics	Adj. R-squared Sigma-squared Log-Likelihood Function	0.3496 0.37997 -60.1828	0.3496 0.37997 -60.1828

Although this is not an econometric analysis, it is obvious that another statistical problem is non-homogeneity. Table 5 below presents results for heteroskedastic models. The estimates in Table 5.1 are consistent with the usual understanding that instabilities are not good for economic performance. For both unweighted and weighted, a 10% increase in instability tends to lower performance by up to 15%. At the annual level the effects are also strong but of opposite sign. What all this seems to suggest is that we cannot reject that instabilities have had negative effects on performance, but we must accept that there exists a strong correlation between performance and instability and the nature of that correlation to be empirical. More likely the effects of instability are strong close to the times in which the events occurred, and they tapper off with the passage of time. If that is the case, the duration of effects of instability would depend not only on the type and duration of events that caused it, but also, perhaps more so, on the institutions for dealing with instability.

Table 5.1: Heteroskedastic Models of Performance and Instability Based on Total Deaths
(Dependent variable log GDP per capita; Parenthesis = T-tatio at 5% Significance Level)

Variable	Parameter Symbol	Unweighted Estimate	Weighted Estimate
Constant	a_0	0.60983(6.9821)	0.60983(6.9821)
y(t-1)	β	0.46641(9.2676)	0.46641(9.2676)
$x^*(t)$	λ	-0.24978(-1.9847)	-1.4987(-1.9947)
Heteroskedasticity	α	0.81260(7.5420)	0.81260(7.5420)
Inferential Statistics	Adj. R-squared Sigma-squared Log-Likelihood Function	0.2514 0.41083 -67.3790	0.2514 0.41083 -67.3790

Table 5.2: Heteroskedastic Models of Performance and Instability Based on Annual Deaths
(Dependent variable log GDP per capita; Parenthesis = T-ratio at 5% Significance Level)

Variable	Parameter Symbol	Unweighted Estimate	Weighted Estimate
Constant	a_0	0.20261(5.5027)	0.20261(5.5027)
y(t-1)	β	0.53354(10.235)	0.53354(10.235)
$x^*(t)$	λ	6.9789(5.3514)	41.874(5.3514)
Heteroskedasticity	α	0.7449(7.9099)	0.7449(7.9099)
Inferential Statistics	Adj. R-squared Sigma-squared Log-Likelihood Function	0.36815 0.36463 -71.9369	0.36815 0.36463 -71.9369

6. Conclusion

In this brief and svelte paper I calculate a time-insensitive index of instability based on real deaths caused by real anthropogenic events that have afflicted Africa over more than 1000 years. While the events are historical, the index is not, allowing for time-invariance. Such an approach is not only data economical; in fact, it circumvents the dearth of data that tends to frustrate effective policy in Africa. The index can be used to assess the importance of historical legacies without overstressing them. Let's face it: There is no doubt the TransAtlantic Slave Trade, for example, has lingering effects both in Africa and the diaspora. Reparations may be good policy for the descendants of slaves, but it is no policy for African countries. Indices like this one help policymakers separate the effects of the things they can do something about from those they cannot do anything about, which allows for efficient resource allocation. This paper has shown that the dearth of data, should not be the death of good policy.

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