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# Experimenting With the Forecasting Power of Publicity in the Predictability of Climate Change in Africa

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Motivated by the fact that the majority of news outlets in Africa have not sufficiently covered climate change issues, we innovatively construct a news-based index, drawing from the big data archive of Google Trends, as a proxy for publicity in the predictability of climate change. We show that increasing publicity about climate change has the potential to cause emission reduction and slow climate change.

### I. Introduction

Despite increasing declarations about the importance of public awareness of climate change mitigation, most African news outlets have not adequately covered climate change topics. Beyond the general lack of publicity regarding the causes and consequences of rising climate change in Africa, compared to other continents, the majority of existing studies on public awareness and climate change have mainly focused on developed economies. While climate change is a global issue that requires a worldwide response, there are major regional variances in knowledge and understanding of what causes climate change, who is impacted by it, and how it may be addressed (see Althor et al., 2016; Bathiany et al., 2018). Several African economies have signed on to the global goal of low carbon emissions, but they have been hesitant to adopt some of the globally accepted emission control mechanisms. This could be due to a lack of financial resources, technical capacity, and other resources, but the extent to which publicity can prevent climate change is largely unknown. We contribute to the literature by offering evidence-based insight into the potential of publicity to mitigate climate change. The few extant studies on the role of awareness in the mitigation of climate change (Ghazali et al., 2016; Li et al., 2019; Motoshita et al., 2015; Oluoch et al., 2020; Tschötschel et al., 2020) are predominantly microdata-based and ex-post. Thus, our study is the first to create a news-based index using Google Trends with plausible variants of climate change-related words to determine the extent to which publicity matters in climate change forecasting. The goal of

this study is to provide policymakers with evidence-based insights on the role of publicity in the predictability of climate change. Essentially, our findings from both the in-sample and out-of-sample forecasts suggest that raising awareness about the effects of climate change has the potential to facilitate both behavioural change and societal support for reducing greenhouse gas (GHG) emissions.

### II. Data and Methodology

#### A. Data description and source

The predicting variable, “climate change,” is measured as mean temperature (*TMP*) anomalies spanning January 2004 to December 2021. The theoretical postulations of the environmental Kuznets curve (*EKC*) hypothesis and the pollution haven hypothesis (*PHH*) designate industrialization (*IND*) and foreign direct investment (*FDI*) as our traditional predictor series. Both *IND* and *FDI* data were obtained from the WDI online database, while the climate change data were sourced from the Food and Agriculture Organization Statistics (FAOSTAT) online database. Finally, we used various keywords—frequently used in the literature on climate change as a proxy for publicity—to extract worldwide Google search volumes.<sup>1</sup> Using the principal component analysis, the resulting search volume variables were combined to arrive at our novel news-based index (*Pub*), which is further normalized using the following procedure:

$$Pub_{scaled} = (b - a) \times \frac{Pub_{unscaled} - \min(Pub_{unscaled})}{\max(Pub_{unscaled}) - \min(Pub_{unscaled})} + a$$

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1 The keywords/phrases utilized to extract the index are: “Greenhouse gas emissions”, “Carbon emissions”, “Climate change”, “Climate change news”, “Climate change conference”, “Intergovernmental Panel on Climate Change”, “Climate change policy”, “Climate change act”, “Climate change mitigation”.

The ‘ $a$ ’ component of terms  $(b - a)$  measures the least values while ‘ $b$ ’ measures the highest values of the index. Thus, the index uses the values between  $a = 1$  (the lowest levels of publicity about climate change) and  $b = 1$  (the highest level of publicity about climate change).

## B. Econometric method

Presented in equation (1) is an adjusted ordinary least squares (OLS) predictive model, which aligns with Westerland & Narayan’s (2015) procedure (see Isah et al., 2022; Salisu & Isah, 2018):

$$tmp_t = \alpha + \beta^{Adj} z_{t-1} + \eta(z_t - \rho z_{t-1}) + \varepsilon_t \quad (1)$$

The term on the left hand-side of the equation measures our predicting variable (climate change), while the  $z_t$  term represents the predictor series. The  $\beta^{Adj}$  is the coefficient that measures the relative predictability of *IND*, *FDI* and *Pub* in climate change. The first order autocorrelation coefficient is measured by the parameter ( $\rho$ ) while the inclusion of the second term, for example  $(z_t - \rho z_{t-1})$ , is intended to account for the presence of a persistence effect in the predictive model. The term  $\eta$ , on the other hand, is intended to capture the likelihood of an endogeneity effect in the model. Estimating equation (1) with the OLS method after correcting for the probable presence of persistence and endogeneity is expected to yield a bias-adjusted OLS estimator for the parameter  $\beta$  described as:  $\hat{\beta}_{adj} = \hat{\beta} - \delta(\hat{\rho} - \rho)$ .

In order to determine the most accurate predictive model for enhancing the predictability of climate change, we consider the following pair of predictive models:

$$\begin{aligned} tem_t = & \alpha + \beta_{ind} ind_{t-1} + \beta_{fdi} fdi_{t-1} \\ & + \eta_{ind}(ind_t - \rho_{ind} ind_{t-1}) \\ & + \eta_{fdi}(fdi_t - \rho_{fdi} fdi_{t-1}) + \varepsilon_t \end{aligned} \quad (2)$$

We further extend equation (2) to accommodate the role of publicity in the predictability of climate change as follows:

$$\begin{aligned} tmp_t = & \alpha + \beta_{ind} ind_{t-1} + \beta_{fdi} fdi_{t-1} \\ & + \beta_{EC} inf\_pub_{t-1} \\ & + \eta_{ind}(ind_t - \rho_{ind} ind_{t-1}) \\ & + \eta_{fdi}(fdi_t - \rho_{fdi} fdi_{t-1}) \\ & + \eta_{inf\_pub}(pub_t - \rho_{inf\_pub} pub_{t-1}) + \varepsilon_t \end{aligned} \quad (3)$$

Equation (2) is the traditional predictor of climate change named “Model (1)”, while equation (3) is the extended predictive model that includes the role and publicity of the predictability of climate change and was named “Model (2).”

## C. Forecast performance measures

To determine whether Model (1) or Model (2) is the most accurate for predicting climate change, we used both the single and pairwise approaches to evaluate forecast performance. Beginning with Model (1), the forecasting accuracy of the individual model was evaluated via Mean Square Error (MSE), while the Campbell & Thompson (2008) test was used for Model (2). For a positive Campbell & Thompson C-T statistic, the implication is that Model (2) is the most accurate to forecast climate change, while the reverse will be the case if the statistic is negative.

## III. Empirical Results

### A. Preliminary analysis results

Our empirical results section begins with a preliminary examination of both the predicting and predictor series. The mean values reported in Table 1(a) reveal Morocco, Tunisia, and Algeria as the countries with the highest incidence of climate change, on average. With respect to *Pub*, the mean statistic seems to suggest that the discernibility and accessibility of information about climate change are generally low in Africa. The unit root testing results is presented in the (b) part of the table. We also tested for the presence of persistence and endogeneity in the predictor series and found a high degree of persistence as well as the potential for endogeneity bias. This, among other things, motivates our preference for the Lewellen (2004) adjusted OLS as the most appropriate estimator in the context of this study.

### B. Predictability results

Based on Table 2, there is a negative coefficient of the variable “publicity,” confirming our prediction of decreasing effects of publicity on climate change. However, the statistical significance of the effects, which also implies the rejection of the null hypothesis of no predictability, appears to be viable only in three of the nine African countries considered. Notwithstanding, the potential of *IND* and *FDI* as the underlying sources of carbon emissions and predictors of climate change appears to be statistically evident in all the countries, which aligns with findings in the previous studies (see Opoku & Boachie, 2020; Vitenu-Sackey, 2020).

### A. In-sample and out-of-sample forecasts

Utilizing 75% of the total sample, the number of observations used for our in-sample forecast were 162. For the out-of-sample forecast, we considered three different forecast horizons such as four months ahead period forecast ( $h = 4$ ), eight months ahead period forecast ( $h = 8$ ), and 12 months ahead period forecast ( $h = 12$ ).

In absolute terms, the MSE values in Table 3 are lower for Model (2) than for Model (1), which is an indication that the model that incorporates publicity has the most accurate forecasting power for the predictability of climate change. This evidence is consistent across both the in-sample and out-of-sample forecasts. Given the nested nature of the two models, we further complemented the forecast performance results with those of a pairwise approach to evaluate the forecast performance. The C-T test statistics, like the MSE results, were positive for all countries, implying that, in addition to industrialization and FDI, publicity matters in the accuracy of climate change forecasts.

## IV. Conclusions

This study innovatively constructs a news-based index, drawing from the big data archive of Google Trends as a proxy for publicity in a predictive model. The predictability testing results show that publicity and awareness have the

**Table 1. Preliminary results**

	Algeria	Angola	Egypt	Kenya	Libya	Morocco	Nigeria	South Africa	Tunisia
Panel A: Descriptive Statistics									
<i>TMP</i>	1.41	1.13	1.04	0.97	0.97	1.53	1.11	0.87	1.50
<i>IND</i>	5.05	33.71	16.22	10.23	3.87	15.76	9.42	13.68	15.30
<i>FDI</i>	-1.08	1.00	3.20	0.98	1.41	2.42	1.39	13.68	1.25
<i>PUB</i>	32.79	4.47	7.95	8.76	2.53	4.50	14.72	24.14	7.17
Panel B: ADF unit root test results									
<i>TMP</i>	-11.750 <sup>a</sup>	-5.334 <sup>a</sup>	-16.358 <sup>a</sup>	-16.286 <sup>a</sup>	-16.286 <sup>a</sup>	-5.789 <sup>a</sup>	-14.036 <sup>a</sup>	-14.286 <sup>a</sup>	-13.544 <sup>a</sup>
<i>IND</i>	-3.918 <sup>b</sup>	-3.3012 <sup>a</sup>	-2.952 <sup>b</sup>	-3.210 <sup>a</sup>	-4.773 <sup>b</sup>	-3.276 <sup>a</sup>	-3.877 <sup>b</sup>	-2.378 <sup>b</sup>	-3.742 <sup>b</sup>
<i>FDI</i>	-3.329 <sup>a</sup>	-7.209 <sup>b</sup>	-3.505 <sup>b</sup>	-2.872 <sup>a</sup>	-6.368 <sup>b</sup>	-4.682 <sup>a</sup>	-3.995 <sup>a</sup>	-2.942 <sup>a</sup>	-3.816 <sup>a</sup>
<i>PUB</i>	-5.695 <sup>a</sup>	-5.648 <sup>a</sup>	-6.552 <sup>a</sup>	-4.667 <sup>a</sup>	-8.318 <sup>a</sup>	-7.828 <sup>a</sup>	-10.912 <sup>a</sup>	-4.776 <sup>a</sup>	-5.581 <sup>a</sup>
Panel C: Persistence test results									
<i>IND</i>	0.99***	1.00***	1.00***	1.01***	0.98***	0.96***	1.02***	0.98***	0.99***
<i>FDI</i>	0.95***	0.98***	0.99***	0.98***	0.99***	0.99***	0.99***	0.97***	0.95***
<i>PUB</i>	0.52***	0.09***	0.70***	0.52***	0.05	0.39***	0.05***	0.49***	0.38***
Panel D: Endogeneity test results									
<i>IND</i>	0.219***	0.237***	-0.115*	-0.109	-0.109	0.098	0.036	0.021	0.088
<i>FDI</i>	0.206***	0.212***	-0.112	-0.109	-0.109	0.151**	0.015	0.020	0.092
<i>PUB</i>	0.204***	0.228***	-0.109	-0.108	-0.104	0.096	0.040	0.021	0.036

Note: This table reports preliminary test results. Panel A reports mean value of all variables used in this study. Panels B reports ADF unit root test results. In Panel C we report persistence test results. The persistence test is performed by regressing each of the predictor on its first lag. Finally, we report the endogeneity test results in Panel D. We follow a three-step approach test proposed by Westerlund & Narayan (2015).

**Table 2. Predictability results**

	Model (1) Predictors: IND, FDI		Model (2) Predictors: IND, FDI, PUB		
	<i>IND<sub>t</sub></i>	<i>FDI<sub>t</sub></i>	<i>IND<sub>t</sub></i>	<i>FDI<sub>t</sub></i>	<i>PUB<sub>t</sub></i>
Algeria	0.3175*** (0.0193)	-0.0480*** (0.0171)	0.3252*** (0.0326)	-0.0481*** (0.0171)	-0.0010 (0.0038)
Angola	0.0399*** (0.0044)	-0.3971*** (0.1409)	0.0445*** (0.0045)	-0.4523*** (0.1393)	-0.0168*** (0.0058)
Egypt	0.0766*** (0.0078)	-0.0437 (0.0288)	0.0809*** (0.0083)	-0.0420 (0.0288)	-0.0095 (0.0063)
Kenya	0.0904*** (0.0056)	-0.0194 (0.0436)	0.0963*** (0.0081)	-0.0376 (0.0473)	-0.0041 (0.0041)
Libya	0.2359*** (0.0148)	-0.0269 (0.0223)	0.2416*** (0.0156)	-0.0277 (0.0223)	-0.0077 (0.0061)
Morocco	0.0792*** (0.0228)	0.1308 (0.1314)	0.1326*** (0.0275)	-0.1110 (0.1473)	-0.0467*** (0.0142)
Nigeria	0.0666*** (0.0136)	0.3128*** (0.0639)	0.0649 (0.0134)	0.0764*** (0.0764)	-0.0066 (0.0043)
South Africa	0.0743*** (0.0119)	-0.0676 (0.0562)	0.0839*** (0.0135)	-0.0272*** (0.0604)	-0.0088 (0.0056)
Tunisia	0.0900*** (0.0113)	0.0411 (0.1082)	0.1124*** (0.0129)	-0.0655 (0.1099)	-0.0235*** (0.0074)

Note: This table reports predictability test results. Values reported in parentheses are standard errors. \*\*\*, \*\*, and \* implies statistical significance at 1%, 5% and 10% levels, respectively.

potential to cause emissions reductions and slow climate change. This consistent evidence across both the in-sample and out-of-sample forecasts indicates that raising awareness about the effects of climate change can facilitate behavioural change and societal support to reduce GHG emissions.

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**Table 3. Single method forecast performance results**

	Model (1)				Model (2)			
	In-sample	Out-of-sample			In-sample	Out-of-sample		
		$h=4$	$h=8$	$h=12$		$h=4$	$h=8$	$h=12$
Algeria	1.1977	1.1741	1.1919	1.1783	1.1916	1.1679	1.1868	1.1732
Angola	0.6177	0.6143	0.6119	0.6025	0.5847	0.5833	0.5812	0.5718
Egypt	1.0034	0.9941	1.0098	1.0284	0.9873	0.9809	0.9976	1.0182
Kenya	0.2590	0.2560	0.2524	0.2519	0.2573	0.2545	0.2511	0.2502
Libya	0.2919	0.2866	0.2839	0.2845	0.2861	0.2811	0.2785	0.2790
Morocco	1.4526	1.4325	1.4643	1.4679	1.3555	1.3333	1.3700	1.3752
Nigeria	0.4405	0.4335	0.4247	0.4188	0.4198	0.4136	0.4051	0.4004
South Africa	0.4677	0.4617	0.4525	0.4731	0.4550	0.4496	0.4421	0.4593
Tunisia	1.3780	1.4165	1.3944	1.5008	1.2848	1.3089	1.2891	1.3852

Note: This table reports results based on the single method forecast performance. The smaller the MSE values the better the forecast accuracy of a predictive model.

**Table 4. C-T pairwise forecast performance results**

	In-sample	Out-of-sample		
		$h=4$	$h=8$	$h=12$
Algeria	0.0051	0.0053	0.0043	0.0043
Angola	0.0534	0.0504	0.0501	0.0509
Egypt	0.0160	0.0132	0.0123	0.0099
Kenya	0.0065	0.0057	0.0054	0.0064
Libya	0.0198	0.0191	0.0190	0.0193
Morocco	0.0668	0.0692	0.0643	0.0630
Nigeria	0.0469	0.0457	0.0462	0.0439
South Africa	0.0271	0.0263	0.0230	0.0290
Tunisia	0.0676	0.0759	0.0754	0.0769

Note: In this table a positive C-T value implies that Model (2) outperforms Model (1) and the reverse holds if the statistic is negative.



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