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Abstract

This paper estimates the total effect of power outages on economic growth in Sub-Saharan Africa over the period 1995-2007. Outages are instrumented using a satellite-based measure of lightning density. As suggested by Henderson et al. (2011), we also combine Penn World Tables GDP data with satellite-based data on nightlights to arrive at a more accurate measure of economic growth. Our results suggest that the annual economic growth drag of a weak power infrastructure is about 2 percentage points.

JEL Classification: H4, O1, O4

Keywords: economic growth; public utilities; electricity; earthlights; Africa

1. Introduction

Since the mid 1990s Sub-Saharan Africa has, for the first time in three decades, started growing at about the same rate as the rest of the world (World Bank, 2008). There is even econometric evidence that finds that a structural break in the rate of African GDP per capita growth occurred in 1995 (Arbache and Page 2009). Average growth in per capita GDP, from 1995 until the outbreak of the crisis, was about 3% per year (Penn World Tables, 7.0). Yet the observed variation in growth performance is equally astonishing; across Sub-Saharan Africa the standard deviation in growth is about 5%. What accounts for this variation?

Power problems could be a culprit, as it is widely acknowledged that Sub-Saharan Africa is in the midst of a power crisis (Eberhard et al. 2008; UN 2007).[1] Outages are not just frequent and long but also erratic. According to the World Bank's Enterprise Surveys, pertaining to the years 2006-2010, the average number of power outages during a typical month is 10.5, while the average length of an outage is 6.6 hours. Unsurprisingly, more than 50% of African businesses surveyed cite inadequate power supply as a major business constraint.[2] Overall, there is no doubt that a deficient power infrastructure dampens economic growth (Jones 2011; Eberhard et al. 2008; IMF 2008, Chapter IV). But how large is the effect? This paper provides an estimate.

Our paper is related to a large literature investigating the importance of infrastructure for growth and development. In a recent contribution, Dinkelman (2011) estimates the impact of household

[1] See "Toiling in the Dark: Africa's Power Crisis" by Michael Vines in the New York Times (July 29, 2007) for a vivid description of Africa's ongoing power crisis.
[2] http://enterprisesurveys.org/Data/ExploreTopics/infrastructure#--7

electrification on employment growth in rural communities by analyzing rural electrification roll-out in post-apartheid South Africa. While Dinkelman contributes to what we know about the *microeconomic effects* of the *quantity* of physical infrastructure in developing countries, we focus on the *macroeconomic effects* of the *quality* of physical infrastructure. The 1994 version of the World Development Report, which was devoted to "Infrastructure for Development", also made the distinction between the quantity and the quality of infrastructure services. The tradition in the macroeconomics literature has been to estimate quantity effects of public infrastructure on total factor productivity using time-series data, with Aschauer (1989) being a classic reference. The World Bank (1994) and Jimenez (1995) provide overviews relevant for developing countries. This paper departs from the macroeconomic tradition in three ways. First we focus exclusively on the quality of infrastructure. Secondly, we estimate the total effect of infrastructure as opposed to a partial effect. Thirdly, we pay more attention to the intricacies of obtaining identification.

The remainder of this paper is organized as follows. The next section discusses the empirical specification, identification and data. Section 3 presents and discusses the main results, while Section 4 concludes.

2. Empirical Strategy

Consider the following parsimonious regression model:

$$g_i = \alpha_0 + \alpha_1 \log(\text{OUTAGES}_i) + \varepsilon_i, \tag{1}$$

where g is the average annual growth rate of real income per capita over the period 1995-2007; the pre-crisis period in which Sub-Saharan Africa evidently witnessed something of a growth revival. Since GDP is likely to be particularly plagued by non-random measurement error in Africa, we follow Henderson et al. (2011, Section 2) in producing "adjusted" real GDP per capita growth rates by employing satellite data on nightlights. Briefly, the growth observations used below are a convex combination (weight: 0.5) of observed real (chained PPP) GDP per capita growth (from Penn World Tables 7.0) and the fitted values from a regression of this variable on growth in nigthlights 1995-2007. Our results are qualitatively the same if we employ the "raw" GDP per capita numbers; *quantitatively*, however, our estimates are (numerically) smaller using adjusted data. Accordingly, using adjusted growth rates provides more conservative estimates. The OUTAGES variable refers to the (log) number of outages in a typical month and derives from World Bank's Enterprise Surveys 2011. Our final sample consists of 39 countries in Sub-Saharan Africa. Interest centers on retrieving a consistent estimate of α_1.

Power supply is a *general purpose technology*, which affects the economy directly and/or indirectly through multiple channels. This has important implications for the selection of control variables. To see this, assume that power outages only have indirect effects on economic growth; i.e., assume the following causal structure: OUTAGES → PROXIMATE FACTORS → GROWTH. If we include all proximate factors, $\mathbf{X}$, assumed to be a vector valued function of power outages, $\mathbf{X} = \mathbf{f}\left(\text{OUTAGES}\right)$, and estimate (2):

$$g_i = \tilde{\alpha}_0 + \tilde{\alpha}_1 \log(\text{OUTAGES}_i) + \mathbf{X}_i{}' \boldsymbol{\alpha}_2 + \upsilon_i, \tag{2}$$

then $\text{plim}\,\tilde{\alpha}_1 = 0$ (Achen 2005) Adding all proximate factors may thus lead to a vanishing estimate. More generally, since the potential proximate factors are too numerous to account for, and since the *total effect* (= direct + indirect) is what should really interest us when dealing with a general purpose technology, the parsimonious specification (1) is appropriate. Consequently, α_1 in equation (1) is the *total effect of power outages on economic growth*.

The outages variable is endogenous in (1). It is both correlated with a number of economic growth determinants, subject to reverse causal influence, and measured with error. An appropriate identification strategy is thus called for. We adopt the strategy proposed by Andersen et al. (2011a, b), which entails using lightning density as an exogenous determinant of power disturbances. Lightning damage accounts for about 65% of all over-voltage damage to electrical distribution networks in South Africa; over-voltage damage in turn is thought to account for one-third of all outages.[3] In Swaziland more than 50% of power outages on transmission lines are attributed to lightning (Mswane and Gaunt 2005). These numbers are roughly in line with (though somewhat bigger than) measurements reported for the U.S (McGranaghan et al. 2002; Chisholm and Cumming 2006). For instance, Chisholm and Cummins argue that lightning is the direct cause of one third of all U.S. power quality disturbances.[4] In areas with greater lightning density (strikes/km^2/year) we should therefore expect to see more power outages, ceteris paribus.

[3] See http://www.liveline.co.za/lightning-stats.php.

[4] In 1997 that the Tennessee Valley Authority (TVA) implemented a system at TVA's Chattanooga facility that integrated lightning strike data with power quality data. TVA has about 17,000 miles of transmission lines spread across 7 U.S. states, and lightning is found to be responsible for about 45% of all power quality disturbances (McGranaghan et al. 2002).

Is lightning density a valid instrument? It is certainly external in the sense of Deaton (2010). However, this does not imply that it fulfills the exclusion restriction required for instrument validity: $\text{Cov}(\text{lightning}, \varepsilon) = 0$. In particular, it could correlate with geographical factors, say, which themselves exert an effect on economic growth. In an African context, the most obvious factor is natural resources. We therefore check the robustness of our results with respect to this particular concern. We also check the robustness of our results to the inclusion of initial (or predetermined) income per capita, a coastal dummy, precipitation, temperature, and absolute latitude.

3. Results

Table 1 reports regression output from estimation of equation (1). Column 1 reports OLS estimates, which are expected to be biased. The OLS estimate implies that a one log point change in the number of outages during a typical month is associated with on average 0.4 percentage points lower growth in GDP per capita. The outlier robust LAD (median) estimator provides a roughly similar estimate, cf. column 2. Turning to the IV estimate in column 3, where outages are instrumented by lightning density, we find a considerably larger point estimate: a one log point change in the number of outages during a typical month leads to a reduction in average annual growth of GDP per capita of about two percentage points. Put differentially, an increase in outages by one standard deviation (about 0.85 log points, or approximately 2.3 outages) instigates a reduction in growth of about 1.5 percentage points, or slightly less than one standard deviation in growth in our sample (std. dev. of adjusted growth is approximately 1.7%). Of course, this is the *total* effect of outages, which may work through a number of more proximate channels.

[Table 1 about here]

Figure 1 pictures the correlation between the exogenous component of outages and economic growth. Inspection of the figure reveals that Congo (Democratic Republic) and Liberia are potential outliers. Yet excluding them makes no difference to the IV estimate in column 3 of the table (coeff. = -0.016, std. err. = 0.007).

[Insert Figure 1 about here]

So far we have said little about statistical significance. However, inspection of Table 1 reveals that OLS and LAD estimates are insignificant at conventional levels, whereas IV estimates are significant at five percent or better. This confirms that outages are endogenous in column 1 and 2 (column 4 and 5, respectively). Moreover, our IV estimates are not plagued by weak instrument issues, as can be seen from the weak instrument statistics reported in the table.

As alluded to above, a potential concern with our identification strategy is that prices of natural resources surged during the period 1995-2007. If lightning is correlated with the presence of natural resources, the exclusion restriction is jeopardized. To explore this possibility we re-estimate column 3 of Table 1 with two resource dummies, taken from Arbache and Page (2009). The first is an oil exporter dummy, which is coded as one if *net* oil exports make up 30 percent or more of total exports. The oil exporters are Angola, Cameroon, Chad, Congo (Rep.), Equatorial Guinea, Gabon, Nigeria, and Sudan. Côte d'Ivoire is also producing oil, but its net exports of oil are still low. The second dummy, which is a dummy indicating whether the country is resource rich, takes the value one for Angola, Botswana, Cameroon, Chad, Congo (Dem. Rep.), Congo (Rep.), Equatorial Guinea, Gabon, Guinea, Namibia, Nigeria, Sao Tome and Principe, Sierra Leone, Sudan, and Zambia. As is evident from columns 1 and 2 of Table 2, including these measures one at a time does not change any of our results. In the Appendix we show that our IV results are robust to the inclusion of a list of alternative natural resource variables.

[Table 2 about here]

Another potential concern is that lightning picks up influences from factors such as coastal access, precipitation, temperature, and absolute latitude. To control for coastal access, we employ a coastal dummy taken from Arbache and Page (2009). The other climatic variables are from Yale University's Geographically based Economic (G-Econ) data version 3.4.[5] As is evident from columns 4-7, including these measures one at a time does appear to change any of our results. This conclusion, however, is premature. The lightning instrument turns weak in columns 1-2, 4 and 6. We therefore turn to the Anderson-Rubin (AR) statistic, which is robust to weak instruments. The AR statistic tests the null that the endogenous variable is zero, a null

[5] Data are available at http://gecon.yale.edu. Absolute latitude is measured in degrees, temperature is average annual level 1980-2008, and precipitation is average annual level 1980-2008.

which we always reject at the five percent level in all columns. Thus, our IV results are robust to the inclusion of key geography variables.

4. Conclusion

In this paper we ask by how much power outages have affected Africa's recent growth experience. Our estimates suggest that if all African countries were to experience South Africa's power quality, the continent's average annual rate of real GDP per capita growth would have been increased by 2 percentage points and, measured by the coefficient of variation, the cross-country variation in growth rates would have been reduced by around 20%. These numbers, we believe, underscore the importance of solving the power crisis in Africa.

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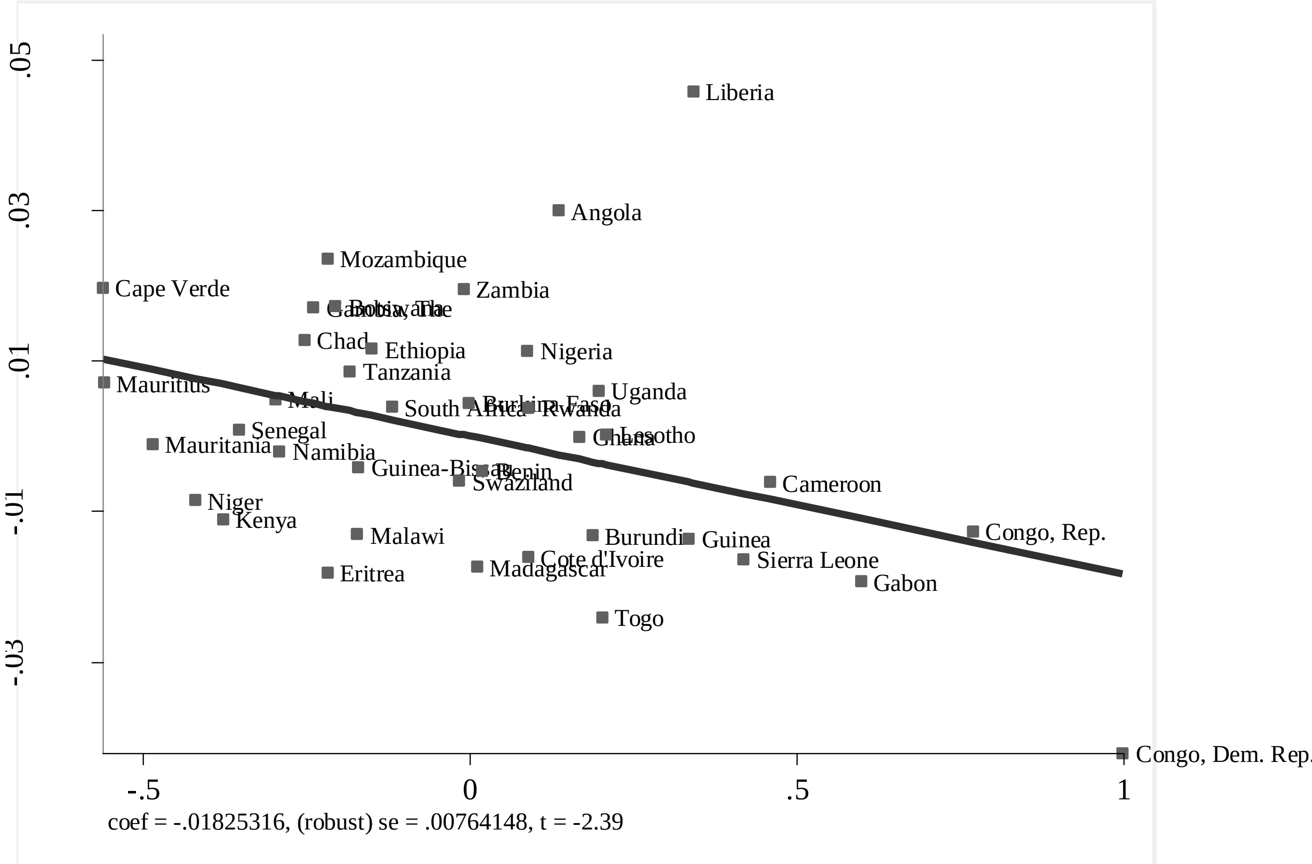
Figure 1: Scatter plot of the regression corresponding to column 3, Table 1.



The *x-axis* plots the exogenous component of power outages, while the *y-axis* plots growth in real GDP per capita.

Table 1. Outages and Economic Growth in Sub-Saharan Africa

	(1)	(2)	(3)	(4)	(5)	(6)
Estimation method	OLS	LAD	IV	OLS	LAD	IV
Outages	-0.004	-0.004	-0.018	-0.005	-0.005	-0.020
	(0.003)	(0.005)	(0.008)	(0.004)	(0.006)	(0.009)
GDP per capita, 1995				-0.003	-0.008	-0.007
				(0.004)	(0.006)	(0.004)
Constant	0.035	0.034	0.064	0.058	0.091	0.118
	(0.007)	(0.011)	(0.018)	(0.034)	(0.047)	(0.041)
Observations	39	39	39	39	39	39
K-P F-Statistic			13.33			11.93
A-R Wald test (p-value)			0.014			0.010
R-squared	0.038			0.061		

Notes: The dependent variable is adjusted average annual growth in (chained PPP) GDP per capita, 1995-2007. All standard errors (robust) are reported in parenthesis below the point estimate. LAD is reported with bootstrapped standard errors, replications 500. K-P F-Statistic refers to the Kleibergen-Paap statistic, and A-R Wald Test refers to the Anderson-Rubin test, where H_0 is the insignificance of the instrumented variable.

Table 2. Robustness to natural resources and geography/climate variables

	(1)	(2)	(3)	(4)	(5)	(6)
Estimation method	IV	IV	IV	IV	IV	IV
Outages	-0.031	-0.029	-0.021	-0.038	-0.018	-0.036
	(0.010)	(0.014)	(0.008)	(0.020)	(0.008)	(0.026)
Oil exporter	0.025					
	(0.012)					
Resource rich		0.013				
		(0.013)				
Coastal			-0.000			
			(0.007)			
Precipitation				1.5×10^{-5}		
				(1.3×10^{-5})		
Temperature					0.001	
					(0.001)	
Absolute latitude						-0.002
						(0.001)
Constant	0.085	0.082	0.069	0.091	0.028	0.119
	(0.022)	(0.027)	(0.017)	(0.035)	(0.021)	(0.071)
Observations	38	38	38	38	38	38
K-P F-Statistic	8.62	6.83	13.80	3.95	17.09	2.59
A-R Wald test (p-value)	0.000	0.000	0.001	0.024	0.024	0.039

Notes: The dependent variable is adjusted average annual growth in (chained PPP) GDP per capita, 1995-2007. All standard errors (robust) are reported in parenthesis below the point estimate. The dummies indicating whether a country is an oil exporter, resource rich, or a coastal nation are taken from Arbache and Page (2009). Precipitation, temperature and absolute latitude are from Yale University's G-Econ database version 3.4. Data are available at http://gecon.yale.edu.

Appendix

Table A. Robustness to natural resource rents

	(1)	(2)	(3)	(4)	(5)	(6)
Estimation method	IV	IV	IV	IV	IV	IV
Outages	-0.019	-0.027	-0.019	-0.018	-0.025	-0.027
	(0.009)	(0.013)	(0.008)	(0.008)	(0.011)	(0.012)
Coal rents	-0.573					
	(0.353)					
Forest rents		0.191				
		(0.132)				
Mineral rents			-0.033			
			(0.041)			
Natural gas rents				0.002		
				(0.002)		
Oil rents					0.037	
					(0.022)	
Total resource rents						0.041
						(0.024)
Constant	0.066	0.077	0.066	0.063	0.076	0.078
	(0.019)	(0.024)	(0.018)	(0.018)	(0.021)	(0.023)
Observations	39	39	38	39	39	39
K-P F-Statistic	12.21	6.78	12.23	12.72	8.03	7.68
A-R Wald test (p-value)	0.018	0.005	0.018	0.018	0.008	0.003

Notes: The dependent variable is adjusted average annual growth in (chained PPP) GDP per capita, 1995-2007. All standard errors (robust) are reported in parenthesis below the point estimate. Natural resource rents (in 2007) are the difference between the value of production at world prices and their total costs of production, with rents expressed as a share of GDP. All resource rent variables are taken from World Development Indicators (2011).