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# Power outages and economic growth in Africa

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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. We pay close attention both to potential errors of measurement of African economic growth and to the endogeneity of outages. As suggested by Henderson et al. (*American Economic Review* 102(2): 994–1028, 2012), we combine Penn World Tables GDP data with satellite-based data on nightlights to arrive at a more accurate measure of economic growth. Following Andersen et al. (*Review of Economics and Statistics* 94(4): 903–924, 2012), we also employ lightning density as an instrument for power outages. Our results suggest a substantial growth drag of a weak power infrastructure in Sub-Saharan 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).[2] 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 h. Unsurprisingly, more than 50% of African businesses surveyed cite inadequate power supply as a major business constraint.[3] Overall, there is no doubt that a deficient power infrastructure dampens economic growth (Eberhard et al., 2008; International Monetary Fund, 2008, Chapter IV; Jones, 2011). 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 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.[4] 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 Jimenez (1995) and World Bank (2008) provide overviews relevant for developing countries.

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[1] Tel.: +45 35324407; fax: +45 35323000.
[2] 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.

[3] http://enterprisesurveys.org/Data/ExploreTopics/infrastructure#–7.
[4] For a general survey of the relationship between energy use and economic growth, see Ozturk (2010) and Payne (2008).

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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, using IV estimation and adjusted data, 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

### 2.1. Specification

Consider the following parsimonious regression model:

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

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. Interest centers on retrieving a consistent estimate of $\alpha_1$, i.e., the impact of power outages on economic growth.

In order to appreciate this parsimonious specification, note that power supply is a *general-purpose technology*, which affects the economy directly and/or indirectly through multiple channels. This has important implications for identification. 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, $\mathbf{X} = \mathbf{f}(\mathrm{OUTAGES})$, and estimate (2):

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

then plim $\tilde{\alpha}_1 = 0$ (Achen, 2005). Adding all proximate factors thus leads 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, $\alpha_1$ in Eq. (1) is the *total effect of power outages on economic growth*, which we attempt to identify below.

### 2.2. Identification

The outages variable is endogenous in Eq. (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. (2011, 2012), 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.[5] 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. (Chisholm and Cummins, 2006; McGragnaghan et al., 2002). For instance, Chisholm and Cummins argue that lightning is the direct cause of one third of all U.S. power quality disturbances.[6] In areas with greater lightning density (strikes/km$^2$/year) we should therefore expect to see more power outages, ceteris paribus.

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: Cov(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, tropical disease, precipitation, temperature, and absolute latitude.

### 2.3. Data sources

Since GDP is likely to be particularly plagued by non-random measurement error in Africa, we follow Henderson et al. (2012) 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 nightlights 1995–2007.[7] 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.

As with nightlights, the lightning data also derives from satellites. The National Aeronautics and Space Administration (NASA) provides the raw data (strikes/km$^2$/year). More specifically, we rely on the data from the so-called Optical Transient Detector (OTD), a space-based sensor launched on April 3, 1995. For a period of roughly 5 years the satellite orbited Earth once every 100 min at an altitude of 740 km. At any given instant it viewed a 1300 km × 1300 km region of Earth. Lightning is determined by comparing the luminance of adjoining frames of OTD optical data. When the difference was larger than a specified threshold value, an event was recorded.[8] These satellite-based data are archived and cataloged by the Global Hydrology and Climate Center, where they are also made publicly available.[9] We apply the data from a high-resolution (0.5° latitude × 0.5° longitude) grid of total lightning bulk production, expressed as a flash density, from the completed 5-year OTD mission.[10] We then construct average flash densities for each country by first mapping the corresponding geographic areas into the lightning data grid and then taking the average of flash densities within each of these areas. The coordinates describing the areas are taken from the GEOnet Names Server (GNS) at the U.S. National Geospatial-Intelligence Agency's (NGA),[11] and the U.S. Board on Geographic Names' (U.S. BGN) database of foreign geographic names and features.[12] We used the GNS database released on October 7, 2008.[13] For further information on the data and its construction, see Andersen et al. (2011).

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

[6] In 1997, 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 was found to be responsible for about 45% of all power quality disturbances (McGragnaghan et al., 2002).

[7] Even if changes in light from space are subject measurement error, it is well known that several error-prone measures are better than one, especially if there is no reason to think that the measurement errors are correlated (Henderson et al., 2012).

[8] Basically, these optical sensors use high-speed cameras designed to look for changes in the tops of clouds. By analyzing a narrow wavelength band (near-infrared region of the spectrum) they can spot brief lightning flashes even under daytime conditions.

[9] http://thunder.msfc.nasa.gov/data/#OTD_DATA.

[10] ftp://microwave.nsstc.nasa.gov/pub/data/lightning-satellite/lis-otd-climatology/HRFC/LISOTD_HRFC_V2.2.hdf.

[11] http://earth-info.nga.mil/gns/html/namefiles.htm.

[12] http://geonames.usgs.gov/domestic/download_data.htm.

[13] ftp://ftp.nga.mil/pub2/gns_data/geonames_dd_dms_date_20081007.zip.

To address the possibility that our lightning instrument could be correlated with important geographical factors, which exert an effect on economic growth, we include a number of geographical controls. In an African context, and given the period in question, the most obvious geographical factors are natural resources. We therefore include 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% or more of total exports. The oil exporters in our sample are Angola, Cameroon, Chad, Congo (Rep.), Gabon, and Nigeria. 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. In an appendix we report results based on an alternative set of natural resource indicators, namely natural resource rents (in 2007). Rents are measured as the difference between the value of production at world prices and their total costs of production; rents are expressed as a share of GDP. All resource rent variables are taken from World Development Indicators (2011). Finally, we also include measures of precipitation, temperature and absolute latitude, all from Yale University's G-Econ database version 3.4.[14]

Our final sample consists of 39 countries in Sub-Saharan Africa.

## 3. Results

Table 1 reports regression output from estimation of Eq. (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 (numerically) 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.[15]

Fig. 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).

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 columns 1 and 2 (columns 4 and 5, respectively). Moreover, weak instrument issues do not plague our IV estimates, 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, coded as one if *net* oil exports make up 30% or more of total exports. The second dummy indicates whether the country is resource rich. 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: differences in point estimates are statistically insignificant. In Appendix Table A we show that our IV results are robust to the inclusion of a list of alternative natural resource variables.

Another potential concern is that lightning picks up influences from factors such as coastal access, precipitation, temperature, and absolute latitude.[16] 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.[17] As is evident from columns 3 to 6, including these measures one at a time does not 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 that we always reject at the five percent level in all columns. Thus, our IV results are robust to the inclusion of key geography variables: the most conservative IV point estimate in both Tables 1 and 2 is −0.018.

In Appendix Table B we also show that inclusion of malaria incidence does not change our conclusions. Moreover, we also investigate the robustness of our results when we measure real GDP per capita growth in local currency units (LCU). As shown by Hanousek et al. (2008), this may make a difference. They also cite studies that suggest that using LCU based data may be superior when the aim is to measure growth rates (p. 1191). In our sample, there is in fact a discrepancy between the uses of PPP based data versus local currency data, which can be traced to the six large net oil-exporting countries in our sample. All results reported in the main text hold regardless of how we measure economic growth when we either exclude these oil exporters or add an oil exporter dummy, where the latter is always statistically significant, cf. Appendix Table B. The fact that the dummy

**Table 1**
Outages and economic growth in Sub-Saharan Africa.

| Estimation method | (1) OLS | (2) LAD | (3) IV | (4) OLS | (5) LAD | (6) IV |
|---|---|---|---|---|---|---|
| Outages | −0.004 | −0.004 | −0.018 | −0.005 | −0.003 | −0.020 |
| | (0.003) | (0.005) | (0.009) | (0.004) | (0.006) | (0.010) |
| GDP per capita, 1995 | | | | −0.003 | −0.006 | −0.007 |
| | | | | (0.004) | (0.006) | (0.004) |
| Constant | 0.033 | 0.031 | 0.062 | 0.058 | 0.071 | 0.117 |
| | (0.007) | (0.011) | (0.019) | (0.037) | (0.052) | (0.044) |
| Observations | 39 | 39 | 39 | 39 | 39 | 39 |
| K–P F-statistic | | | 13.33 | | | 11.93 |
| A–R Wald test (p-value) | | | 0.033 | | | 0.027 |
| R-squared | 0.037 | | | 0.061 | | |

Notes: The dependent variable is adjusted average annual growth in real (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 F statistic, and A–R Wald test refers to the Anderson–Rubin test, where $H_0$ is the insignificance of the instrumented variable.

[14] Data are available at http://gecon.yale.edu.

[15] Measurement error and/or omitted variables are the cause of the discrepancy between OLS and IV results. Assuming no measurement error, a standard result from econometrics holds that if $q$ is erroneously omitted from our estimating Eq. (1) then $plim\ \alpha_{OLS} = \alpha + \beta[cov(OUTAGES,q)/var(OUTAGES)]$, where $\beta$ is the correlation between $g$ and $q$ once OUTAGES is partialled out. If our exclusion restriction is fulfilled then $plim\ \alpha_{IV} = \alpha$. Hence, given our estimates, it must be that $\beta cov(OUTAGES,q) < 0$. Assuming no omitted variables, classical errors-in-variables lead to attenuation bias with OLS being biased towards zero.

[16] For empirical evidence on the geography-economic development nexus, see Easterly and Levine (2003) and Olsson and Hibbs (2005).

[17] 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.

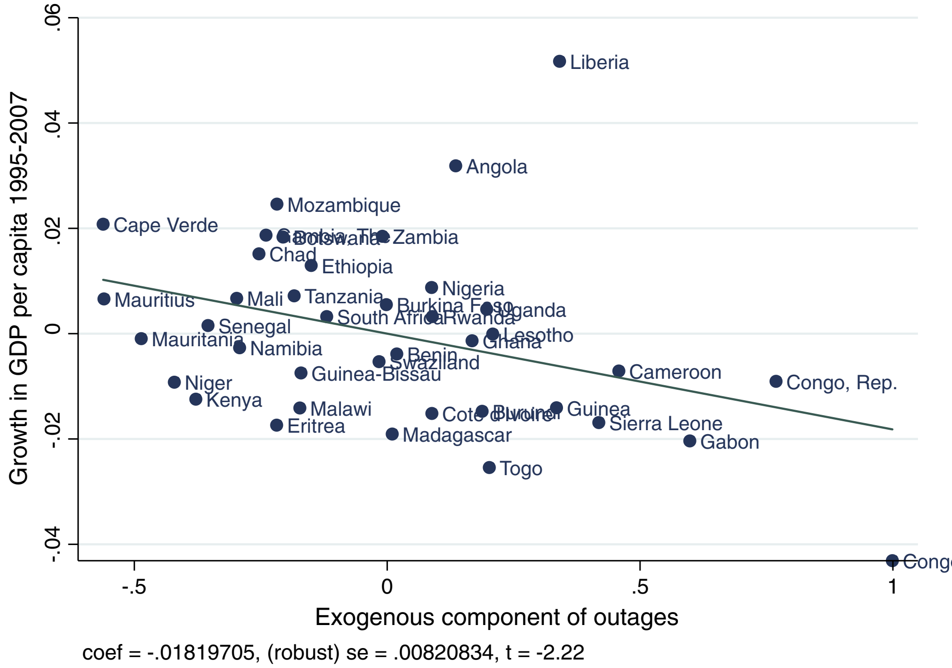


**Fig. 1.** Scatter plot of the regression corresponding to column 3, Table 1. The *x*-axis plots the exogenous component of power outages, while the *y*-axis plots growth in adjusted real GDP per capita over the period 1995–2007.

is always significant means that excluding it would amount to a specification error in the LCU sample. This also means that using LCU based data does not change any of our results.[18]

## 4. Conclusion

In this paper we ask by how much power outages have affected Africa's recent growth experience. We believe our estimates show that the economic impact is likely to have been substantial.

One way to appreciate the economic significance of the results is to view them through the lens of a neoclassical growth model (e.g., Solow, 1956). In the context of the Solow model, where the long-run growth rate is exogenously given, changes in OUTRAGES will have long-run levels effects. How big is the implied impact? As seen from column 6 of Table 1, conditional convergence prevails (initial GDP per capita is significant at the 10% level). The long-run level effect implied by our estimates can then be assessed by setting $g = 0$ (or given at some exogenous non-zero level; a steady state assumption) and then proceed to isolate $log(GDP\ per\ capita)$ in the regression equation. We obtain $\log(\text{GDPper capita}) = -(0.02/0.007) * log(OUTAGES) = -2.86 * log(OUTAGES)$. Hence, a one percent increase in outages reduces long-run GDP per capita by 2.86%.

Note that while conditional convergence apparently is present, the rate of convergence is only 0.7% per year, which is considerably below the "iron law of convergence" involving a rate of convergence of 2% per year (Barro, 2012). Taken at face value, the estimate for the rate of convergence implies it takes about 100 years (=72/0.7) to close half the gap to the steady state after a shock to the economy. The "long-run" is very far away.

Accordingly, as an alternative way to gauge the economic significance of our findings, suppose we ignore convergence. Judged from the point estimate for OUTAGES, our results then suggest that if all African countries had experienced 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

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

| Estimation method | (1) IV | (2) IV | (3) IV | (4) IV | (5) IV | (6) IV |
|---|---|---|---|---|---|---|
| Outages | −0.032 | −0.030 | −0.022 | −0.038 | −0.018 | −0.036 |
| | (0.011) | (0.014) | (0.008) | (0.021) | (0.009) | (0.026) |
| Oil exporter | 0.027 | | | | | |
| | (0.013) | | | | | |
| Resource rich | | 0.013 | | | | |
| | | (0.013) | | | | |
| Coastal | | | −0.000 | | | |
| | | | (0.007) | | | |
| Precipitation | | | | $1.5 \times 10^{-5}$ | | |
| | | | | $(1.3 \times 10^{-5})$ | | |
| Temperature | | | | | 0.002 | |
| | | | | | (0.001) | |
| Absolute latitude | | | | | | −0.001 |
| | | | | | | (0.001) |
| Constant | 0.085 | 0.082 | 0.068 | 0.089 | 0.024 | 0.117 |
| | (0.023) | (0.028) | (0.018) | (0.037) | (0.021) | (0.072) |
| 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 | 0.041 | 0.036 | 0.054 |

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

[18] The most obvious explanation for the significant oil-exporter dummy is that the oil-exporters have experienced real exchange rate appreciations since the mid-1990s. This appreciation was the result of an increase in the relative prices of domestic goods and services due in turn to an increase in aggregate demand. Higher wages in the resource-based sector lead to higher wages in other activities. The wealth effect associated with the increase in overall wages leads to higher demand for domestically produced goods and services and hence higher prices (see Treviño, 2011).

believe, underscore the importance of solving the power crisis in Africa.

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## Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.eneco.2013.02.016.

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