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The centrality of electricity to ICT use in low-income countries

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ABSTRACT

A growing body of literature that extols the ability of information and communication technologies (ICTs) to enhance well-being in developing countries tends to focus on long run institutional and socio-economic changes as key to driving Internet uptake. The literature, however, too often ignores one factor in discussions of ICTs' importance and employment: electricity. Overlooking the centrality of electricity to any ICT for development (ICT4D) initiative has enormous consequences; countless initiatives have failed to consider the (in)ability to power the technology that is central to such development efforts. The present article seeks to address this gap by emphasizing the primacy of electricity in ICT4D initiatives. Utilizing a unique dataset that avoids issues associated with unreliably measured and inequitably distributed grid power, we examine the drivers of Internet adoption in low-income countries. We find robust evidence that increasing the distribution of electricity within under-served countries—and thereby making electricity available to a larger proportion of the population—significantly increases the number of Internet users. Arguably, improvements in infrastructure may bring about significant changes in Internet use, even in places where advancements in education and political representation remain elusive.

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> *I came to Uganda to run the technical side of a mobile phone company. Instead, I'm running the largest diesel fuel distribution company in the country—in order to run the mobile phone company.* –Francis Kazinduki, CTO of MTN, Uganda

1. Introduction

Many believe that information and communication technologies (ICTs) have the potential to improve quality of life around the world. Recent times have seen the emergence of an entire body of scholarly literature devoted to defining, conceptualizing, debating, measuring, and addressing the use of ICTs in developing countries. Our contribution concerns an underemphasized factor impacting all technology use, particularly for less-developed locations: *lack of electricity*. Its presence is a prerequisite to ICT use, and its under-emphasis in the digital divide literature has significant consequences for the developing world: countless initiatives have failed to consider the ability to power the technology that is central to such development efforts (Hosman & Baikie, 2013).

Our intention, therefore, is to foreground electricity as a fundamental consideration in ICT for development. We use an innovative approach for measuring countries' electrical infrastructure using data on the distribution of night light as measured from space by satellite. This dataset provides both a measure of distribution (rather than quantity) of electricity used in developing countries, and includes off the grid power use in low-income countries where an electrical grid constitutes only a small proportion of the electric power available.

We use country fixed effects to distinguish within-country drivers of Internet adoption from cross-country differences. We believe that these within-country differences are more important for short-run within-country policy considerations.

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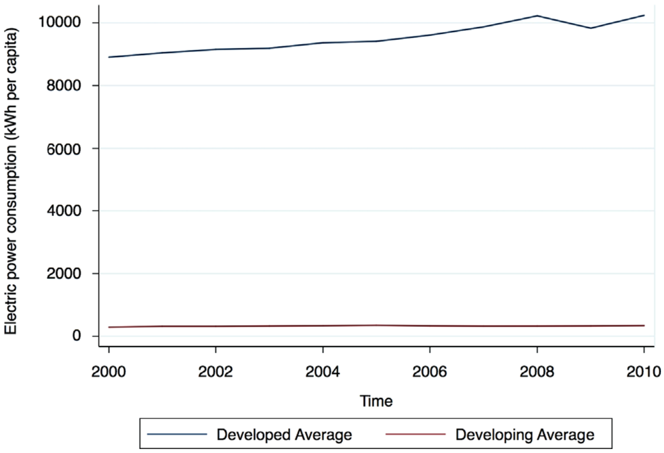

Fig. 1. Electricity consumption.

Moreover, this is one of the first papers on this topic to use dynamic panel data analysis, which allows us to model the S-shaped curves and dynamic processes that characterize technology adoption. In addition, the use of newer data, 2000–2010, offers novel insights into disparities in Internet adoption because it has been a period of change and divergence of Internet adoption in developing countries.

We find significant evidence that the distribution (i.e. availability), rather than the quantity of electricity, significantly increases within-country demand for the Internet. We posit that there is latent demand for the Internet within low-income countries, and that when electricity becomes available, more people will become Internet users.

In other words, using a dataset that more precisely measures the use of electricity in low-income countries, on and off grid, we find that greater numbers of people having access to electricity is a far better predictor of Internet uptake (the most commonly used dependent variable in the digital divide literature), than is the overall amount of electricity produced on a national level. Our policy recommendations follow from these findings.

2. Literature overview

In high-income countries, increased use of electricity enables the “new digital economy,” as well as improves individuals' productivity and quality of life (Ebohon, 1996; Rosenberg, 1998). Very little has been written, however about increased access to electricity in developing countries and its parallel benefits in terms of information and communication technologies' (ICT) adoption.

This issue should be pertinent to a variety of bodies of literature. For example, an entire body of literature has focused on economic, social, and quality of life differences—often called the digital divide—that exist between groups of people due to differing levels of access to, use of, or knowledge of, (ICT)—(for overviews, discussions, and/or critiques of this literature see DiMaggio, Hargittai, Celeste, and Shafer (2001), Howard (2007), Norris (2001), Vehovar, Sicherl, Husing, and Dolnicar (2006), and Warschauer (2004)). Much of the debate in this literature centers around a haves vs. have-nots dichotomy and a persistent focus on hardware provision rather than on the creation of the entire ICT ecosystem necessary for meaningful quality of life improvements to accrue (Di Maggio & Hargittai, 2001; Warschauer, 2002). Rather than engaging in this debate, this article seeks to draw attention to a crucial pre-requisite for all ICT use, the provision of energy.

A small but growing group of scholars, in the ICT for development field, acknowledges the importance of electricity in ICT4D (Heeks, 2008; Unwin, 2009). Heeks (2008) calls for innovation to address the scarcity of electricity in poor, rural areas. Still, such an assertion of electricity's importance in this body of literature generally merits no more than a mention. In fact, in his seminal book on the subject, simply titled *ICT4D*, Tim Unwin boldly asserts, “Without electricity there can be no ICT4D” (2009:99). Yet the book's entire discussion of energy and electricity vis-à-vis ICT4D takes place on one page, within a 386-page book. We make this point not as a reproof toward Unwin's work in any way—quite the opposite. This article is in complete agreement with Unwin's bold assertion, and it attempts to answer Heeks' call for more innovative work in this area.

Data suggest that this oversight is not because electricity provision is a minor issue. The International Energy Agency (2010) estimates that 1.4 billion people, approximately 20% of the world's population, live with no access to electricity, and one billion more (for a total of about one third of the global population) have access only to extremely unreliable electricity networks. The World Bank asserts that “no country in the world has succeeded in shaking loose from a subsistence economy without access to the services modern energy provides,” (1996) and annually publishes the *World Development Indicators*, which reports how much grid electricity is generated in each country. Fig. 1 uses World Bank data to illustrate the differences between grid electricity use in the developed (OECD) world and least developed countries.

There is a growing gap in the use of grid electricity between these two groups of countries. Moreover, although its data on the topic is scant, the World Bank (2010) estimates that 99% of OECD country residents have access to electricity but that only 26% of developing country residents do.

Yet, while useful, these data do not reflect that access to grid electricity is extremely unevenly distributed and that in many low-income countries grid electricity represents but a fraction of the electricity a country produces (Wolde-Rufael, 2006). In addition, grid electricity in much of the developing world suffers from efficiency losses (30–40%) far higher than industry standards (Damhaug, 2009) and is extremely unreliable, subject to blackouts, brownouts, and voltage spikes, surges, and dips that can destroy ICT-related equipment not properly protected against such electrical irregularities. Again, using World Bank Data, Fig. 2 illustrates the differences in efficiency of electrical networks between developed and less developed countries on average. The graph shows percentage losses during transmission and distribution, which are notably higher in developing countries, compounding availability problems with inefficient networks.

Collecting reliable data on electricity use in low-income countries has proven challenging. The reasons for this closely mirror Henderson et al.'s (2009) reasoning for the difficulties of measuring Gross Domestic Product (GDP) accurately in developing countries: in poor countries government statistical infrastructure is frequently weak (poor economies often engender poor data collection); a large proportion of economic activity takes place outside the formal sector; and economic integration and price equalization across regions is lower. All of these contribute to the difficulty in obtaining reliable data.

The widespread use of off-grid sources for electricity corresponds to the "outside the formal sector" economic activity noted by Henderson, Storeygard, and Weil (2009). In fact, in Wolde-Rufael's (2006) study of electricity consumption and economic growth in 17 African countries, the author utilizes only grid-supplied electricity data, yet acknowledges that such consumption accounts for less than 4% of total energy consumed. Thus, if we are to obtain a more accurate understanding of actual electricity use in data-poor and economically-poor countries, we must use a different data source.

Henderson et al. (2009) address the paucity of reliable GDP data in economically- and data-poor countries by employing the amount of light observable at night from outer space as a proxy for GDP. While a number of other researchers have made use of this data for other purposes (see Chen & Nordhaus, 2010; Doll, Muller, & Morley, 2006; Ebener, Murray, Tandon, & Elvidge, 2005; Sutton, Elvidge, & Ghosh, 2007), Henderson et al. are the first to use it to measure real economic growth. This article uses the same data set, though for a different purpose: to measure real electricity use and distribution.

These factors combine to provide reason for the dearth of research on energy and electricity usage and demand in developing countries (De Vita, Endresen, & Hunt, 2006). Still, there have been studies published that focus directly on this topic (see De Vita et al., 2006; Ferguson, Wilkinson, & Hill, 2000; Sari & Soytas, 2007; Wolde-Rufael, 2006; Yoo, 2006) though all of these studies employ reported data on grid-only use. Some of these studies examine the directional causality of energy or electricity use: whether energy or electricity use leads to economic growth or vice-versa. While Yoo (2006) and Ferguson et al. (2000) are among those who examine such directional causality, they also make the argument that electricity consumption is far more relevant to the measurement of modern economic growth than general energy consumption because modern economic growth depends on the use of electricity. This is true in the case of either industrial development (Rosenberg, 1998) or a knowledge-based economy (Yoo, 2006).

We believe it unproductive to talk about addressing the digital divide or increasing ICT4D in locations where the electricity to power the relevant technologies does not exist, is unreliable, or is prohibitively expensive—the case for most low-income countries. Electricity is necessary for modern economic growth in general and, in particular, for Internet adoption—the main variable utilized in digital divide measurements. In fact, in places that experience an "electricity divide," there will, by definition, also be a "digital divide." Failing to acknowledge this fact and investigate policies that will provide for the necessary electrical infrastructure before launching into ICT-for-development initiatives has led to innumerable failed projects and policy initiatives (Hosman & Baikie, 2013).

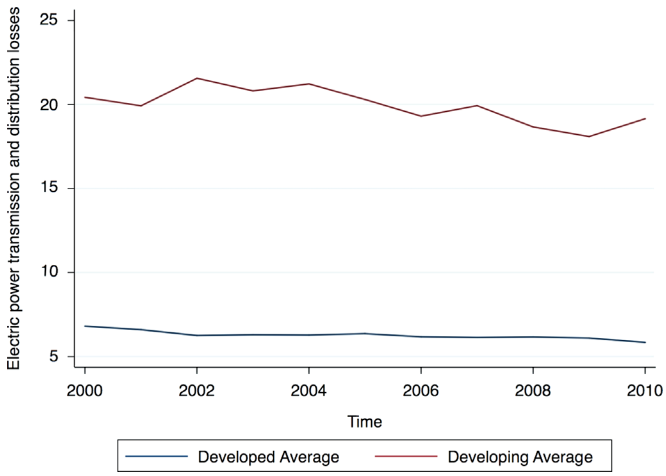

Fig. 2. Percentage of distribution losses.

3. Methodology

The literature typically frames empirical models of Internet demand in terms of Rogers's (2003) *Diffusion of Technology* model, which classifies consumer behavior into five categories: innovators, early adopters, early majority, late majority and laggards. This leads to an S-shaped diffusion model. Bohlin, Gruber, and Koutroumpis (2010), among others, call these *epidemic models,* because they evolve similarly to disease contagions. Many empirical studies (Gruber & Verboven, 2001; Martins & Andres, 2009) suggest that differences in both the rate of adoption and timing of adoption can shift the placement of the curve.

Our study builds on previous work that has employed a variety of empirical techniques. Many of these studies used random-effects models (Banerjee & Ros, 2002; Chinn & Fairlie, 2006, 2010) which exploit both cross country and within country variation. As far as we can tell, few studies have used fixed-effects to measure strictly within-country differences in Internet diffusion (Lee, Marcu, & Lee, 2011, use fixed effects to analyze OECD country broadband diffusion).

Several papers have utilized more sophisticated econometric modeling, Gruber and Verboven (2001), for example, fit a logistic curve with non-linear least squares. Subsequent work by Bohlin et al. (2010) abandoned the non-linear least-squares approach and used a dynamic panel data approach to estimate mobile broadband diffusion. Shchetinin and Baptiste (2008) came closest to our study, using a dynamic panel model to estimate global Internet use, but their dataset ends in 2002, before much of the variation in developing country adoption rates became apparent. These studies found that differences in telecommunications infrastructure, human capital, and regulatory environments all impact Internet usage rates.

Much of the literature approximated the S-shaped curve for technological diffusion using either the logistic curve or Gompertz curve. Both of these generate S-shaped curves with a few early adopters, then a more rapid period of adoption, then a slower conclusion. The Gompertz curve is less symmetric than the logistic curve, wherein the initial growth rate is not as high and its decline more gradual. Here we adopt the Gompertz model, which one can interpret as linear in its parameters, as we demonstrate below, and thus fit with a standard dynamic panel data model (Shchetinin and Baptiste, 2008).

3.1. Derivation of the model

The Gompertz model for Internet diffusion, with a baseline of 0, can be written as

$$y(t) = \frac{c}{1+e^{-a(t-t_0)}} \tag{1}$$

where y is the level of Internet diffusion; c is the maximum level of penetration such that $c=\lim_{\infty} y(t)$; a is the speed of convergence of $y(t)$ to its limit and characterizes the curvature of the diffusion path; and $t_0=(c/2)$. The corresponding ordinary differential equation for the Gompertz model is given by

$$\dot{y} = a(y)(\ln c - \ln y) \tag{2}$$

If we define the maximum level of ln(c), or latent demand for the Internet, as a linear function of a vector of parameters X such that $\ln(c)=f(X)$ and $f(X)=\beta X$. Substituting into Eq. (2) gives the discrete empirical equation:

$$\ln(y_{it}) - \ln(y_{it-1}) = a \tag{3}$$

Which can be rearranged to

$$\ln(y_{it}) = (1-a)\ln(y_{it-1}) + a\beta X_{it} \tag{4}$$

3.2. Empirical interpretation

The basic estimation equation from the literature is as follows:

$$\text{Log}\ (Internet_{it}) = \tau X_{it-1} + k_i + \varphi_t + u_{it} \tag{5}$$

where subscripts i and t designate country and year, X is the vector of independent variables, k and φ are the unobserved country and time effects, respectively. We assume that the error term $u_{i,t}$ follows a random walk.

Turning to the econometric strategy, the relevance of country and time on the level of internet use eliminate the use of pooled OLS and suggest the use of random-effects and fixed-effects models. While the literature has occasionally used random-effects models, (Chinn and Fairlie, 2007) fixed effects models are more appropriate here because they allow for country specific characteristics and time to influence the independent variables as well as the dependent variable. To do this fixed-effects models measure deviations of all of the independent variables from the mean for each variable per country. In addition, the models include dummy variables for all years in the study to address time effects that may have an impact across countries (Wooldridge, 2001). Fixed-effects models account for any unobserved characteristics of a country that impact its ICT use, but because fixed-effects models eliminate the need to identify all country fixed effects that impact the dependent variable, time-invariant independent variables are unusable in these models. Variables that change very little over time are also less likely to register significant effects. In addition, in fixed effects models one would include Fixed effects are models are most appropriate here for the sake of our policy recommendations as we are more interested in the within-country variation, where changes affect a country's Internet adoption trajectory, which is measured by fixed-effects and difference GMM models.

Still, standard fixed effects models do not take into account persistence in ICT use over time nor do they accurately portray the leading functional forms, S-curves, espoused in the literature. Consumption models typically take persistence into account by including lagged dependent variables (Baum, 2006) and in the case of technology adoption it seems likely that if someone used a cell phone or had Internet access in the previous year they will continue to use it and that dynamic panel data estimation is in order (Bohlin et al., 2010). Thus, to account for this persistence, and isolate the drivers of different rates of change, one should include the log of the lagged level of ICT use as an independent variable, in the following estimation equation:

$$Log\ (Internet_{it}) = \rho\ Log\ (Internet_{it-1}) + \tau X_{it-1} + k_i + \varphi_t + u_{it} \tag{6}$$

We follow Shchetinin and Baptiste (2008) and fit the S-curve using a dynamic panel data model, as it is an empirical version of Eq. (4). This reordering forms the basis of our analysis with dynamic panel data models.

However, in standard econometric models, the lagged level of Internet use is necessarily correlated with the error term. In order to address this issue, most authors employ one of two instrument variable solutions. The first possibility, proposed by Anderson and Hsiao (1982), is to use the first difference of the model (to eliminate country fixed effects), and to use the second lag of the level of the dependent variable as an instrument for the difference between the first lag and the second lag of the dependent variable.

The GMM estimator proposed by Arellano and Bond (1991) is a more efficient estimator; it essentially uses all available lagged levels of the dependent variable as instruments for the lagged difference of the dependent variable. The GMM estimator also allows one to instrument for other potentially endogenous variables. In our case, we treat the lagged dependent variable, GDP per capita, and openness as endogenous, using second and deeper lagged levels as instruments for lagged differences. All other variables are treated as predetermined but not strictly exogenous. We include year dummy variables in all of these models to account for heteroskedasticity.

In all its forms, the GMM estimator provides standard errors that are robust to heteroskedasticity and serial correlation. We tested our dependent and independent variables for non-stationarity using the Fisher test and find that unit-roots are not a problem either in levels or differences. We report the small sample corrected model, with orthogonal standard errors (this allows for the use of future values as instruments and is helpful in unbalanced panels), but had very similar results without these specifications.

Finally, we report the results of several standard tests employed to validate GMM estimates. We test the hypothesis that the error term is serially correlated in the first order and not serially correlated in the second order. We test the validity of the moment conditions using the Sargan test and robustness of additional moment conditions with the Hansen difference test. These tests indicate that instruments are valid and that endogeneity is not a problem in the GMM models.

4. Data

Following much of the recent work mentioned above, we attempt to look at the drivers of Internet adoption rate changes. Our data includes a panel of 40 countries, which the World Bank classifies as low-income countries, over ten years (see Table 1 for countries and years). As a dependent variable we follow Chinn and Fairlie (2007 and 2010) and Shchetinin and Baptiste (2008) who use the number of Internet users per 100 people from the World Bank's World Development Indicators. Unlike Thompson and Garbacz (2011), we do not look at broadband adoption because it is still at a very low level in developing countries. While many of these countries still lag behind, the first decade of the 21st century has seen Internet use take off in several less developed countries.

For our electricity distribution variable we use the Gini-coefficient from Henderson et al.'s (2009) data on lights from space. Electricity consumption and dispersion data up until now has been unavailable for many lower income countries (Henderson et al., 2009) and therefore has been impossible to measure or include in studies that would aid policy development. Henderson et al. (2009) point out that light information from space is readily available for many countries, particularly low-income countries, which do not reliably report other data on electricity consumption (or GDP). This data uses US Air Force satellite reports, averaged annually from nightly readings between 8:30 and 10:00 PM local time, of light density per 30″ output pixel for the whole world between 65° latitude south and 75° north (thus excluding only about ten thousand people who live outside this range). The data give a digital number: an integer between 0 (no light) and 63 per pixel. Henderson et al. (2009) use this data to measure both annual average light intensity data per country and a Gini-coefficient of light distribution inequality per country (the Gini-coefficient approaches one the more unequal the distribution). The former, they argue, is closely aligned with GDP growth, particularly in lower and middle-income countries where changes in light intensity are more observable. In order to avoid problems with endogeneity, we do not include the night lights measure because of its relationship with the level of development.

The night lights *Gini-coefficient* provides a measure of electricity availability rather than quantity or quality. It does not measure economic activity, nor is it strongly correlated with GDP per capita, making it better suited for our model. A Gini-coefficient is a measure of the equality of distribution of something, in this case light at night. A Gini-coefficient approaching one indicates very concentrated light at night within a country, a Gini-coefficient of zero would indicate perfectly contiguous night lights. On average, developed countries have more dispersed lights than developing countries, with an average Gini in the 0.6 range rather than an average around 0.9. Fig. 3 compares the developed and developing samples over the time horizon we studied.

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Table 1
Sample.

Country	Years	Country	Years
Afghanistan	2001–2009	Lao	2000–2009
Bangladesh	2000–2009	Liberia	2000–2009
Benin	2000–2009	Madagascar	2000–2009
Burkina Faso	2000–2009	Malawi	2000–2009
Burundi	2000–2009	Mali	2000–2009
Cambodia	2000–2009	Mauritania	2000–2009
Central African Republic	2000–2009	Mozambique	2000–2009
Chad	2000–2009	Myanmar	2001–2009
Comoros	2000–2009	Nepal	2000–2009
Dem Rep of Congo	2000–2009	Niger	2000–2009
Eritrea	2000–2009	Rwanda	2000–2009
Ethiopia	2000–2009	Sierra Leone	2000–2009
Gambia	2000–2009	Solomon Islands	2000–2009
Ghana	2000–2009	Somalia	2000–2009
Guinea	2000–2009	Tajikistan	2000–2009
Guinea-Bissau	2000–2009	Tanzania	2000–2009
Haiti	2000–2009	Togo	2000–2009
Kenya	2000–2009	Uganda	2000–2009
Korea	2000–2009	Zambia	2000–2009
Kyrgyz Republic	2000–2009	Zimbabwe	2000–2009

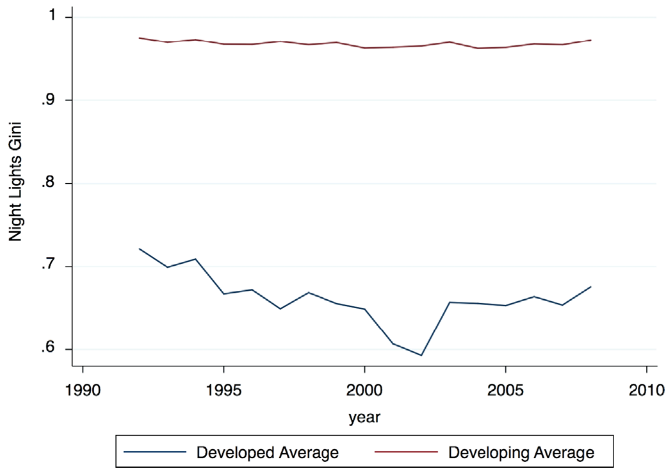

Fig. 3. Night lights Gini-coefficient averages.

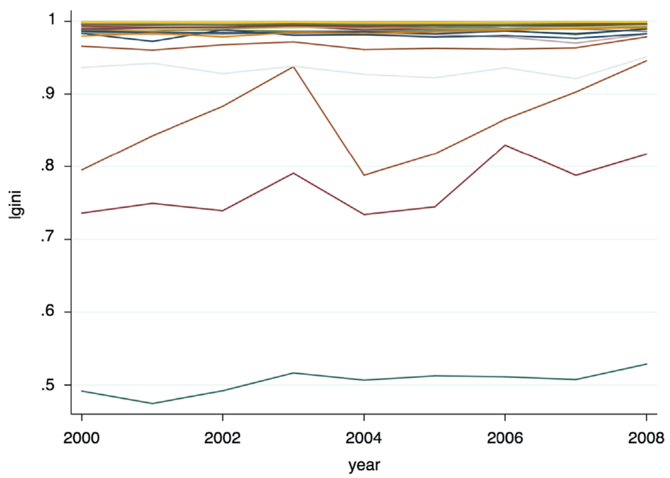

Fig. 4. Night lights Gini-coefficient panel overlay.

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The Gini-coefficient measures changes in electricity availability. Specifically, when the Gini-coefficient decreases within a country, electricity is being more widely used. We acknowledge that cross country differences, as seen in Fig. 4, in the Gini-coefficient are driven by differences in population density in addition to development, which is why we focus on within country changes. The notable cross country differences are a kind of country fixed effect that do not affect our results.

We thus hypothesize that within country reductions in inequality of electricity distribution, or reductions of the Gini-coefficient, should lead to increases in adoption of the Internet. We follow Wolde-Rufael's (2006) argument that the distribution of electricity matters a great deal when it comes to the drivers of economic development. Accordingly, our model attempts to measure the changes in the distribution of electricity, using the Gini-coefficient, instead of electricity use. By doing so, we capture changes in the numbers of people who are able to access basic infrastructure, in the form of electricity, for productivity. Notably, this variable does not tell us whether electricity is from a grid or non-grid source. We believe that this study represents a stride forward regarding both electricity consumption and our understanding of its effects on the digital divide in low-income countries.

In several of our models we include a variety of political, economic, demographic, and infrastructure variables that might drive these differences and that are largely included in existing models of internet adoption. Specifically, from the *World Bank World Development Indicators* we include GDP per capita adjusted for purchasing power parity, trade as a share of GDP as a measure of openness, and urbanization as urban residence might reduce the costs of Internet access. We treat both GDP per capita and trade share of GDP as endogenous in the GMM models, using the second and deeper lagged level as an instrument for the lagged difference. We also include the Polity IV model of democracy, or political openness to measure the impact of institutional change on Internet adoption. To look at infrastructure, we include the number of telephone lines per 100 people from the World Development Indicators, which is included in many models as a proxy for the availability of the Internet. It is problematic because with the rise of mobile technology, there is now substitute infrastructure availability in many places, and less impetus to build phone lines. We include it here for consistency with past studies along with the number of mobile subscribers per 100 people (Tables 2 and 3).

5. Results

Examining the impacts of changes in electricity use in a Difference-GMM framework, we find consistent support for our hypothesis that changes in electricity distribution alter internet adoption in a meaningful way, and that other potential

Table 2
Variables.

Variable	Definition	Units	Source
Internet users	Measures the number of people per 100 people who have access to the Internet	0–100	World Bank, World Development Indicators.
Lights Gini	Gini coefficient that measures the distribution of lights within a country based on inequality between output pixels	0–1	Henderson et al. (2009)
Democracy (Polity IV)	The degree of openness of democratic institutions	−10–10	Marshall, Jaggers, and Gurr (2011)
GDP per capita	GDP per capita at the start of the period		World Bank, World Development Indicators.
Openness to trade	Measured as the sum of exports and imports as a share of GDP		World Bank, World Development Indicators.
Urban population	Percentage of people residing in urban areas		World Bank, World Development Indicators
Telephone lines	Number of connections between user terminals and public switched network. Per 100 inhabitants	0–100	World Bank, World Development Indicators
Mobile phones	Number of mobile phone subscriptions per 100 inhabitants	1–100	World Bank, World Development Indicators

Table 3
Descriptive statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
Internet users per 100 people	346	1.474739	2.438189	0	16.10489
Night lights Gini coefficient	346	0.9799041	0.0434258	0.7340066	0.9996852
GDP per capita	265	963.3459	334.8842	315.6061	2026.926
Democracy	337	0.7418398	4.96192	−9	9
Urban population share	346	29.47092	12.03693	8.3	62.68
Trade share GDP	312	66.84664	31.70884	0.1952842	219.1791
Telephone lines per 100 people	342	1.238754	1.536795	0.0527232	9.369313
Mobile Phones per 100 people	436	12.54268	17.76726	0	98.9

factors offer little to explain these changes. In Table 4 we examine the impacts of night light distribution changes on internet adoption rates. We include two difference GMM estimators because the Arellano-Bond estimator can lead to many instruments and thus its test statistics can lose precision. Thus Roodman (2006) suggests limiting the number of lags for GMM style instruments. To account for this technical issues we report the results both with unconstrained lags and lags constrained to 4 periods.

In Table 4, we present models with only the night-lights data, which allows for an expanded sample and to examine the relationship between these variables without controls. We include the OLS and fixed effects models as tests on our specifications. In a well-specified model, the coefficient on the lagged dependent variable will be bound between the OLS and fixed effects coefficients (Roodman, 2006). The results in Table 4 thus suggest that omitting controls cause a specification problem.

In Table 4, the Gini-coefficient for power distribution is negative and significant in both the GMM models at the 95% level. Also notably, the OLS coefficient on the Gini coefficient for electricity is positive. We believe this is because cross country variation in Gini coefficients in much greater than within country variations, and that across countries greater concentrations of electricity, associated with greater levels of electrification and less population spread, would be associated with greater adoption, reinforcing the need to eliminate the cross-country comparisons and focus on within country variation. When we do, our findings consistently support our hypothesis.

Adding control variables in Table 5, the relationship between electricity distribution and internet use remains significant. In Table 5, the Gini coefficient is significant and negative at the 95% level in the unconstrained model and at the at the 90% level in the lag-limited model. We take these findings together as solid evidence that increasing the distribution of electricity within a country, and therefore making electricity available to a larger proportion of the population, increases use of the Internet.

The magnitude of these effects is also important: using our difference GMM models, we estimate a 10–11% increase in adoption of the Internet per standard deviation decrease in the night lights Gini coefficient. In the developing country models, small changes in the distribution of power, from what are typically very concentrated power distributions, seem to have a large effect. As one would expect, electricity availability does not change much over time in more developed countries and additional tests, available on request, showed that this result is sensitive to limiting the sample to lower income countries.

Our other control variables are limited in their ability to explain short-run changes in Internet use in developing countries. None of the control variables are significant in the difference GMM models. We posit that this is because these variables change slowly within countries, and their impact in previous studies results from cross-country, not within-country, variations.

There are limitations to this study that will provide fertile ground for future scholarly work in this area. First, our work does not aim to understand cross-country differences, and while we believe this makes it a better foundation for policy making because it focuses on where adoption has actually changed, it is not able to add as much to the literature on what makes poor and rich countries different except through conjecture. Second, there is insufficient data available on Internet pricing to make it a useful variable in our study, and while prices are endogenous in this system, they offer useful information about the affordability of the Internet and might be a useful variable in future studies if given careful treatment.

Table 4
Panel results without controls.

	OLS	Fixed-effects	Diff GMM All lags	Diff GMM Lags 2–4
Lag log internet	0.910***	0.692***	0.681***	0.607***
Users per 1000	(0.0179)	(0.0337)	(0.0508)	(0.0541)
Lag Gini of night lights	0.119	−2.371	−2.408**	−2.664**
	(0.505)	(1.896)	(0.996)	(0.992)
Constant	0.0987	2.156		
	(0.503)	(1.863)		
Observations	369	369	331	331
Instruments			100	37
Sargan test			177.776	103.593
p-Value			0.000	0.000
Hansen test			34.155	23.577
p-Value			1.000	0.600
Difference Hansen			0.110	6.581
p-Value			1.000	0.764

Standard errors in parentheses.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

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6. Conclusion and policy recommendations

We find that increasing the distribution of electricity within a country, and therefore making electricity available to a larger proportion of the population, increases use of the Internet. This suggests that policies in low-income countries that would increase populations' access to electricity could thereby increase Internet usage rates and enable both industrial and knowledge-based economic growth. However, simply increasing access to electricity in low-income countries, particularly to rural or underserved areas, is not as straightforward as it may seem at first blush. Policy challenges include the following: a history of multilateral organization-led rural electrification development projects with mixed results at best, the lack of local capacities to realize successful projects, and the mental decoupling of any link between electricity and the digital divide. This article posits that all of these challenges can and should be addressed.

From 1980 to 2008, the World Bank made loans to implement 120 rural electrification projects across the developing world, investing more than US$11 billion. Results were highly mixed (World Bank Group, 2008). In fact, because of reports that cast serious doubts on the effectiveness of these loans and projects, the Bank itself published a comprehensive reassessment of its rural electrification efforts in 2008. Yet even this far-reaching report on electrification contains absolutely no mention of telecommunications, Internet, or the digital divide. Around the same time, the World Bank published *Information Communications for Development 2009*, which put forth the argument that the Internet, and more specifically broadband connectivity, contributes significantly to economic growth among even the lowest income countries, thus making the case that countries around the globe, even the poorest ones, should adopt public policies allowing the significant benefits of broadband Internet usage to accrue (Zhen-Wei Qiang, Rossotto, & Kimura, 2009). This comprehensive report on broadband around the world fails to address—or even mention—the topics of energy or electricity in any meaningful way.

Although these examples do not offer scientific proof, they do underscore the silo-effect and mental divide that still remains among development experts and organizations that focus on rural and developing world electrification and the digital divide—albeit separately. Policy makers should not take this phenomenon lightly. Not only are billions of dollars at stake, but human lives and aspirations are also negatively affected when projects fail—the article authors have firsthand experience in this area. This article emphasizes the connection between electrification and Internet uptake in the attempt to eradicate the false divide that up until now has existed.

Table 5
Dynamic panel results with controls.

	OLS	Fixed-effects	Diff GMM All lags	Diff GMM Lags 2–4
Lag log internet users per 1000	0.931***	0.774***	0.816***	0.913***
	(0.0252)	(0.0440)	(0.0478)	(0.0621)
Lag Gini of night lights	0.862*	−2.579	−2.564**	−2.263*
	(0.452)	(1.608)	(1.167)	(1.146)
Lag log GDP per capita	0.224***	0.502**	0.512	0.258
	(0.0733)	(0.206)	(0.342)	(0.353)
Lag democracy	−0.0130***	−0.00327	−0.00624	−0.00911
	(0.00465)	(0.00934)	(0.00657)	(0.00673)
Lag urban pop share	−0.00512**	−0.0123	−0.0129	−0.00998
	(0.00206)	(0.0266)	(0.0159)	(0.0179)
Lag trade share GDP	−0.00116	−0.00354**	−0.00248	−0.00338
	(0.000775)	(0.00147)	(0.00362)	(0.00436)
Lag telephone lines per 100 people	0.0359**	0.0607	0.0772	0.0787
	(0.0161)	(0.0938)	(0.112)	(0.113)
Lag mobile phones per 100 people	−0.00199	−0.00290	−0.00351	−0.00367
	(0.00310)	(0.00356)	(0.00271)	(0.00333)
Constant	−1.712**	0.491		
	(0.697)	(2.230)		
Observations	252	252	222	222
Instruments			163.000	73.000
Sargan test			163.379	69.020
p-Value			0.168	0.132
Hansen test			13.695	19.638
p-Value			1.000	1.000
Difference Hansen			3.313	5.705
p-Value			0.997	0.956

Standard errors in parentheses.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

When it comes to national policy recommendations regarding electrification, the World Bank posits that a sustained, long-term (at least 15–20 years) commitment by governments toward electrification within their borders is necessary and constitutes the most important factor contributing to the success of such a program (World Bank, 2010:12). This may indeed be the case for middle-income countries; the Bank acknowledges that the task will be far more challenging for low-income countries, because the hurdles they face are much greater. Henderson et al. (2009) posit that low-income countries face challenges in terms of human capacity and qualified skilled personnel within their governments; we believe that this also means that the government-regulated sectors relevant to this study within these same countries, will face similar challenges.

On a more positive note, Taverner (2010) asserts that in even the lowest-income countries reform efforts aimed at liberalizing energy sectors have begun to promote private sector involvement where the government currently lacks indigenous capacities (and where multilateral development organizations' loans and programs may have failed). The same situation—of increasing liberalization and private sector involvement—holds true for countries' telecom sectors around the globe. This opens the door for public–private or other forms of multi-sector partnerships (Cholez, Trompette, Vinck, & Reverdy, 2012) that can help bridge the lack-of-skills-and-expertise challenges facing low-income countries in both the energy and telecom sectors; countries can introduce outside experts and financing. They must make a business case to bring electricity and connectivity to rural and underserved areas.

Thus, where governments are weak, distracted, or otherwise unable to play this role, coordinated efforts by non-governmental actors can still yield significant progress, even in the absence of government leadership or subsidies (Blantz & Baikie, 2012). Though it is beyond the scope of this paper to examine or categorize specific types of public–private partnerships, there is one activity we believe that any such partnership operating in lowest-income countries should endeavor to employ: local capacity building. If local capacity- and skills-building become part and parcel of such partnered projects, the likelihood of their long-term sustainability increases (Hosman & Fife, 2012). The importance of building the government's human-skills capacity, as well as promoting good governance and transparency in all sectors, cannot be overemphasized. In the meantime, we predict, in addition, that local initiatives involving renewable energy and micro-grids will increasingly spring up in locations where governments have demonstrated a lack of interest or capacity to address energy and electricity demands, and that policy should support these initiatives.

Linking electricity back to the digital divide and Internet usage, we note that there are many scholars today asserting that the mobile phone will be the form factor of choice for the "next billion" people accessing the Internet, citing as evidence estimates that there are nearly six billion mobile phone users today (ITU, 2011). This explosive rate of mobile phone uptake across the globe bears witness to the (latent) demand for technology that allows people to better communicate, and access and share information. Whether the mobile phone form factor prediction comes to pass, the challenge presented by the dearth of electricity remains. The "next billion" to connect to the Internet is comprised of those increasingly off-grid and rural. Yet every aspect of Internet usage still requires electricity to function: the switches, transmitters, amplifiers, routers, web servers, data centers, cell towers, base stations, not to mention the end-user devices. Where there is grid power, connecting to it can take years and can be prohibitively expensive, so mobile phone network operators, who have seen demand for their services skyrocket over the past decade, particularly among the lowest-income countries, have become adept at meeting their electricity demands by running diesel generators and, increasingly, employing renewable energy equipment, to power their base stations (Taverner, 2010). In fact, in the poorest and/or most remote locations, telecom companies have become some of the largest consumers, distributors, *and producers* of electricity, an on-the-ground reality to which the opening quote of this article attests.

Beyond these efforts, creating a demand for ICT may require an increase in public–private partnerships on projects that include local capacity building in order to promote local ownership and proper incentives. Grid-based power is not a prerequisite for electricity production, as our data shows, and governments should encourage alternative forms of electricity production, such as those employing renewable energy and micro-grids, in order to increase the availability of electricity to a greater number of people—which we find to be the strongest predictor of Internet uptake. Without reliable, affordable, and dependable electricity, the use of information and communications technology—of a meaningful nature that can promote productivity, quality of life improvements, and economic growth—is not possible. It is fruitless to attempt to analyze the global digital divide without understanding the electricity divide underpinning it.

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