The Effects of Rural Electrification on Employment: New Evidence from South Africa

Taryn Dinkelman

Web Appendix

**Web Appendix 1: Data description, variable construction and sample selection**

This appendix describes all of the data sources used in the paper.

# 1 Census data

Census community data 1996 and 2001: 100% sample obtained from Statistics South Africa. Census is adjusted for undercount after enumeration.[1]. Data are provided at an aggregated enumeration area level in 1996 and at an aggregated sub-place level in 2001.

Variables in the Census include: counts of employment, population, levels of educational attainment and recent in-migrant status by sex, race and age group; counts of households, female-headed households, and households living below a poverty line (demarcated by annual household income of ZAR 6,000 or less); counts of households using different sources of fuel for lighting and counts of households with access to different types of water and sanitation facilities. Statistics South Africa also provided me with counts of households using different fuels for cooking at the enumeration area (1996) and sub-place level (2001). A limited set of cross-tabulated variable counts are also available in these data.

Employment variables in the Census: As in most Census data, measures of employment are broad. In 1996, adults are asked: 'Does the person work?' Activities listed as work include formal work for a salary or wage, informal work such as making things for sale or selling things or rendering a service, work on a farm or the land, whether for a wage or as part of the household's farming activities. I define everyone answering yes to this question as employed, else not employed.

In 2001, adults were asked: 'Did the person do any work for pay, profit or family gain for one hour or more?' Possible responses were: yes (formal, registered, non-farming), yes (informal, unregistered, non-farming), yes (farming) and no (did not have work). Everyone who answers yes to this question is defined as employed, else not employed.

[1]Personal Communication with Piet Alberts, Senior Statistician in the Census department of Statistics South Africa, May 2007

Questions about employment are similar across Census waves, although the 2001 employment definition is somewhat broader than the 1996 variable, describing individuals who work for even one hour per week as employed. Since the main outcome variable is the change in employment rate, these differences will only be problematic if reported part-time work differentially contributes to new employment with lower gradient.

Creating the Census panel of communities: The 2001 Census geography is hierarchically ordered as follows, from largest to smallest unit:

- District: represents a local labor market area in KwaZulu-Natal, containing between 30,000 and 50,000 households.
- Main place or sub-districts: correspond to groupings of towns and surrounding areas.
- Community or sub-places: the lowest unit of observation in the 2001 Census data. Average community size is small: between 200 and 250 households on average.

Boundaries for communities from the 2001 Census define the main unit of analysis. I aggregate the 1996 (smaller) areas up to the (larger) 2001 boundaries.[2] The matched identifiers from this panel of areas are used to extract Census aggregate data in 1996 and 2001. For each 1996 EA, the proportion of the EA polygon area that falls inside each 2001 community is calculated. This proportion is used as a weight to assign a proportion of the 1996 EA data to the 2001 community. The key assumption in this process is that people are uniformly distributed over 1996 EA's.

Selection of communities for sample: Within the set of 4,030 communities in KwaZulu Natal, I restricted the sample to include rural, tribal areas. Communities that were defined as national parks and mines were also excluded. This left 1,992 communities. A final exclusion of communities with fewer than 100 adults in either Census year reduced the sample further by 176 communities, leaving 1,816 in the final analysis sub-sample.

## 2 Household Surveys: 1995, 1997, 1999, 2001

Obtained from Statistics South Africa. Four waves of household survey data (October Household Surveys for the 1990s and the September Labor Force Survey in 2001) resembling the

[2]Statistics South Africa notes that EA boundaries should never cut across existing administrative boundaries, and all "social boundaries should be respected" (StatsSA, 2000). However, boundaries have shifted over time (Christopher, 2001). In most cases, re-demarcation involved the following real changes to 1996 EA's: "splits" that occurred when obstacles or boundaries divided the EA naturally, and "merges" that occurred between EA's that were small or that were legally, socially or naturally a geographical entity. Changes were made only when "absolutely necessary" (StatsSA, 2000: 21, 26).

World Bank LSMS surveys. Each wave is a nationally representative sample of individuals. The lowest level of geography that can be identified in these household surveys is the Magisterial District, of which there are 38 in rural KZN. I include all Magisterial Districts in the analysis.

Selection of individuals for inclusion in sample: I use the sample of African male and female adults (ages 15-59) living in rural KwaZulu-Natal who report information about employment as well as about hours of work and total monthly earnings. I compute hourly wages using monthly earnings and usual hours of work reports.

## 3 Schools Register of Needs 1995 and 2000

These data are provided by the South African Department of Education for schools in 1995 and 2000. GPS coordinates for each school are used to assign schools to Census community boundaries. Each community is assigned the total number of schools in each year as well as the change in the total number of schools over the five-year period.

## 4 Geographic data

Land gradient: The source for these data is the 90-meter Shuttle Radar Topography Mission (SRTM) Global Digital Elevation Model available at www.landcover.org. Digital elevation model data was used to construct measures of average land gradient for each Census community using GIS software (ArcMap 9.1). Gradient is measured in degrees from 0 (perfectly flat) to 90 degrees (perfectly vertical). The distribution of land gradient in my sample area is shown in Web Appendix 1 Figure 1.

Other measures of proximity: Spatial data on Eskom's 1996 grid network (high and medium voltage lines and substations) was provided by Steven Tait at Eskom. These data were used to calculate straight line distances between Census centroids and the nearest electricity substation.

Census 1996 spatial data were used to generate straight line distances from each community centroid to the nearest road and town in 1996.

Census 2001 spatial data were used to create measures of the area of the sub-place. I used these area measures in conjunction with total household counts from the Census community data to create household density variables in 1996 and 2001.

## 5 Electricity project data

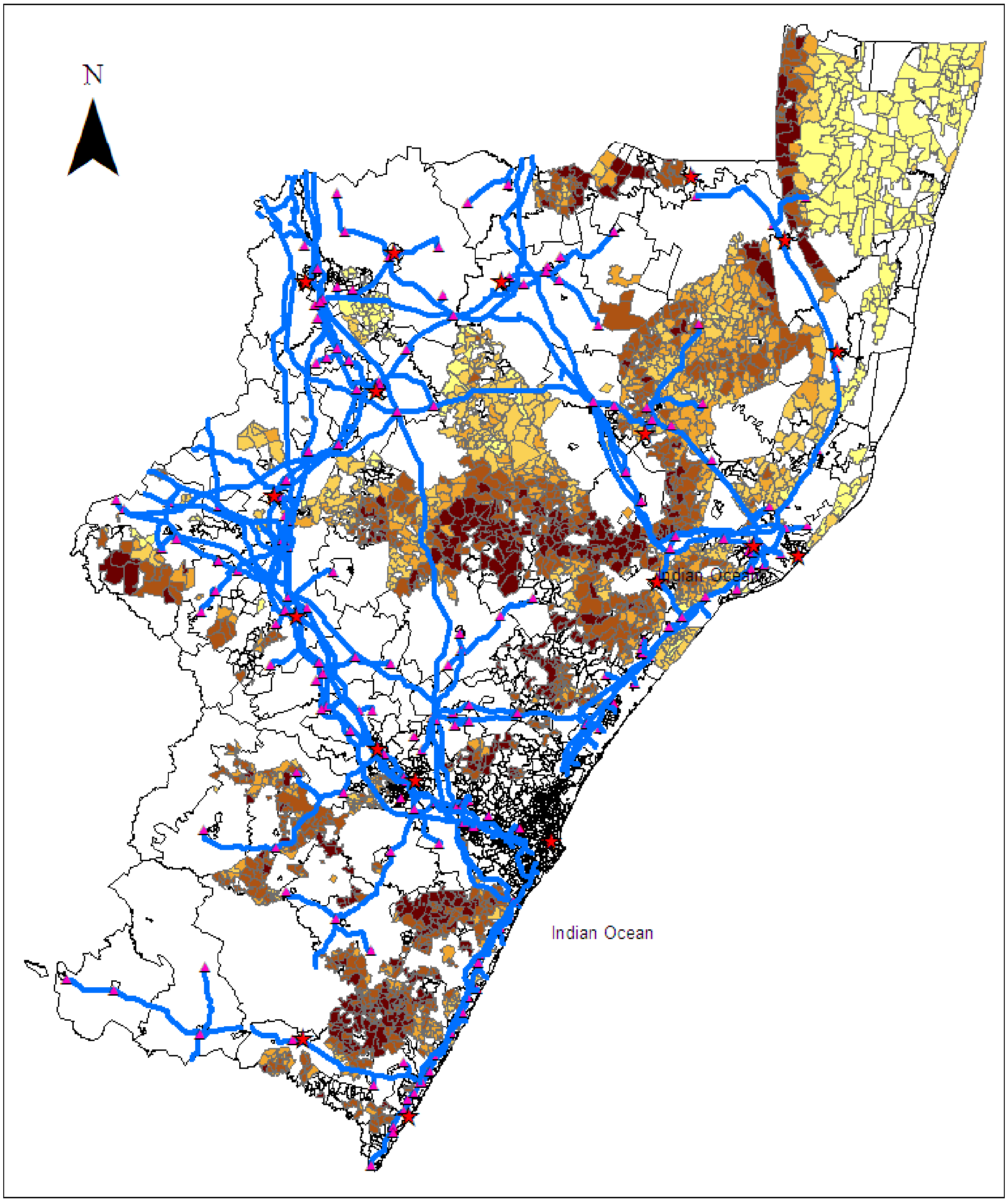
Data on Eskom projects in KwaZulu-Natal were provided by Sheila Brown at Eskom. The project list gives the number of pre-paid electricity connections per Eskom-defined area in each year from 1990 to 2007. I define the year of electrification as the year in which a community experienced a spike in household connections (concentrated project activity). Areas are referenced by name and village code. Eskom's planning units do not line up accurately with Census regions. To match project data to Census regions, I map the project data to a physical location using a spatial database of transformer codes linked to project codes and then merge these locations to Census boundaries. Areas designated as Eskom project and non-project areas are displayed in Web Appendix 1 Figure 2.

# References

**Africa, Statistics South**, "Census Mapping Manual," Technical Report, Statistics South Africa *http://www.statssa.gov.za/africagis2005/presentations/oralcolemandube.pdf* 2000.

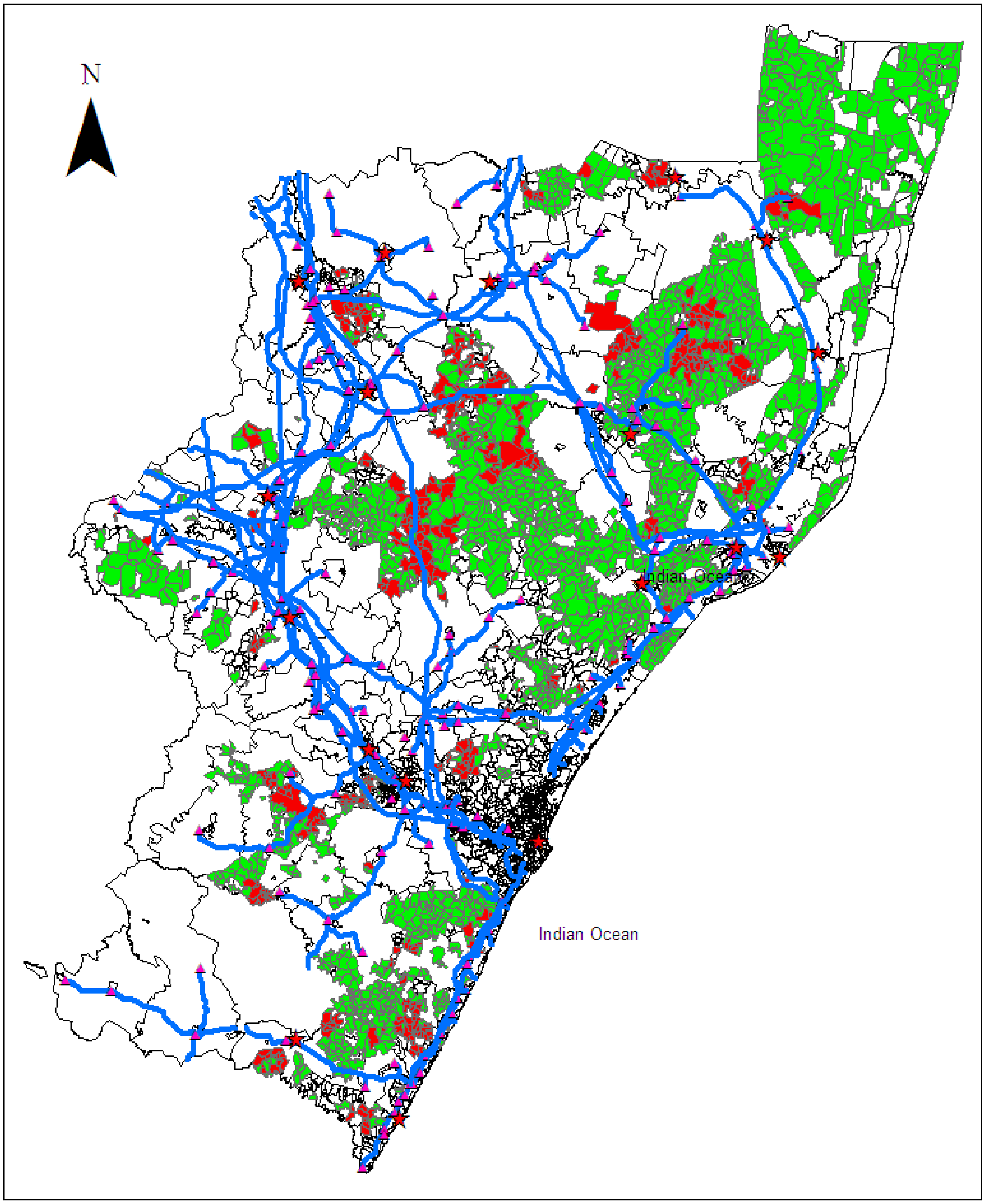
**Christopher, A.J.**, *The Geography of Apartheid*, Johannesburg: Witwatersrand University Press, 2001.

**Web Appendix 1 Figure 1: Spatial distribution of gradient in KwaZulu-Natal, South Africa**




Communities included in the sample are shaded (N=1,816). Map shows 1996 grid lines (thick lines) and substations (triangles), and towns (stars). Steeper areas are shaded dark, flatter areas are shaded light.

**Web Appendix 1 Figure 2: Spatial distribution of electricity project areas in KwaZulu-Natal, South Africa**




Communities included in the sample are shaded (N=1,816). Map shows 1996 grid lines (thick lines) and substations (triangles), and towns (stars). Dark shaded areas are electrified before 2001; lighter shaded areas are electrified after 2001 or not at all.

**Web Appendix 2: Heterogeneity in electrification effects**

In this appendix, I explore the characteristics of communities that contribute the most to the main employment results from the IV strategy.

# 1 Heterogeneous effects related to income

As part of the South African electrification, once an area had been targeted for new access, each household received a basic connection package: an electric circuit board, a pre-payment meter, three plug points and one light bulb. Households received a default supply of 2.5 amperes or could upgrade to a 20 ampere supply for a fee of about ZAR40 (USD6.00), which most of Eskom's 3 million customers chose to do (Gaunt, 2003). Although industry experts agreed that "Electric lighting was synonymous with the roll-out", and that the NEP did reach poor households, the subsidized roll-out really changed the option to use electricity. Households were still required to pay for using the service by purchasing electricity credits loaded on to pre-paid cards. In 1999, household electricity cost $0.039 per kilowatt hour (kWh). Estimates of load demand from Eskom reports suggest that most rural households used between 35 and 60 kWh per month, translating into energy expenses of between $1.37 and $2.34 per month (Gaunt, 2003), or 1.8 percent of median monthly household income in rural KZN in 1995. Because of this positive marginal cost, the poorest households are likely to have been the least responsive to the new technology in the short-run.

The main IV strategy used in the paper identifies employment effects for communities that are cheaper to electrify by virtue of having a flatter gradient. As is well known, the IV coefficient is a weighted sum of effects for different groups, each of which may be differently affected by the gradient instrument (Kling, 2001). If different groups also experience a different electrification effect, then the IV result will be driven by the groups that are weighted most heavily in the IV parameter estimate. These weights determine which group's effect contributes the most to the total measured effect in the IV regressions.

In communities with flatter gradient, female employment may be more responsive to electrification than in an average newly electrified community. One way in which marginal communities could differ from average communities is in their ability to switch home production technologies when the new service arrives. In creating the IV weights below, I investigate how much of the IV coefficient is driven by changes in communities that look as if they would be in a better position to switch to using electricity once the new connections are made. Using electricity more effectively involves buying complementary appliances so this requires focusing on heterogeneous effects of electrification by some measure of household income.

Since the Census provides only a crude measure of poverty (household income is reported in intervals not consistent over time), I combine the three poverty indicators into a poverty index and consider the characteristics of communities in each quintile of this index. To create the index, I follow Card (1995) and Kling (2001): for the sample of communities in the steepest half of the gradient distribution, I use a logit model to estimate the probability of receiving an electricity project using the baseline poverty rate, the baseline female/male sex ratio and the baseline share of female-headed households. Using coefficients from this regression, a value for every community in the sample is predicted. Each community is then assigned to a quintile of the predicted poverty index, where quintile cut-points are defined on the estimation sample only.

The graph in Web Appendix 2 Figure 1 shows the fraction of communities in each predicted poverty quintile that is electrified between 1996 and 2001, separately for communities in the flattest and steepest halves of the gradient distribution. Both lines slope upwards, indicating that areas with higher predicted values of the poverty index (i.e. richer areas) are more likely to receive an electricity project at all. The gap between the two lines shows that flatter areas are systematically more likely to be electrified than steeper areas. The middle-poorest and second-richest quintiles are most likely to have the probability of a project manipulated by the instrument, which can be seen in the larger gap between the lines occurring at these quintiles.

Some of the same information is provided in Web Appendix 2 Table 1. This table builds up the IV weights for each poverty quintile of the sample. The fraction of the sample falling within each predicted poverty quintile is presented in column (1); the variance of gradient across communities within each quintile is very similar across quintiles, as column (2) indicates. Column (3) echoes Web Appendix 2 Figure 1: there is a larger difference in the fraction of communities electrified across flat and steep areas, in the third poorest and second richest quintiles. In column (4) of that table, I compute the contribution of each quintile to the final IV estimate by calculating the relevant weight (explained in the table notes): we see from the results that middle quintile and the second richest quintile together contribute over 65 percent to the IV result.

Middle quintiles in particular may have larger employment effects because they contain households that experience larger changes in home production technology when electricity arrives compared to richer quintiles, and they are more able to effectively use the new technology than the poorest quintiles. Web Appendix 2 Table 2 shows that middle-poor areas are initially less likely to be using electricity than richer areas and are more reliant on wood for cooking (columns 1 to 3). Columns (4), (5) and (6) of this table present within-quintile reduced-form coefficients from regressions of the change in fuel use on a gradient dummy (1 is flat, 0 is steep). These columns indicate large increases in the use of electricity and large decreases in reliance on wood for cooking in flatter areas for middle-poor, second-richest and richest areas.[1] Finally, column (7) of Web Appendix 2 Table 2 indicates that the female employment result is indeed driven by women living in middle- and second-richest quintile communities: the effects for these communities are large, positive and significant and are weighted most heavily in the final IV results. The coefficients in this table are akin to reduced-form coefficients from a regression of the outcome variable on a binary version of the instrument and all controls. Dividing each coefficient by the corresponding coefficient in column (3) of Web Appendix 2 Table 1 will reproduce the IV coefficient.

## 2 Heterogeneous effects related to other constraints on women's time

Women who have home-production responsibilities are less likely to be able to respond to new access to electricity, even though productivity at home may be substantially enhanced by the use of electricity. For example, child-care responsibilities raise the value of a woman's time at home and in the absence of pre-school care, this value only falls when children start school. Officially, school-starting age is between ages 6 and 7 in South Africa, but enrollment only reaches 90% by around age 9 (results from 2001 10% Census micro data, not shown). Children also create work at home though, and so the more children in the house that require child-care, the more time can potentially be saved with access to a more efficient power source. It is therefore not clear whether women with younger children will supply more or less of their labor to the market, in response to new household electrification.

Census micro data from 1996 give some indication of which women are more likely to live with a child younger than age 9. Web Appendix 2 Figure 2 is a lowess-smoothed graph of the fraction of women of each age living with at least one child aged 9 or under. The graph is drawn for African women between ages 15 and 59 living in rural areas of KZN and shows a clear distribution of youngest children to households with both younger and older women.[2] After age 30 and up to about age 50, the probability of a woman living with a child who requires constant care falls substantially.

To investigate whether the employment effects of household electrification are largest for this latter group of women, I redefine the outcome variable to be $y_{ajdt} = \frac{E_{ajdt}}{P_{jdt}}$, where $E_{ajdt}$ is the number of employed women in age group $a$ for each of nine five-year cohorts and $P_{jdt}$ is the total adult female population in each community in each year. This definition decomposes the employment result into effects for each age cohort: the estimated coefficients sum to

[1] This is related to the point by Greenwood et al (2005) who argue that poorer households are the last to adopt durable goods for home production.

[2] The allocation of young children to households with older women is a common pattern in South Africa, where pension-aged women care for grandchildren in skip-generation households (Case and Deaton, 1998).

the main electrification coefficient in the final column of Table 4 in the main paper. Web Appendix 2 Table 3 presents OLS and IV coefficients (and robust standard errors clustered at the sub-district level) on the electrification dummy for separate regressions.[3] IV results are large and positive for each age group, but significant only for women in their thirties and late forties. Employment grows by 3 percentage points for women between the ages of 30 and 34, by 1.7 percentage points for the 35 to 39 year old group and by a smaller but still significant 1.4 percentage points for women in their late forties. Together, these age groups account for 65 percent of the total female employment result. This indicates that women in age groups in which care of young children is not a significant constraint, are those women most responsive to the arrival of electricity in the home.

[3]Results for men are not shown as the electrification coefficient was never significant for any cohort.

# References


**Card, David**, "Using geographic variation in college proximity to estimate the returns to schooling," in L.N. Christofides et al, ed., *Aspects of labour market behaviour: Essays in honor of John Vanderkamp*, Toronto: University of Toronto Press, 1995, pp. 201–221.

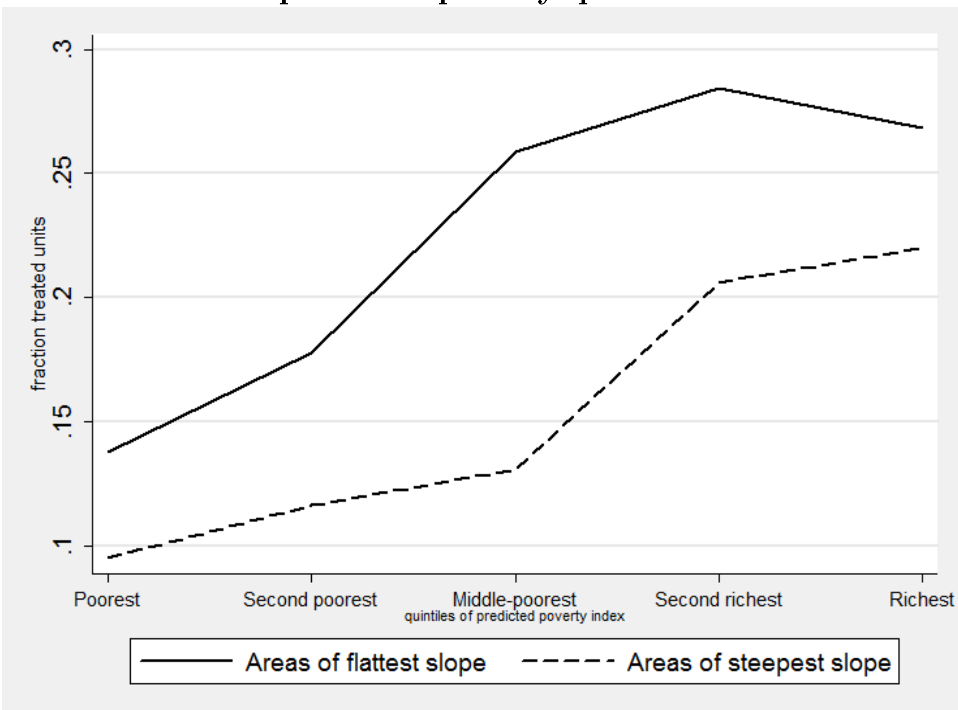
**Case, Anne and Angus Deaton**, "Large cash tranfers to the elderly in South Africa," *Economic Journal*, September 1998, *108* (450), 1330–1361.

**Gaunt, Trevor**, "Electrification technology and processes to meet economic and social objectives in Southern Africa." PhD dissertation, University of Cape Town 2003.

**Greenwood, Jeremy, Ananth Seshadri, and Mehmet Yorukoglu**, "Engines of Liberation," *Review of Economic Studies*, 2005, *72*, 109–133.

**Kling, Jeffrey**, "Intepreting instrumental variables estimates of the returns to schooling," *Journal of Business and Economic Statistics*, July 2001.

## Web Appendix 2 Figure 1: Effect of gradient on electrification probability, by predicted poverty quintile




Lines show fraction of each predicted poverty quintile that is electrified, by top (steep) and bottom (flat) halves of the gradient distribution. See notes for Table 10 for a description of how poverty index is created. The gap between the two lines indicates at which part of the poverty index the gradient manipulates the probability of electrification the most.

**Web Appendix 2 Figure 2: Women living with young children, by age - Census 1996 10% micro sample**


Lowess-smoothed graph of the fraction of women of each age living with at least one child under the age of 9. Data are from the 1996 South African Census 10% micro data and include African women aged 15-59 living in rural KwaZulu-Natal. N=116,381 collapsed to 45 age-specific data points.

**Web Appendix 2 Table 1: Contribution of each poverty quintile to IV results**

| Quintiles of predicted poverty index | Fraction of Sample in Quintile | Variance of Gradient by Quintile ($\lambda_q$) | E(Δelec\|z=1, q,x) - E(Δelec\|z=0, q,x)\|Q) | IV weight ($\omega_q$) |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Poorest quintile | 0.16 | 0.20 | 0.01 | 0.04 |
| | | | (0.04) | |
| Second poorest | 0.18 | 0.21 | 0.04 | 0.13 |
| | | | (0.04) | |
| Third poorest | 0.21 | 0.21 | 0.10 | 0.34 |
| | | | (0.04) | |
| Second richest | 0.21 | 0.20 | 0.10 | 0.33 |
| | | | (0.04) | |
| Richest quintile | 0.23 | 0.20 | 0.05 | 0.16 |
| | | | (0.05) | |

This table follows Kling (2001) in building the weights for each poverty quintile of the sample. These weights in column (4) indicate how much each poverty quintile contributes to the overall IV results. First, predicted poverty quintiles are assigned as follows: for communities in the steepest half of the gradient distribution, I project the indicator of electricity project on to community poverty rate, the fraction of female-headed households and the female/male sex ratio. Predicted values are created for every community using these regression coefficients. Communities are assigned to quintiles, where quintile cut-points are defined by the regression sub-sample. Column (1) shows the fraction of the sample that is in each poverty quintile. Column (2) shows λq, the conditional variance of the gradient dummy (1=flat, 0=steep) within each quintile (q): predicted E(P[Z|x,q][1-P(Z|x,q)|q]). Column (3) shows the estimated difference in the fraction of communities with and without Eskom projects by gradient, within each poverty quintile and controlling for covariates: Predicted Δelec|q=predicted E(E((elec|z=1,x,q) - predicted E(elec|z=0,x,q)|q)), Each estimated coefficient in column (3) is on the interaction of the gradient dummy (1=flat, 0=steep) with each predicted quintile dummy. Column (4) assembles these pieces to create the weights: ωq= ([(1)q*(2)q*(3)q])/(Sum of q [(1)q*(2)q*(3)q]).

**Web Appendix 2 Table 2: Household energy use by poverty quintile: At baseline and over time, 1996 to 2001**

| Quintile of predicted poverty index | Fuel Use in Home Production: Fraction using [X] in 1996 | | | $\Delta_t$ in Fuel Use for Home Production: Within-quintile difference by gradient | | | $\Delta_t$ in employment by gradient | |
|---|---|---|---|---|---|---|---|---|
| | Electric Lighting | Electric Cooking | Wood Cooking | Electric Lighting | Electric Cooking | Wood Cooking | Females | Males |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Poorest quintile | 0.02 | 0.01 | 0.90 | 0.00 | 0.002 | 0.000 | 0.001 | -0.005 |
| | (0.08) | (0.05) | (0.15) | (0.02) | (0.01) | (0.02) | (0.00) | (0.01) |
| Second | 0.04 | 0.02 | 0.85 | 0.00 | 0.004 | -0.012 | 0.00806* | 0.001 |
| | (0.14) | (0.08) | (0.19) | (0.02) | (0.01) | (0.01) | (0.00) | (0.01) |
| Third | 0.07 | 0.03 | 0.81 | 0.04 | 0.0152* | -0.0193* | 0.00792* | 0.002 |
| | (0.17) | (0.10) | (0.22) | (0.02) | (0.01) | (0.01) | (0.00) | (0.01) |
| Fourth | 0.12 | 0.05 | 0.72 | 0.03 | 0.0214** | -0.0337** | 0.0101* | 0.002 |
| | (0.23) | (0.12) | (0.26) | (0.02) | (0.01) | (0.01) | (0.01) | (0.01) |
| Richest quintile | 0.18 | 0.09 | 0.64 | 0.04 | 0.0258** | -0.025 | -0.002 | -0.012 |
| | (0.27) | (0.16) | (0.30) | (0.03) | (0.01) | (0.02) | (0.01) | (0.01) |

Columns (1)-(3) present the quintile means of outcome variables in 1996, columns (4)-(8) present coefficients from regression of interactions of gradient dummy and predicted poverty quintile. Significant at p<0.01***, p<0.05** or p<0.1* level.

**Web Appendix 2 Table 3: Age-specific effects of Electrification on Female Employment**

| $\Delta_t$ Female Employment | OLS | IV |
|---|---|---|
| | (1) | (2) |
| Ages 15-19 | 0.000 | 0.000 |
| | (0.000) | (0.005) |
| Ages 20-24 | 0.000 | 0.009 |
| | (0.001) | (0.013) |
| Ages 25-29 | -0.001 | 0.015 |
| | (0.001) | (0.012) |
| Ages 30-34 | -0.001 | 0.030* |
| | (0.001) | (0.012) |
| Ages 35-39 | 0.000 | 0.017 |
| | (0.001) | (0.013) |
| Ages 40-44 | 0.001 | 0.007 |
| | (0.001) | (0.012) |
| Ages 45-49 | 0.001 | 0.014* |
| | (0.001) | (0.008) |
| Ages 50-54 | -0.001 | -0.001 |
| | (0.001) | (0.007) |
| Ages 55-59 | 0.001 | 0.004 |
| | (0.001) | (0.006) |

Each cell in the table shows the coefficient (standard error) on the Eskom Project indicator from an OLS or IV regression of the change in the age-specific female employment rate on all controls, as in Table 3. Age-specific female employment rate is measured as the fraction of employed African women of age [X] over all females, where [X] is one of nine age groups. Robust standard errors clustered at sub-district level. Significant at p<0.01***, p<0.05** or p<0.1* level. N=1,816 in each regression.

**Web Appendix 3: Robustness checks**

This appendix provides a set of additional statistical tests and robustness checks for the paper.

# 1 Reduced form for second stage estimates

Web Appendix Table 1 presents the coefficients on gradient in the reduced form regressions of the main outcomes– the change in female employment and change in male employment rates– on gradient and all other controls. The results show that there is a reduced form relationship between community land gradient and the change in community-level female employment; but the reduced form relationship between gradient and male employment growth is not statistically significant at conventional levels.

# 2 Controlling for political factors

I collected election outcomes data for the KZN municipalities for the first municipal elections in 2000 and matched my sample of Census communities (smaller entities) to the municipality boundaries (larger entities). Using the number of voters voting for each of 9 parties $i$ in each municipality in the 2000 elections, I create a standard measure of political competition (see Banerjee and Somanathan, 2007), assigning to each community $j$ the corresponding value of $H_j$:

$$H_j = (1 - \sum_{i=1}^{9} voteshare_j) \tag{1}$$

A higher level of $H_j$ indicates more political competition. Results for results, controlling for political heterogeneity are presented in Web Appendix 3 Table 2 and Table 3.

- Table 2 columns (1) and (2) show that the measure of political competition predicts whether a community gets an Eskom project, but only when we do not control for district fixed effects. Once all other controls and district FE are added, the political competition measure has no predictive power in the first stage. More importantly, its inclusion does not change the impact of gradient on the probability of being allocated an Eskom project

- Table 3 columns (1) - (8) show that the inclusion of the political competition variable changes the effects of electrification on female employment only slightly. In areas with more political competition, female employment grows by 3.8 percentage points (going from no to complete competition). In the IV results, female employment is higher by 8.9 percentage points but given the reduction in sample size, this coefficient is not significantly different from zero (not all communities could be mapped to municipal boundaries). Male results are not affected by including the control for political heterogeneity

Although it would be preferable to control for earlier elections outcomes than 2000, this is not possible since the earlier election was "transitional" and those political boundaries were in flux before 2000. The exercise here indicates that while political competition may be important for employment growth, this variable is uncorrelated with gradient after controlling for all other variables and district fixed effects; and so has no substantial effect on the IV employment growth results.

## 3 Restricting the sample to areas without roads

I do not have access to road-building data in the province over time; only an indicator for whether a major national road runs through a community in 1996. In Web Appendix 3 Table 2 and Table 3, I present results from re-estimating the first stage assignment model and the model for employment on a smaller sample, where I omit communities with a main road running through them. The results for female employment (Table 2, columns (9) - (18)) remain large and positive, although, since the sample shrinks with the exclusion of some communities, the estimate is no longer statistically significant at conventional levels. The AR confidence interval extends from [0; 0,2].

## 4 Main results with corrections for spatial correlation in unobservables

To check that the main results (both coefficient estimates and statistical significance) are robust to spatial correlation in the error term, I re-estimate all regression results using the approach of Conley (1999). Results appear in Web Appendix Tables 4 to 7. In this approach, standard errors are generated using a weighted estimator, where the weights are the product of two weight functions, or kernels (one with an East-West orientation and the other with a North-South orientation). Each kernel declines linearly and is zero beyond a cutoff number. The cutoff number I choose here is 0.7 degrees (roughly 70 kilometers) and results are robust to cutoffs from 0.6 degrees to 1 degree (60 kms to 100kms).

Two points are apparent from these tables. For the chosen cutoff values, the coefficient estimates remain stable. And, standard errors are not uniformly larger when corrected for spatial correlation: sometimes they are larger and sometimes smaller than standard errors clustered at the sub-district level. The reason for this is that clustering standard errors at the sub-district level already takes account of most of the spatial correlation in errors.

Overall, the tables show that OLS and IV estimates and inference related to these estimates is robust to this alternative form of computing standard errors.

## 5 Testing for differences between male and female employment effects

Web Appendix 3 Table 8, I test for differences in the effect of electrification on male and female employment. I implement the test by differencing male and female outcome variables within community and then estimating the same set of OLS and IV regressions on this new variable. This test respects the correlated structure of errors across male and female regressions. Results indicate we cannot reject that new Eskom Projects had the same impact on male and female employment growth.

## 6 Characteristics of outmigrants compared to incumbents across high and low electrification areas, LFS 2002

The September 2002 Labor Force Survey contains a special module on migrants attached to households, from which information on outmigrants can be derived. In Web Appendix 3 Table 9, I show the fraction of people who are outmigrants from rural KZN magisterial districts as measured in these data. The table also presents mean employment rates and mean years of education for outmigrants and incumbents.

The table show differences in these summary statistics across communities with high and low rates of electrification (column 3) and indicates whether these differences are statistically significant (column 4). High electrification areas are defined as any magisterial districts in which more than 40% of the households have electric lighting: 66 percent of individuals live in such areas. The remaining 34% of individuals live in areas where less than 25 percent of households have electric lighting (there is no density in between 25 and 40 percent coverage).

Note that:

- Outmigration rates from rural KZN are high, and significantly higher in areas with low rates of electrification
- Outmigrants have higher average education than those who remain behind
- Employment rates of either group are about the same across high and low electricity districts

- Employment rates are significantly (significant at the 1% level) higher among incumbents compared to outmigrants in both low and high electrification rate districts.

## References

**Banerjee, Abhijit and Rohini Somanathan**, "The political economy of public goods: Some evidence from India," *Journal of Development Economics*, 2007, *82*, 287314.

**Conley, Timothy**, "GMM Estimation with Cross Sectional Dependence," *Journal of Econometrics*, September 1999, *92* (1), 1–45.

**Web Appendix 3 Table 1: Reduced form results from second stage regressions**

| *Outcome is* $\Delta_t$ *employment rate* | *Females* | *Males* |
|---|---|---|
| | (1) | (2) |
| Gradient*10 | -0.007** | -0.003 |
| | (0.003) | (0.005) |
| | | |
| Other baseline controls? | Y | Y |
| District Fixed effects? | Y | Y |
| N | 1,816 | 1,816 |

Table shows coefficient ong land gradient*10 from a regression of the growth in employment rate for females (males) on land gradient and all other controls as described in Table 3 of the paper. Robust standard errors clustered at sub-district level. Significant at p<0.01***, p<0.05** or p<0.1* level.

**Web Appendix 3 Table 2: First stage OLS regressions**

| | *Outcome is Eskom Project indicator* | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Gradient*10 | -0.082** | -0.074*** | -0.083** | -0.087*** |
| | (0.003) | (0.003) | (0.003) | (0.003) |
| Political competition index | 0.42*** | 0.122 | | |
| | (0.153) | (0.171) | | |
| Other baseline controls? | Y | Y | Y | Y |
| District Fixed Effects? | N | Y | N | Y |
| Sample | Full sample | | Sample excluding communities with main roads | |
| N | 1,781 | 1,781 | 1,792 | 1,792 |
| R2 | 0.10 | 0.18 | 0.10 | 0.18 |
| Mean of outcome variable | 0.20 | 0.20 | 0.20 | 0.20 |
| F-statistic on instrument | 6.39 | 7.32 | 6.135 | 10.43 |
| Probability>F | 0.01 | 0.01 | 0.079 | 0.179 |

Robust standard errors clustered at sub-district level. Significant at p<0.01***, p<0.05** or p<0.1* level. Ten district fixed-effects included in columns (2) and (4), all other controls included in each regression. Land gradient in degrees. Political competition is a measure of political heterogeneity: 1-the sum of (vote share)$^2$ where the sum is over all parties and elections data are from 2000 municipal elections.

**Web Appendix 3 Table 3: Effects of electrification on employment: Additional controls and different subsamples**

| | *Outcome is* | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $\Delta_t$ female employment rate | | | | $\Delta_t$ male employment rate | | | | $\Delta_t$ female employment rate | | | | $\Delta_t$ male employment rate | | | |
| | OLS | OLS | IV | IV | OLS | OLS | IV | IV | OLS | OLS | IV | IV | OLS | OLS | IV | IV |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) | (16) |
| Eskom Project | -0.001 | -0.001 | 0.084 | 0.089 | -0.009 | -0.010* | 0.012 | 0.012 | 0.000 | 0.001 | 0.059 | 0.069 | -0.014** | -0.009 | 0.056 | 0.019 |
| | (0.005) | (0.005) | (0.055) | (0.057) | (0.006) | (0.006) | (0.066) | (0.069) | (0.005) | (0.005) | (0.050) | (0.045) | (0.006) | (0.006) | (0.071) | (0.060) |
| Political competition index | 0.034* | 0.038* | 0.020 | 0.021 | 0.029 | 0.035 | 0.025 | 0.031 | | | | | | | | |
| | (0.021) | (0.020) | (0.030) | (0.030) | (0.026) | (0.027) | (0.030) | (0.031) | | | | | | | | |
| Other baseline controls? | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| District Fixed effects? | N | Y | N | Y | N | Y | N | Y | N | Y | N | Y | N | Y | N | Y |
| Sample | Full sample | | | | | | | | Sample excludes communities with main roads | | | | | | | |
| N | 1,781 | 1,781 | 1,781 | 1,781 | 1,781 | 1,781 | 1,781 | 1,781 | 1,792 | 1,792 | 1,792 | 1,792 | 1,792 | 1,792 | 1,792 | 1,792 |
| Standard 95% C.I. | [-0.01;0.01] | [-0.01;0.01] | [-0.06;0.11] | [-0.02;0.19] | [-0.02;0] | [-0.02;0] | [-0.12;0.14] | [-0.12;0.15] | [-0.01;0.01] | [-0.01;0.01] | [-0.04;0.16] | [-0.02;0.16] | [-0.03;0] | [-0.02;0] | [-0.08;0.2] | [-0.1;0.14] |
| AR C.I. | | | | [0.05;0.35] | | | | [-0.15;0.2] | | | | [0;0.20] | | | | [-0.09;0.15] |

Robust standard errors clustered at sub-district level. Significant at p<0.01***, p<0.05** or p<0.1* level. Ten district

**Web Appendix 3 Table 4: First stage assignment to Eskom Project: OLS results with standard errors corrected for spatial correlation**

| | Outcome is Eskom Project = 1 | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Gradient*10 | -0.083** | -0.075** | -0.078*** | -0.077*** |
| | (0.040) | (0.034) | (0.027) | (0.027) |
| | *[0.054]* | *[0.042]* | *[0.031]* | *[0.031]* |
| District FE | N | N | Y | Y |
| Sample | All | All | All | All |
| Mean of Y variable | 0.201 | 0.201 | 0.201 | 0.201 |
| N | 1,816 | 1,816 | 1,816 | 1,816 |

Table shows coefficients from OLS regression of Eskom project indicator on gradient, all other control variables and district fixed effects. Robust standard errors, clustered at the sub-place level are shown below each coefficient in (parentheses). Standard errors adjusted for spatial correlation using Conley's spatial weighting matrices and a cutoff of 0.7 degrees (about 70 kilometers) are also presented in square [brackets]. Significant at p<0.01***, p<0.05** or p<0.1* level.

**Web Appendix 3 Table 5: Effects of electricity projects on household energy sources and other services, standard errors corrected for spatial correlation**

| | OLS | | | IV | |
|---|---|---|---|---|---|
| Outcome is $\Delta_t$ | No controls | Controls | Reduced form coefficient on gradient*10 | No controls | Controls |
| | (1) | (2) | (3) | (4) | (5) |
| (1) Lighting with electricity | 0.251*** | 0.239*** | -0.077*** | 0.577*** | 0.658*** |
| (Mean=0.8) | (0.032) | (0.031) | (0.017) | (0.188) | (0.144) |
| | *[0.046]* | *[0.04]* | *[0.014]* | *[0.228]* | *[0.271]* |
| (2) Cooking with wood | -0.045*** | -0.039*** | 0.022** | -0.266 | -0.275* |
| (Mean=-0.04) | (0.012) | (0.012) | (0.010) | (0.179) | (0.147) |
| | *[0.012]* | *[0.01]* | *[0.009]* | *[0.203]* | *[0.161]* |
| (3) Cooking with electricity | 0.068*** | 0.056*** | -0.019*** | 0.250** | 0.228** |
| (Mean=0.04) | (0.009) | (0.009) | (0.006) | (0.107) | (0.101) |
| | *[0.01]* | *[0.008]* | *[0.005]* | *[0.12]* | *[0.121]* |
| (4) Water nearby | -0.029 | 0.005 | 0.029 | -0.483* | -0.372 |
| (Mean=0.01) | (0.029) | (0.024) | (0.018) | (0.249) | (0.248) |
| | *[0.028]* | *[0.023]* | *[0.02]* | *[0.271]* | *[0.225]* |
| (5) Flush toilet | 0.003 | 0.008 | -0.005 | 0.018 | 0.067 |
| (Mean=0.03) | (0.006) | (0.005) | (0.005) | (0.069) | (0.068) |
| | *[0.007]* | *[0.006]* | *[0.005]* | *[0.075]* | *[0.061]* |

Each cell contains the coefficient on Eskom Project indicator from OLS or IV regressions of dependent variable on electrification dummy; all control variables listed in Table 3 are included in columns (2) and (5). Robust standard errors, clustered at the sub-place level are shown below each coefficient in (parentheses). Standard errors adjusted for spatial correlation using Conley's spatial weighting matrices and a cutoff of 0.7 degrees (about 70 kilometers) are presented in square [brackets]. Significant at p<0.01***, p<0.05** or p<0.1* level. Each regression contains N=1,816 except for change in fraction of households using wood; I set 9 observations to missing (rather than to zero) for the 2001 observations.

**Web Appendix 3 Table 6: Effects of electrification on female employment with standard errors corrected for spatial correlation**

| Outcome is $\Delta_t$ female employment rate | OLS | | | | Reduced form | IV | | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Eskom Project | -0.004 | -0.001 | 0.000 | -0.001 | | 0.025 | 0.074 | 0.090* | 0.095* |
| | (0.005) | (0.005) | (0.005) | (0.005) | | (0.045) | (0.060) | (0.055) | (0.055) |
| | *[0.005]* | *[0.005]* | *[0.005]* | *[0.005]* | | *[0.057]* | *[0.07]* | *[0.056]* | *[0.056]* |
| Gradient*10 | | | | | -0.007** | | | | |
| | | | | | (0.003) | | | | |
| | | | | | *[0.003]* | | | | |
| Other control variables | N | Y | Y | Y | Y | N | Y | Y | Y |
| District Fixed Effects | N | N | Y | Y | Y | N | N | Y | Y |
| N | 1,816 | 1,816 | 1,816 | 1,816 | 1,816 | 1,816 | 1,816 | 1,816 | 1,816 |

Table shows OLS and IV regression coefficients for the outcome change in employment rate of African females. Robust standard errors, clustered at the sub-place level are shown below each coefficient in (parentheses). Standard errors adjusted for spatial correlation using Conley's spatial weighting matrices and a cutoff of 0.7 degrees (about 70 kilometers) are presented in square [brackets]. Significant at p<0.01***, p<0.05** or p<0.1* level. See Table 3 for notes on additional control variables included.

**Web Appendix 3 Table 7: Effects of electrification on male employment with standard errors corrected for spatial correlation**

| Outcome is $\Delta_t$ male employment rate | OLS | | | | Reduced form | IV | | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Eskom Project | -0.017** | -0.015*** | -0.009 | -0.010* | | -0.063 | 0.069 | 0.033 | 0.035 |
| | (0.007) | (0.006) | (0.006) | (0.006) | | (0.073) | (0.082) | (0.064) | (0.066) |
| | *[0.009]* | *[0.005]* | *[0.006]* | *[0.006]* | | *[0.099]* | *[0.111]* | *[0.064]* | *[0.065]* |
| Gradient*10 | | | | | -0.003 | | | | |
| | | | | | (0.005) | | | | |
| | | | | | *[0.005]* | | | | |
| Other control variables | N | Y | Y | Y | Y | N | Y | Y | Y |
| District FE | N | N | Y | Y | Y | N | N | Y | Y |
| N | 1,816 | 1,816 | 1,816 | 1,816 | 1,816 | 1,816 | 1,816 | 1,816 | 1,816 |

Table shows OLS and IV regression coefficients for the outcome change in employment rate of African males. Robust standard errors, clustered at the sub-place level are shown below each coefficient in (parentheses). Standard errors adjusted for spatial correlation using Conley's spatial weighting matrices and a cutoff of 0.7 degrees (about 70 kilometers) are presented in square [brackets]. Significant at p<0.01***, p<0.05** or p<0.1* level. See Table 3 for notes on additional control variables included.

**Web Appendix 3 Table 8: Effects of electrification on Female employment growth - Male employment growth**

| | $\Delta_t$ female employment rate - $\Delta_t$ male employment rate | |
|---|---|---|
| | OLS | IV |
| | (1) | (2) |
| Eskom Project | 0.010** | 0.060 |
| | (0.004) | (0.060) |
| Other baseline controls? | Y | Y |
| District Fixed effects? | Y | Y |
| N | 1,816 | 1,816 |
| R2 | 0.13 | 0.00 |
| Standard 95% C.I. | [0;0.02] | [-0.06;0.18] |
| AR C.I. | | [-0.09;0.35] |

Table shows coefficients from regressions of the differential difference in employment rates for women - men on all control variables and district fixed effects. Robust standard errors clustered at sub-district level. Significant at p<0.01***, p<0.05** or p<0.1* level.

**Web Appendix 3 Table 9: Characteristics of outmigrants and incumbents by district-level electrification status in rural KZN: LFS 2002 data**

| | District has high electrification rates | District has low electrificaton rates | Difference | Significant? |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Fraction of adult who outmigrate | 0.39 | 0.43 | -0.04 | ** |
| Mean yrs of education of adults remaining | 6.99 | 6.54 | 0.46 | *** |
| Mean yrs of education of outmigrant adults | 7.21 | 6.83 | 0.38 | ** |
| Mean employment rate among adults remaining | 0.38 | 0.36 | 0.01 | |
| Mean employment rate among outmigrants | 0.18 | 0.18 | 0.00 | |

Table shows descriptive statistics for adult Africans attached to households in rural KZN and enumerated in the September 2002 Labor Force Survey. Means are weighted using survey weights. Outmigrants are individuals identified by the household as belonging to the household, but who are outmigrants. There are 3,201 adults who are not migrants, and 2,146 adults who are outmigants. I define high electrification areas as any magisterial districts in which more than 40% of the households have electric lighting: 66% of individuals live in such areas. The remaining 34% of individuals live in areas where less than 25% of households have electric lighting (there is no density in between 25 and 40% coverage). Significant differences in variable means between high and low electrification areas are presented in columns (3) and (4) (t-tests).

**Web Appendix 4: Measurement error**

# 1 Measurement error in the Census data: Employment

The Census data undoubtedly measures employment with some error. While the employment questions are broad, the Census does not probe for employment information as the household surveys do. This section discusses the extent of this measurement error by comparing the Census data to individual level household survey data.

In Web Appendix 4 Table 1, I present population totals and employment rates for six different surveys: columns (1) and (4) present household-level data from the 1996 October Household Survey and the 2001 September Labor Force Surveys. These are the closest surveys we have to the relevant Census years and I use the weights in these surveys (constructed using the relevant Census as a benchmark) to create population totals and employment rates. In columns (2) and (4), I use the micro data from the 10% sample of the Census in 1996 and 2001 to create the same statistics using the Census weights; and in columns (3) and (6) I present the statistics taken from the 100% Census community databases in 1996 and 2001. Note that the unit of observation is the individual in columns (1), (2), (4) and (5) and the community in columns (3) and (6). Another important difference is that the individual level data in the Census and household surveys can only be restricted to African adults living in rural KZN while the Census community data can be disaggregated further to include adult Africans living in tribal areas of KZN. Tribal areas refer to the former homelands.

The difference between columns (1) and (2), and between (4) and (5) is largely the result of differences in the Census questions for employment versus the more detailed household survey questions. The difference between columns (2) and (3), and columns (5) and (6) is due to a restriction to tribal areas as well as the use of communities (rather than individuals) as the unit of observation.

The individual Census and household survey data provide population totals that are not substantially different from each other in most cases (the largest difference is in the male population total in 2001). However, employment rates are quite different across household survey and Census data. In every case, employment rates are lower in the 10% Census data compared with the 1996/2001 household survey data. The gaps also seem to be larger in 2001 than in 1996.

In addition to these differences over time in how closely the individual level data correspond, there are differences between the community data and the individual Census data. In every year, for men and for women, the Census community data present lower employment rates: between one quarter and one half of the employment rate is measured in the community data. A large part of the explanation for this is that the community data are restricted to tribal areas, which are not identical to all of the rural areas in the province (the Census community data does not provide a clean variable to separate rural areas into tribal/non-tribal). Hence individuals who live in rural communities with better average labor market outcomes than in the tribal, rural areas of the province are excluded from the community level data.

Web Appendix 4 Table 2 shows correlations between the individual and community Census data for different years and for men and women at the magisterial district level. The first four columns show that the community census employment data predict only a fraction of the individual census employment data and that the fraction explained for women is higher than it is for men. The final two columns show the correlation between the change in employment rates measured at the individual level and the change in employment rates measured at the community level. Again, more of the change in female employment at the individual level is predicted by the change in female employment in the community data than for men. This suggests that the Census community data may undercount male employment to a larger extent than female employment.

There are a few important points to note from Web Appendix 4 Table 1:

- The Census community data that is restricted to tribal areas under-counts employment, relative to all rural areas.

- The 2001 Census data (both individual and community data) measure lower levels of employment compared to the household survey data. This is probably due to the way the Census asked about employment in 2001: "Did you work for at least 1 hour last week?" compared with the 1996 question, "Did you work for a formal wage/salary, in informal work, or on a farm last week?" The 2001 question may not have been interpreted to include informal sector work or farm work by respondents in 2001, so the main types of employment that are under-counted in 2001 are probably these types of jobs. As long as the prevalence of these jobs is uncorrelated with gradient, then under-counting of employment in the 2001 data should not be problematic for the paper's main research design.

- Changes in employment in the Census community data more strongly predict changes in employment in the individual level data for women compared to men. This suggests that the community level data may be missing more of the employment story for men, than for women, in these areas.

- Even though the Census community data under-counts employment, the strong message from the individual level data is that there are very low levels of employment in these rural areas: under 50% of men are employed and under 30% of women are employed. These employment rates fall even further when we restrict to tribal areas of the province in using the Census community data. The low levels of employment in these areas are not an artifact of mis-measured (i.e. missing) employment.

- Finally, focusing on the occupation distribution for men and women, the individual Census data count fewer men and women employed in agriculture than the household surveys do. Agricultural employment in both of the individual sources is higher than in the Census community data - bearing in mind that the community data count people living only in tribal areas - and yet is still very low, below 10%. Regardless of which data set is considered, only a small fraction of individuals work in agriculture in the rural areas of KZN.

## 2 Measurement error in the electrification project variable

Since Eskom region boundaries do not line up with Census boundaries, I assign values of $T_{jdt}$ in the following way: for any community that lies even partially inside an Eskom project area, all information from that project is assigned to that community. This means some communities are assigned full electrification status when only a fraction of households in the area are electrified. In addition, non-NEP electrification continued during this period in areas where households were willing to pay for their connections.

Measurement error in the binary project status variable could contribute to the difference between OLS and IV coefficients. OLS will underestimate the effect of electricity on outcomes when there is a negative covariance between $\delta_j$ and $\Delta T_{jdt}$ (which I have argued is likely) and when $\Delta T_{jdt}$ is measured with error. However, the valid IV that is uncorrelated with $\delta_j + \Delta\epsilon_{jt}$ will tend to be correlated with any non-classical measurement error in the binary variable $\Delta T_{jdt}$. In this situation, even if the instrument deals with the omitted variables bias, the measurement error in $\Delta T_{jdt}$ could lead to an upwards-biased IV estimator.[1]

To get a sense of how much of the difference in OLS and IV results is due to measurement error, I restrict to samples where I expect $\Delta T_{jdt}$ to be measured with less error. The first two columns of Web Appendix 4 Table 4 reproduce the main result for females in the full sample while columns (3) to (6) present results for successive sample limitations. To identify communities where projects had greater coverage, I exclude electrified areas with less than a 10 percent change in coverage of electric lighting, and areas where the connection rate

[1] This result is conditional on the measurement error in electrification status not being too extreme (Kane et al, 1998). See Bound and Solon (1999) and Kane, Rouse and Staiger (1998) for a discussion of what the IV estimator is consistent for in the presence of non-classical measurement error.

between 1996 and 2001 was under 80 percent of households. All communities that did not have an electricity project during the period are included in all columns. Under the first restriction in columns (3) and (4), the OLS coefficient rises substantially and the IV coefficient is the same as the main result at 13 percentage points. The movement in the OLS coefficient suggests that there is some measurement error is present in the electrification variable. Columns (5) and (6) impose the second restriction. Again, the OLS estimate is large and positive and the IV result is now slightly higher than the main result (at 0.155), although neither is statistically significant due to the smaller sample size.

Although effects estimated under the OLS specification for these sub-samples are between 1 and 1.2 percentage points higher than the OLS result for the full sample, they are still well smaller than the IV results. This is evidence that measurement error in the electrification dummy alone is unable to account for the entire gap between OLS and IV estimates.

# References

**Bound, John and Gary Solon**, "Double Trouble: on the value of twins-based estimation of the returns to schooling," *Economics of Education Review*, 1999, *18*, 169–182.

**Kane, Thomas, Cecilia Elena Rouse, and Douglas Staiger**, "Estimating returns to schooling when schooling is misreported," 1998. NBER Working Paper No. 7235.

**Web Appendix 4 Table 1: Comparing measures of employment in the Census and October Household/Labor Force Surveys**

| | 1996 | | | 2001 | | |
|---|---|---|---|---|---|---|
| | OHS 1996 | 10% Census | 100% Census | LFS 2001 | 10% Census 2001 | 100% Census |
| Unit and place of observatio | Indiv. RURAL | Indiv. RURAL | Comm. TRIBAL | Indiv. RURAL | Indiv. RURAL | Comm. TRIBAL |
| *Panel A: Women* | | | | | | |
| Population totals | 1,398,856 | 1,299,475 | 709,285 | 1,144,854 | 1,442,057 | 839,521 |
| Total employment/populatio | 0.19 | 0.13 | 0.07 | 0.28 | 0.13 | 0.07 |
| Occupational distribution | | | | | | |
| Managers, profs, assoc. prof | 0.03 | 0.02 | 0.02 | 0.03 | 0.02 | 0.02 |
| Clerks | 0.01 | 0.00 | 0.00 | 0.01 | 0.01 | 0.00 |
| Services | 0.02 | 0.01 | 0.00 | 0.03 | 0.01 | 0.00 |
| Agriculture[1] | 0.01 | 0.01 | 0.00 | 0.01 | 0.01 | 0.00 |
| Crafters | 0.01 | 0.01 | 0.00 | 0.01 | 0.01 | 0.00 |
| Machine Operators | 0.00 | 0.00 | 0.00 | 0.02 | 0.00 | 0.00 |
| Elementary Occupations[2] | 0.09 | 0.07 | 0.03 | 0.16 | 0.06 | 0.04 |
| Missing occupations data | 0.01 | 0.02 | 0.01 | 0.00 | 0.02 | 0.00 |
| *Panel B: Men* | | | | | | |
| Population totals | 1,036,785 | 993,888 | 504,272 | 777,350 | 1,125,483 | 617,858 |
| Total employment/populatio | 0.39 | 0.25 | 0.14 | 0.38 | 0.19 | 0.10 |
| Occupational distribution | | | | | | |
| Managers, profs, assoc. prof | 0.04 | 0.01 | 0.02 | 0.03 | 0.02 | 0.02 |
| Clerks | 0.01 | 0.00 | 0.01 | 0.01 | 0.01 | 0.01 |
| Services | 0.06 | 0.02 | 0.01 | 0.04 | 0.02 | 0.00 |
| Agriculture[1] | 0.01 | 0.02 | 0.00 | 0.03 | 0.01 | 0.00 |
| Crafters | 0.04 | 0.04 | 0.02 | 0.07 | 0.03 | 0.01 |
| Machine Operators | 0.07 | 0.04 | 0.02 | 0.09 | 0.03 | 0.02 |
| Elementary Occupations[2] | 0.13 | 0.07 | 0.03 | 0.11 | 0.06 | 0.04 |
| Missing occupations data | 0.02 | 0.05 | 0.03 | 0.00 | 0.02 | 0.00 |

Notes: Table shows population totals and means from the October Household Survey (OHS) microdata, the Labor Force Survey (LFS) microdata, the 10% Census microdata and 100% Census community aggregate data. The sample is restricted to rural Africans living in KZN, aged 15-59 inclusive. Means and totals from the OHS/LFS/10% Census data are weighted using population weights provided in each survey. Agriculture [1] includes skilled and subsistence agriculture. Elementary occupations [2] include domestic workers. Census Community data are weighted by the number of people in each community.

**Web Appendix 4 Table 2: Correlation between community Census and individual Census employment data**

| | Female employment | | Male employment | | | |
|---|---|---|---|---|---|---|
| | Census Individual 2001 | Census Individual 1996 | Census Individual 2001 | Census Individual 1996 | Δ Female empl. Individual | Δ Male empl. Individual |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Female employment, Community, 2001 | 0.627*** | | | | | |
| | (0.08) | | | | | |
| Female employment, Community, 1996 | | 0.508*** | | | | |
| | | (0.08) | | | | |
| Male employment, Community, 2001 | | | 0.284*** | | | |
| | | | (0.05) | | | |
| Male employment, Community, 1996 | | | | 0.340*** | | |
| | | | | (0.04) | | |
| Δ Female employment, Community | | | | | 0.384*** | |
| | | | | | (0.09) | |
| Δ Male employment, Community | | | | | | 0.140*** |
| | | | | | | (0.05) |
| N | 42 | 42 | 42 | 42 | 42 | 41 |
| $R^2$ | 0.55 | 0.44 | 0.39 | 0.33 | 0.17 | 0.01 |

Table shows coefficients (standard errors) from OLS regressions of employment rates measured in the individual Census data on employment rates measured in the aggregate Census data, where data from each Census has been aggregated up to the magisterial district level. Robust standard errors in parentheses. Significance at *** p<0.01, ** p<0.05, * p<0.1. Δ variables refer to change in the employment rate between 1996 and 2001.

**Web Appendix 4 Table 3: Comparing the difference in employment measurement error gaps by gradient (OLS regressions)**

| | Females | | Males | | Females | Males |
|---|---|---|---|---|---|---|
| | Community - Individual data, 2001 | Community - Individual data, 1996 | Community - Individual data, 1996 | Community - Individual data, 2001 | [2001 underestimate - 1996 underestimate] | [2001 underestimate - 1996 underestimate] |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Gradient aggregated to MD | -0.00311** | -0.00388** | -0.00631*** | -0.004 | 0.001 | -0.002 |
| | (0.001) | (0.002) | (0.002) | (0.003) | (0.001) | (0.002) |
| N | 41 | 41 | 41 | 41 | 41 | 41 |
| $R^2$ | 0.11 | 0.08 | 0.08 | 0.04 | 0.01 | 0.01 |

*** p<0.01, ** p<0.05, * p<0.1, Robust standard errors in parentheses. Each coefficient is from a regression of the outcome variable on land gradient. The first four columns use the (community - individual data) difference in employment rates wthin a year as the outcome variable. The final two columns use the difference in the difference in employement rates across time as the outcome variable. The unit of observation is the magisterial district.

**Web Appendix 4 Table 4: Contribution of measurement error in electrification project status to female employment result**

| Outcome is $\Delta_t$ in female employment | Full sample | | Restricted to areas with > 10% change in electricity coverage | | Restricted to areas with over 80% coverage by 2001 | |
|---|---|---|---|---|---|---|
| | OLS | IV | OLS | IV | OLS | IV |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Eskom Project | -0.001 | 0.095* | 0.009 | 0.095 | 0.011 | 0.082 |
| | (0.005) | (0.055) | (0.007) | (0.060) | (0.009) | (0.087) |
| N | 1,816 | 1,816 | 1,461 | 1,461 | 1,273 | 1,273 |

Table shows the Eskom project coefficient (s.e.) from an OLS or IV regression of the change in female employment on all controls as described in Table 3, for different samples: the full sample in columns (1) and (2), the sample restricted to areas with a large change in electric lighting in columns (3) and (4), and the sample restricted to areas with the highest levels of electric lighting use by 2001 in the last two columns. Robust standard errors clustered at sub-district level. Significant at p<0.01***, p<0.05** or p<0.1* level.