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Rural electrification, gender and the labor market: A cross-country study of India and South Africa

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ABSTRACT

This cross-country study estimates the effect of household electrification on labor market outcomes for rural individuals in India and South Africa, two developing countries that have implemented large-scale rural electrification schemes in recent decades. Two identification strategies are used: propensity score matching and panel fixed effects estimation. We focus on three indicators of labor market success: employment, earnings and hours worked. We find that electrification raises the annual incomes earned by those who work in paid employment, for both men and women in both countries. For India, both genders work fewer hours, suggesting that electricity raises productivity. For South Africa, where the labor market has less absorptive capacity, there is no employment benefit of electrification. But women who work benefit the most from the productivity gains of electrification: they have greater increases in earnings than men. Our findings suggest that the benefits of electrification do not accrue universally, but rather depend on gender roles, supporting policies and the labor absorptive capacity of the economy.

1. Introduction

The role of electricity in driving growth and development has been an area of much debate over the last few decades. Recently, ensuring that all individuals have access to affordable and reliable sources of modern energy was explicitly set out as one of the United Nations' Sustainable Development Goals. While industrialized nations have prospered from the pervasiveness of electricity, electricity access is lacking in many developing countries, with the problem being particularly chronic in rural areas. Around 45 percent of rural households in India (Census, 2011a) and 24 percent of the rural population of South Africa (Census, 2011b) do not have access to electricity. For many households that do have electricity, reliability of supply and affordability remain major issues. To this end, rural electrification programs with an aim to achieve universal access to electricity have been launched across many developing countries, such as the *Deen Dayal Upadhyaya Gram Jyoti Yojana (DDUGJY)* scheme in India and post-apartheid electrification drives in South Africa. The role and intent of these electrification programs is not only to provide access to electricity but also to improve the quality of life of impoverished and remote rural communities (Khandker, Samad, Ali, & Barnes, 2014). However, Barnes and Binswanger (1986) highlight the more wide-ranging 'blind faith' often placed on rural electrification to solve all problems faced by rural people. They note that "advancing power lines into rural areas has been synonymous with providing the necessary infrastructure for bringing rural areas quickly to higher levels of development".

However, while electricity is a pre-condition to economic development, it is not the only policy lever to achieve development and poverty reduction, and requires other complementary inputs in order to be effective. In spite of the recent electrification programs, there are limitations to the evidence of the impacts of rural electrification on economic outcomes such as employment and wages. In addition to some research being inconclusive, most studies analyze a single country or single program, which makes them difficult to generalize to other developing country contexts. To counteract this, we employ a cross-country comparative methodology in two major developing countries, namely India and South Africa, using two identification strategies and recent data to ascertain the causal impacts of rural electrification on labor market outcomes. Rural electrification has often been promoted as a key means of uplifting women, in particular, and thus our study views the impacts of electrification through a gendered lens.

The analysis is conducted in the form of a comparative study in order to provide insight into the mechanisms by which electrification generates labor market effects. Both countries have

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Table 1
Rural electrification schemes in India and South Africa.

Schemes	Time period	Features
India		
Rural irrigation projects/rural electrification projects	1951–1956	Targeted village level electrification and irrigation
Rural Electrification Corporation	1969	Created to energize pump-sets and provide electricity to villages
Minimum Needs Program	1974–1978	Targeted village level electrification
Kutir Jyoti Program (KJP)	1988–2004	Provided single point light connection (60 W) to Below Poverty Line households. Merged with RGGVY in 2005
Pradhan Mantri Gramodaya Yojna (PMGY)	2000–2005	Provided financial assistance for minimum services (including rural electrification)
Minimum Needs Program (MNP)	2000–2004	Targeted villages with less than 65 percent rural electrification with 100 percent loans for last mile connectivity. Merged with RGGVY in 2005
Accelerated Rural Electrification Program (AREP)	2002–2012	Provided interest subsidy of four percent to states, through approved financial institutions, for rural electrification programs
Rural Electricity Supply Technology Mission (REST)	2002–present	Ensuring electrification of all villages and households through local renewable energy sources and decentralized technologies
Rajiv Gandhi Grameen Vidyutikaran Yojna (RGGVY)	2005–2014	Targeted 100 percent rural electrification and electricity access to all households. Replaced by DDUGJY
Deen Dayal Upadhyaya Gram Jyoti Yojana (DDUGJY)	2014–present	To provide continuous power supply to rural India
South Africa		
National Electrification Programme (NEP)	1994–2001	Aimed to provide electricity access to households that had not had access during apartheid
Integrated National Electrification Programme (INEP)	2001–2010	Focused on rural electrification, as urban electrification had dominated the previous NEP
Integrated Resource Plan (IRP)	2010–present	Emphasizes the use of more renewable energy sources, especially in areas that are not grid-accessible

Source: Compiled by the authors

experienced large-scale electrification programs in recent decades, which have substantially increased household access to electricity, although rural areas remain under-serviced. However, the labor markets in the two countries are very different, in terms of features such as access to employment, types of work, and the distribution of earnings. If the study finds that the impact of electrification is similar in both countries despite these large differences, then it is likely that the conclusions are quite generally applicable. In contrast, if outcomes differ in the two countries, then the impacts of electrification programs are location and case-specific, and must be evaluated on a case-by-case basis. A cross-country comparison of how access to electricity affects labor market outcomes therefore enhances our understanding of the causal links between electrification and wellbeing. Of particular interest is the extent to which rural electrification affects employment and earnings for women, and thus, promotes inclusive and sustainable growth.

The paper uses two key identification strategies in order to assess the causal effect of rural electrification and to assess the robustness of the findings. First, a propensity score matching method is used at a cross-sectional level to compensate for the lack of a selection rule for randomizing households into treatment (household electrification) and control groups. Second, unobserved heterogeneity that may be correlated with both household access to electricity and labor market success is corrected by applying panel data analysis techniques. The panel estimates produced through fixed effects estimation therefore provide the most reliable and informative results.

The key findings of the paper are that the effects of electrification are not universal: access to electricity improves some labor market outcomes, but the nature and extent of the impact differs across labor market indicators, gender and estimation method. The most robust finding is that access to electricity raises the annual incomes earned by those who work in paid employment, for both men and women in both countries. For India, this is accompanied by a decrease in hours worked for both genders, suggesting that electricity raises productivity. Men who gain access to electricity have a decreased probability of working in paid employment. For South Africa, there are no employment effects of electrification, which is consistent with a labor market with less absorptive capacity. But women have greater increases in earnings once employed than men, suggesting that they benefit the most from the productivity gains of electrification.

The remainder of the paper is structured as follows. Section 2 briefly outlines the electrification programs that have taken place in both countries, and the nature of the countries' labor markets. This section provides the context in which the labor market effects of electrification will be studied. Section 3 reviews the existing literature on the impacts of electrification, while Section 4 outlines the research methods used in the paper. The data used for the study are discussed in Section 5, which also presents descriptive statistics of individuals living in electrified and non-electrified rural households. The econometric estimates are presented thereafter, focusing on the impact of rural electrification on three key labor market outcomes: employment status, hours worked and earnings. Propensity score matching estimates are shown in Section 6, with panel analysis conducted in Section 7. Finally, Section 8 discusses the results and concludes the study.

2. Background

2.1. Rural electrification in India and South Africa

Rural electrification has been high on the agenda for policymakers over the past several decades. In India and South Africa, a sequence of electrification programs have addressed the varying needs of each country over time, as outlined in Table 1. Early electrification schemes in India focused on productive uses such as irrigation, before expanding into providing basic access for poor households (the *Kutir Jyoti* program). More recent schemes have centered on renewable energy and universal access. The current *Deen Dayal Upadhyaya Gram Jyoti Yojana* scheme, in place since 2014, focuses on improving the reliability of supply in rural India (GOI, 2017).

In South Africa, electrification became a priority after the advent of democracy, in line with the refocusing of many other

Table 2
Access to electricity (percentage of population), by area type.

	India		South Africa	
	Total	Rural	Total	Rural
1990	45.1	31.9	56.5	26.4
2014	79.2	70.0	86.0	71.5

Source: World Bank (2017).

aspects of social policy. At the end of apartheid, less than 60 percent of the population had access to electricity, with the access rate in rural areas being only half of that. Electrification programs after South Africa's first democratic elections initially focused on improving racial inequalities in electricity access (the National Electrification Program), while later programs focused on rural electrification and the use of renewable energy sources (Stats SA, 2013; World Bank, 2017).

These electrification programs were very successful in raising overall access in both countries, by a similar extent, as illustrated in Table 2. Rural areas experienced the largest improvement in access, such that, by 2014, approximately 70 percent of the rural population in both countries had access to electricity. Nonetheless, access for the rural population continues to lag behind overall access, by almost 10 percentage points in India and 15 percentage points in South Africa.

2.2. The nature of the labor market in India and South Africa

Although both India and South Africa rank at the medium level of human development (UNDP, 2015), the nature of their labor markets is very different. This makes for an interesting comparison of the labor market outcomes for social policy. Key labor market indicators for the two countries are compared in Table 3.[1] While the share of employment in the secondary sector is approximately 20 percent in both countries, the primary and tertiary sectors vary widely. Despite rapid industrialization, India still has a large agricultural sector with around half of the labor force employed on agricultural lands and farming related activities. The proportion of people employed in the agricultural sector is much greater in the rural areas (64 percent) than in urban areas. However, due to improved technology and productivity, employment in the agricultural sector has decreased in the last decade. In contrast, South Africa has already largely transformed into a services-dominated economy, away from its past reliance on mining and agriculture. However, employment in the primary sector remains five times more dominant in rural areas than in urban areas.

India also has a large informal economy, mostly in the agricultural sector. Own-account workers and contributing family workers form a large part of this informal economy, constituting 64 percent and 17 percent respectively. The informal sector has grown in the post liberalization era, which also manifested in increases in female involvement in household businesses. This has led to increases in the labor force participation of females as self-employed business owners, as is illustrated further in the subsequent Table 4. However, despite the increase in the size of the informal sector, the lack of adequate electricity supply poses a significant barrier to its growth (Coad and Tamvada, 2012). A high percentage of employed people in rural areas work on their lands or as casual labor on other farmlands. In contrast, because of the large secondary and tertiary sector in the urban areas, a significant proportion of workers there are wage or salary earners.

The nature of society in South Africa in general, and the labor market in particular, has been heavily influenced by the country's history of legislated and institutionalized discrimination. As a result, there exist very high levels of inequality across a range of dimensions, most especially race, but also including geography (especially urban–rural divides) and, to a somewhat lesser extent, gender. The extent and nature of labor force participation, access to employment, and the level of earnings also differ considerably for individuals across these various dimensions. On aggregate, post-apartheid South Africa has experienced rising levels of participation in the labor market, with a gender gap that has narrowed substantially over time (Casale and Posel, 2002; Banerjee, Galiani, Levinsohn, McLaren, & Woolard, 2008). However, participation in rural areas lags behind that in urban areas by almost 20 percentage points, even when discouraged work-seekers are included in the analysis, as shown in Table 3.

However, as a result of the rise in participation not being met by an increase in job availability, South Africa's unemployment rate increased substantially from 1995 onwards (Banerjee et al., 2008). Unemployment is much higher in rural areas, at more than 40 percent, than in urban areas, at 28 percent. Nonetheless, the nature of employment has remained highly skewed towards wage employment in the formal sector,[2] with low levels of self-employment.

Less than 20 percent of workers were employed in the informal sector by 2014 (Stats SA, 2015). South Africa is considered an international outlier in having such a small informal sector, relative to its high rate of unemployment (Kingdon and Knight, 2007). In part, individuals without employment may rely on the extensive social grant system as means of income support. However, a number of other possible reasons have been suggested for why the informal sector in South Africa is so small, and does not act as a 'sponge' for those who cannot find formal sector employment. High start-up costs, a lack of access to informal credit, high crime rates, and strictly enforced labor regulations have all been suggested as reasons why unemployed individuals do not start small businesses (Kingdon and Knight, 2007; Banerjee et al., 2008). In addition, apartheid spatial planning resulted in poor households living long distances from areas of economic activity. This is especially the case for rural households, where small towns have stagnated while the more distant cities have grown. When coupled with high transport costs, this may prevent individuals from accessing products and markets. Chandra et al. (2002) suggest that lack of access to infrastructure hampers informal sector businesses in urban areas, and it is likely that such issues are even more pressing in remote rural areas. Access to electricity may thus increase the likelihood of unemployed individuals being able to start small businesses.

In both countries, there are considerable earnings inequalities in favor of urban areas. These are particularly notable in the case of wage or salary earners in both countries, and the self-employed in South Africa. This suggests that the benefits to be gained from employment are lower in rural than in urban areas.

The gender disparities in the labor markets of the two countries are further illustrated in Table 4, which disaggregates the labor market statistics above by gender. In India, men have a much higher rate of labor force participation (82 percent) compared to women, at 33 percent. The low participation and employment rates for women are partly attributable to the definition where household work is not counted as work in the national surveys. Social norms, gender discrimination and low access to maternity benefits may also cause many women to stay out of the labor mar-

[1] The figures presented are based on published statistics for India, and thus we cannot test whether the indicators differ significantly between the rural and urban subsamples.

[2] In most studies on the South African labor market, formal sector employment is defined as individuals who work in enterprises that are registered to pay Value Added Tax. Individuals who work for private households (mainly domestic workers) are considered to fall outside the formal/informal sector classification (Stats SA, 2015).

Table 3
Key labor market indicators, by area type.

	India		South Africa	
	Urban	Rural	Urban	Rural
Labor force participation (%)	52.7	60.9	65.0	47.5
Unemployment rate (%)	3.6	1.8	28.3	40.2
Share of employment (%)				
Primary sector	6.7	64.1	4.1	19.1
Secondary sector	35.0	20.4	20.8	19.1
Tertiary sector	58.3	15.5	75.1	61.8
Category of employment (%)				
Wage/salary earners	43.3	8.7	87.7	81.0
Self-employed[a]	41.9	55.9	12.3	19.0
Casual labor[b]	14.8	35.4	–	–
Daily wages (USD)				
Wage/salaried earners	26.91	17.89	72.65	35.87
Self-employed	–	–	127.50	56.35
Casual labor	10.20	8.30	–	–

Source: NSSO (2013, *published statistics) and* QLFS (2013, *author's calculations)*
Notes: For India, the indicators are based on usual principal and subsidiary status (UPSS). A moving reference period of last twelve months from the date of survey is used to derive the estimates.
For South Africa, the estimates are from the fourth quarter of 2013, and refer to employment activities in the last week. The expanded definition of labor force participation is used, which includes discouraged work seekers among the economically active.
Purchasing power parity (PPP) exchange rates: 1 USD = 16.7 INR; 1 USD = 5.2 ZAR in 2013 (OECD, 2018).
[a] Self employment includes both farming and non-farming enterprises.
[b] Casual labor in works other than public works. This category does not exist in the QLFS data.

Table 4
Key labor market indicators, by gender.

	India		South Africa	
	Men	Women	Men	Women
Labor force participation (%)	82.7	33.1	66.4	52.6
Unemployment rate (%)	2.2	2.5	28.8	34.5
Share of employment (%)				
Primary sector	43.6	62.8	10.3	4.0
Secondary sector	25.9	20.0	27.6	11.3
Tertiary sector	30.5	17.2	62.2	84.7
Category of employment (%)				
Wage/salary earners	19.8	12.7	84.6	88.2
Self employed[a]	50.7	56.1	15.4	11.9
Casual labor[b]	29.4	31.2		
Daily wages (USD)				
Wage/salary earners	24.97	17.89	72.63	58.48
Self-employed	–	–	122.28	49.44
Casual labor	10.40	6.68	–	–

Source: NSSO (2013, published statistics) and QLFS (2013, *author's calculations)*
Notes: For India, the indicators are based on usual principal and subsidiary status (UPSS). A moving reference period of last twelve months from the date of survey is used to derive the estimates.
For South Africa, the estimates are from the fourth quarter of 2013, and refer to employment activities in the last week. The expanded definition of labor force participation is used, which includes discouraged work seekers among the economically active.
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[a] Self employment includes both farming and non-farming enterprises.
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ket. In South Africa, rates of labor force participation are also lower among women than among men, although the gap is not nearly as large as for India, and women's participation has risen over time (Casale and Posel, 2002). Women are much more likely than men to be unemployed, and those who find work are typically located in the tertiary sector. In both countries, many women work as household domestic workers, with relatively low pay.

Among those who find employment in India, the wages of female salaried employees and casual labor are much lower than their male counterparts, in both rural and urban areas. Similarly, in South Africa, men earn more than women, with the gender disparity being particularly large among the self-employed. It is highly likely that job type and hence earnings are constrained by household circumstances, including lack of access to electricity, thus it may be the case that electrification increases earnings and reduces some of these wage differences. Both countries have a history of electrification programs that have achieved similar results in terms of access to electricity. However, the labor market context in which these programs have been rolled out differs considerably, and thus it remains an open question as to the extent to which increases in employment and earnings can be directly attributed to electrification.

3. Impacts of rural electrification: Literature review

Most studies on the causal link between electricity consumption and GDP at a national level support the 'growth hypothesis', that electricity consumption positively influences GDP (Khanna and Rao, 2009; Payne, 2010). However, literature is scant in terms of understanding the causal mechanisms linking electricity supply with income generation, or the conditions that enable this causal link (Rao, 2013). At the household level, a large body of literature on rural electrification programs suggests that rural electrification results in welfare gains for rural households (ADB, 2010; Barnes, Peskin, & Fitzgerld, 2003; IEG, 2008; Khandker, 1996; Martins, 2005). But most of these studies, as Khandker et al. (2014) points out, rely on the correlation between rural electrification and development, without taking into account selection and program placement biases, and thus have failed to establish a causal and directional relationship. Other authors support this view that very little "empirical evidence" exists to substantiate the claimed benefits of rural electrification (Bernard, 2012; IEG, 2008). Although the benefits from rural electrification may be intuitive, there is limited empirical evidence because the complex chains that link rural electrification to development outcomes confound attempts at attribution (Rao, 2013).

Rural electrification is expected to affect labor market outcomes through three potential channels: first, household electrification frees up (especially women's) time spent in collecting and preparing fuel, and increases the productivity of household tasks through improved technology. It therefore increases labor supply and results in more engagement in market-based work (Dinkelman, 2011; Grogan and Sadanand, 2013; Köhlin et al., 2011; Wu, Borghans, & Dupuy, 2010). Second, having access to electricity creates opportunities to generate income within the home and allows for new types of jobs outside the home, thus potentially increasing self-employment and labor demand (Barkat et al., 2002; Chowdhury, 2010; Walle, 2013). Women are likely to be the key beneficiaries of any such changes, and thus rural electrification has the potential to empower women. Third, electrification may therefore result in a shift from agricultural to non-agricultural activities that are typically associated with an increase in productivity, and thus in income (Torero, 2015). This is particularly relevant to India, which remains a predominantly agricultural rural economy.

Quantitative empirical research on labor market outcomes has grown considerably in recent years, although with mixed results. Using data from India, Khandker et al. (2014) estimate income impacts of the order of 25–50 percent due to rural electrification. Productivity-related increases in income have been linked to improved lighting in the Philippines, because better lighting enhances the return on education (ESMAP, 2003). However, Bensch, Kluve, and Peters (2011) show that income differences between households with and without access to an electrification program in Rwanda become statistically insignificant when the comparison takes selection bias and regional differences into account.

Increases in labor force participation and employment because of household electrification have figured prominently in the debate around the benefits due to household electrification. Studies by Dinkelman (2011) and Grogan and Sadanand (2013) find positive effects on female employment due to electrification in South Africa and Nicaragua, respectively. Dinkelman (2011) estimates that rural female employment increased by 9–9.5 percentage points in South Africa in the 1990s due to rural electrification and Grogan and Sadanand (2013) find that the probability of women working outside the home increased by 23 percent in Nicaragua as a result of rural electrification. Dinkelman (2011) attributes the increase in labor supply to the use of electric stoves and other time saving appliances. A recent study by Walle (2013) finds some impact on labor supply and wage rates in India based on an old panel survey.

According to another line of inquiry, household electrification may also extend the number of productive hours due to increased use of lighting. These extra hours can be used for income generating activities at home, such as sewing and embroidery. Due to increased lighting, women in Bangladesh use a greater share of their time doing household work that results in generating extra income (Barkat et al., 2002; Chowdhury, 2010).

Most studies have attempted to evaluate the impacts of rural electrification using quasi-experimental methods. Instrumental variable approaches have been fairly common to evaluate electrification impacts. Dinkelman (2011) and Lipscomb, Mobarak, and Barham (2013) use exogenous program placement instruments to identify the impacts. Grogan and Sadanand (2013) and Khandker et al., (2014) use instrumental variables to ascertain the impacts on income generation in Nicaragua and India respectively. In contrast, Walle (2013) and Khandker, Barnes, and Samad (2013) use panel data approaches to evaluate the impacts in India and Vietnam respectively.

In spite of these recent research efforts, the case- and region-specific nature of these studies makes it difficult to generalize to other developing country contexts. In light of this, we employ a cross-country comparative study using two identification strategies and recent data to ascertain the causal impacts of rural electrification on labor market outcomes, particularly on those of women. Our unique contribution to the literature is that we provide a series of methodologically comparable results from two developing countries that speaks to the degree to which the 'impacts' of rural electrification can be generalized.

4. Research methods

The extent to which rural electrification improves labor market outcomes may depend on the existence of supporting policies, the labor absorption capacity of the economy, and the willingness and ability of rural inhabitants to engage in income earning activities, especially in relation to gender norms about work. Is it then possible to generalize about the effectiveness of any particular rural electrification program? We seek to explore this issue by comparing the impacts of rural electrification in India and South Africa, where the labor markets differ quite substantially. We examine three labor market outcomes: employment, number of hours worked and earnings. In each case, the variable of interest is the electrification status of the household.

$$Y_i = \theta S_i + \beta X_i' + \varepsilon_i \tag{1}$$

Y_i is the outcome of interest (employment status, earnings or hours worked), S_i is a dummy variable for household electricity access, X_i' is the vector of covariates, and ε_i is the random error term. The goal of this model is to estimate the causal effect of the household's electrification status on labor market outcomes for individual household members.

However, electrification may not be randomized, and may therefore be endogenous to labor market outcomes in three ways. First, it may suffer from reverse causality if households with better labor market outcomes are more able to demand electrification. Second, if rural electrification is more cost-effective in areas that already have unmeasured economic advantages, which are correlated with individual labor market outcomes, then household electrification status may suffer from omitted variable bias. Finally, rural electrification may also be driven by political economy motives rather than customer demand or the cost-effectiveness of grid expansion. Political economy may also explain the location and timing of other types of public interventions, such as subsidies and industrial parks, which are likely to affect the chosen labor market indicators directly. Household electrification status may thus be endogenous to labor market outcomes via the unmeasured political economy motivations. In all three cases, a simple regression model may thus give biased estimates.

One method of overcoming this potential problem of endogeneity bias would be to use an instrumental variables (IV) approach. However, while the proportion of households in a district or village that are electrified has been used as an instrument for household electricity access in previous studies (Khandker et al., 2013, 2014), it is not clear that electrification at the local level has no general equilibrium effects on labor market outcomes. If this is the case, then the rate of local electrification fails the exogeneity requirement to act as an instrument.[3]

Instead, we use two strategies in order to assess the causal relationship between electrification and labor market outcomes and its robustness. First, we use propensity score matching (PSM) to reduce the bias in the treatment effects arising out of the confounding variables, due to lack of a selection rule for randomizing households into treatment and control groups. PSM mimics randomization by creating a sample of households that are not electrified that is comparable on observed covariates to a sample of households that are electrified. We then compare, at a cross-sectional level, labor market outcomes between individuals in these two groups.

The second identification strategy used in the paper is panel analysis. By comparing the labor market outcomes of the same individuals over time, we are able to control for time-invariant unobserved heterogeneity that may be correlated with both household access to electricity and labor market success. We therefore estimate the impact of electrification on employment status, earnings and hours worked using fixed effects (FE) estimation, as a second means of identifying the causal effect of electrification, as shown in Eq. (2).

$$Y_{it} = \theta S_{it} + \beta X'_{it} + \alpha_i + u_{it} \tag{2}$$

Y_{it} is the outcome of interest for individual i at time t, S_i is individual i's electricity access at time t, X'_{it} is a vector of covariates, α_i is the time-invariant unobserved individual heterogeneity, and u_{it} is the error term.

In general, FE estimation is consistent in the presence of time-invariant unobserved heterogeneity that is correlated with the observed variables. Electricity access is unlikely to be orthogonal to the error term, and therefore random effects estimation is not appropriate here.[4]

5. Data and descriptive statistics

For the cross-sectional analysis for India, we use the 2005 India Human Development Survey-I (IHDS-I) (Desai et al., 2007). We use this round of the survey for the cross-sectional analysis as the later IHDS-II has fewer households without electricity as compared to IHDS-I. Using the earlier data thus has two beneficial implications: first, it provides a larger sample of control households and second, it allows us to generalize the results.[5] The IHDS-I also provides a baseline rate of rural electrification that is very similar to the baseline South African data, as described below.

The IHDS-I is a nationally representative sample, with 41,554 households sampled from 33 states and union territories, 383 districts, 1503 villages and 971 urban blocks. The survey covers multiple topics related to health, energy use, infrastructure, income, expenditure, education, and others. In addition to information regarding access to electricity, the survey asks households to estimate the average hours of electricity supply in the previous month. A second round of the IHDS re-interviewed the first-round households in 2011/12 to examine changes in an era of rapid economic growth (Desai and Vanneman, 2011–12). We use this later wave of data for the panel analysis in Section 7.

The cross-sectional analysis for South Africa uses data from the 2008 National Income Dynamics Study (NIDS), which is wave one of South Africa's first national panel survey that tracks individuals.[6] The survey is conducted by the Southern Africa Labour and Development Research Unit (SALDRU) based at the University of Cape Town. NIDS is a nationally representative sample, with 28,255 individuals in 7305 households surveyed in the first wave.[7] The survey covers topics related to the livelihoods of individuals and households, including labor market participation and economic activity, education, health and migration. Subsequent waves of data collected in 2010/11 and 2012 are used for the later panel analysis.[8] We use the survey's post-stratification weights to correct our analysis for household non-response and to adjust the sample to the population distribution based on age, sex and race (Leibbrandt et al., 2009).

The cross-sectional sample for both countries is restricted to individuals aged 15 and older living in households located in rural areas throughout the analysis. This results in a dataset consisting of 74,464 individuals in India and 7666 individuals in South Africa.[9] In both datasets, electrification can be identified at the household level.

Table 5 shows summary statistics on the labor market variables for each country for the male and female subsamples, by the household's electrification status. In India, 65 percent of rural women and men live in households that are electrified, while 69 percent of rural South African women and 71 percent of men live in electrified households. The India dataset uses a threshold of 240 h per year for distinguishing employment status, rather than the complete absence of work. It also does not distinguish the economically inactive from the unemployed, and therefore it is not possible to assess participation in the labor force. Although the South Africa dataset does make these distinctions, for the sake of consistency and comparability, the 240 h per year threshold has been used in both cases. In India, individuals living in households with electricity are less likely to work for at least 240 h in a year compared to households without electricity, whereas the opposite is true in South Africa. Among those who report any form of labor market earnings,[10] rates of self-employment are very low in rural India, where agricultural wage employment is the dominant form of work. Access to electricity is associated with significantly lower rates of working in a household business for men and significantly higher rates for women, but the magnitudes are very small. Self-

[3] Although we estimated IV models using this instrument, we did not find consistent or conclusive results. The estimates from these IV models are available upon request from the authors.

[4] Random effects estimations, along with corresponding Hausman test results, are presented in the appendices for completeness.

[5] By the time of the IHDS-II, households that remain without electricity access are much poorer than those that have access, and thus it is difficult to find an appropriate control group.

[6] Previous South African national panel surveys tracked dwelling places, but NIDS collects a variety of contact detail information for both the individual and their three closest contacts in order to locate individuals in subsequent waves, even if they change households or geographical location. The extent of attrition in both countries is discussed in Section 7.

[7] The data were collected through a stratified, two-stage cluster sample design. Stats SA's master sample was used to select 400 primary sampling units (PSU). Two clusters of dwelling units, not previously used for other Stats SA surveys, were selected from each PSU (Leibbrandt et al., 2009).

[8] A fourth wave has recently been made available, but had not yet been released to the public at the time that this analysis was conducted.

[9] The substantially smaller sample size for the latter dataset may result in lower precision of the estimated effect of electrification for South Africa.

[10] The earnings variable includes both wage employed and self-employed workers. For the self-employed, earnings consist of total household business income per person working in the business (for India) or business income that is kept by the individual after expenses (South Africa). For South Africa, a small proportion of individuals who are employed report zero earnings. They have been assigned a nominal value of one South African Rand before the earnings value was converted into a logarithm, in order to retain them in the sample of the employed for the regressions.

Table 5
Summary statistics on labor market variables (ages 15 and older in rural areas), by gender and household access to electricity.

	Women				Men			
	India		South Africa		India		South Africa	
	No electricity	Electricity	No electricity	Electricity	No electricity	Electricity	No electricity	Electricity
Proportion of individuals	0.348	0.652***	0.313	0.687***	0.349	0.652***	0.296	0.705***
	(0.0114)	(0.0114)	(0.0356)	(0.0356)	(0.0117)	(0.0117)	(0.0388)	(0.0388)
Employment status								
Employed at least 240 h per year	0.584	0.525***	0.242	0.273	0.827	0.775***	0.354	0.441+
	(0.0101)	(0.00742)	(0.0190)	(0.0180)	(0.00608)	(0.00569)	(0.0344)	(0.0327)
Sample size (all adults)	9832	29,614	1692	2995	9963	30,055	992	1987
Employment characteristics								
Self-employed[a]	0.014	0.019*	0.186	0.167	0.039	0.028***	0.0893	0.126*
	(0.0024)	(0.0028)	(0.0405)	(0.0210)	(0.0037)	(0.0022)	(0.0252)	(0.0202)
Annual earnings (USD)	605.0	915.7***	2159.2	4489.6**	1367.1	2613.5***	3624.8	9609.3*
	(19.04)	(32.63)	(428.4)	(686.7)	(30.79)	(61.74)	(473.0)	(2474.3)
Hourly earnings (USD)	0.594	0.683****	1.971	3.395**	0.897	1.401***	3.984	8.301
	(0.0164)	(0.0170)	(0.297)	(0.407)	(0.0154)	(0.0281)	(0.790)	(3.492)
Hours worked per year	1027.2	1235.0***	1270.1	1604.6**	1497.9	1731.0***	1556.4	2020.0**
	(21.38)	(20.75)	(81.67)	(97.59)	(20.62)	(16.03)	(132.1)	(91.57)
Sample size (employed adults)	3508	6378	439	797	7444	14,583	344	788

Source: IHDS (2005) and NIDS (2008), authors' calculations.
Notes: Standard errors in parentheses. Estimates are weighted to population levels. Monetary values are expressed in 2011 US dollars, converted using PPP exchange rates (World Bank, 2014). $^{+}p < .10$, $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$ indicates that the mean differs between individuals in electrified and non-electrified households
[a] Self-employment does not include working on farming activities. The outcome of interest here is the any generation of self-employment due to electrification. Hence, non-farm activities (or home businesses) are potential outcomes of electrification.

employment is more common amongst working South Africans, but only men are significantly more likely to be self-employed if they have access to electricity.

Annual earnings among the employed are significantly higher for individuals living in households with access to electricity, in both countries. Both men and women living in electrified households also work longer hours, by a margin of more than 200 h in a year in India and approximately 400 h in a year in South Africa. This table shows that men typically are more likely to be employed, earn higher wages, and work longer hours than women in both countries. In order to account for these and other gendered labor market differences, including perhaps the effect of electrification, as well as differing gender norms around work, the paper therefore disaggregates all models by gender.

Table 6 illustrates the demographic and household characteristics that will be used as control variables in the later models. In both countries, individuals in households with electricity have completed approximately two more years of education, and live in households with a greater number of adults and fewer children, more assets and higher average consumption expenditure compared to their counterparts in households without electricity. These summary statistics suggest that individuals living in electrified households have better productive characteristics than those in non-electrified households, which might result in better labor market outcomes. However, their households are also economically better off, which may reduce the need to work.

6. Propensity score matching estimation

As outlined in Section 4, there are concerns that a simple regression analysis of labor market differences by electricity access status would not establish its causal impact, due to the likely endogeneity of electrification. In addition, a multivariate regression analysis depends on the functional form of the covariates to arrive at a relationship between outcomes and explanatory variables. When there is not much overlap between the covariates across groups, the results from such a regression may be implausible (Foster, 2003). The descriptive statistics presented in Table 6 show that the covariates have differing means between those individuals that have electricity and those that do not. We therefore employ propensity score matching to eliminate any risk of implausibility in the comparisons. Propensity score matching is a nonparametric technique that does not rely on any functional form, and matches treated and untreated observations on the estimated probability of being treated (propensity score). The matched observations fall under a region of "common support" where the observations based on certain characteristics have a positive probability of being in either the treatment or control group (Rosenbaum and Rubin, 1985). We use propensity score matching to compare outcomes between individuals in households with electricity to individuals in households without access to electricity.

The process followed the following steps. First, propensity scores were calculated using a probit model with the chosen covariates. To generate the propensity scores, we used a similar set of covariates (age, gender, education, marital status and social group) for India and South Africa. The choice of covariates should be such that they do not influence the treatment (access to electricity). Second, on the basis of the propensity scores, individuals in electrified households were matched with the ones in the control group using three matching algorithms: nearest neighbor, kernel and radius. Finally, the average treatment effect on the treated (ATT) of access to electricity was calculated between the treated and the untreated individuals for each labor market outcome. The estimation was conducted both for the sample as a whole, and by gender.

We performed balancing tests to verify if there was any significant difference in the covariates between the matched groups. In general, we find that the kernel and radius matching algorithms produce the best propensity score matches, for both countries and all labor market outcomes.[11] Therefore, the ATT effects produced by these two methods are our preferred PSM estimates.

[11] The results of the balancing tests and the matching graphs are displayed in Tables A1–A18 and Figs. A1–A18 in the appendices.

Table 6
Summary statistics on control variables (ages 15 and older in rural areas), by gender and household access to electricity.

	Women				Men			
	India		South Africa		India		South Africa	
	No electricity	Electricity	No electricity	Electricity	No electricity	Electricity	No electricity	Electricity
Individual characteristics								
Age	36.00	36.97***	44.00	42.79+	36.73	37.30**	41.29	40.68
	(0.204)	(0.139)	(0.748)	(0.510)	(0.210)	(0.145)	(0.787)	(0.672)
Marital status								
Married	0.726	0.711***	0.307	0.345	0.683	0.678+	0.304	0.382+
	(0.00720)	(0.00404)	(0.0195)	(0.0207)	(0.00716)	(0.00440)	(0.0242)	(0.0289)
Single	0.147	0.164***	0.356	0.407+	0.266	0.283**	0.535	0.488
	(0.00641)	(0.00365)	(0.0247)	(0.0232)	(0.00691)	(0.00449)	(0.0353)	(0.0302)
Widowed	0.112	0.114	0.209	0.147***	0.0429	0.0331*	0.0195	0.0329
	(0.00447)	(0.00264)	(0.0158)	(0.0112)	(0.00327)	(0.00162)	(0.00597)	(0.00710)
Separated/divorced	0.00949	0.00758	0.0180	0.0284	0.00487	0.00302	0.0205	0.0243
	(0.00143)	(0.000861)	(0.00447)	(0.00530)	(0.000845)	(0.000472)	(0.00749)	(0.00580)
Other marital status	0.00564	0.00325	0.110	0.0719	0.00326	0.00306	0.122	0.0733+
	(0.00167)	(0.000780)	(0.0206)	(0.00894)	(0.000710)	(0.000788)	(0.0247)	(0.0105)
Years of education	1.786	3.901***	5.618	7.176***	4.079	6.575***	5.488	7.669***
	(0.0703)	(0.0714)	(0.223)	(0.190)	(0.107)	(0.0796)	(0.281)	(0.238)
Household characteristics								
No. of children (0–14)	2.283	1.891***	2.249	2.069	2.157	1.778***	1.508	1.538
	(0.0601)	(0.0388)	(0.154)	(0.117)	(0.0580)	(0.0374)	(0.198)	(0.145)
No. of teens (15–21)	1.003	1.007	0.764	0.841	1.058	1.050	0.627	0.742
	(0.0276)	(0.0186)	(0.0565)	(0.0848)	(0.0300)	(0.0186)	(0.0841)	(0.105)
No. of adults (22+)	2.940	3.419***	2.488	2.817	3.052	3.499***	2.613	3.063
	(0.0428)	(0.0344)	(0.0817)	(0.174)	(0.0449)	(0.0355)	(0.129)	(0.220)
No. of household assets	5.748	11.96***	3.623	7.474***	5.798	12.00***	3.538	7.766***
	(0.0830)	(0.109)	(0.189)	(0.304)	(0.0828)	(0.109)	(0.224)	(0.389)
Highest education of adult in household (years)	4.594	7.789***	8.018	9.648***	4.931	7.998***	7.723	9.876***
	(0.133)	(0.0947)	(0.226)	(0.173)	(0.139)	(0.0972)	(0.293)	(0.229)
Household annual consumption (USD)	4333.7	6855.3***	4832.9	9379.2***	4377.7	6967.8***	4939.8	11559.0***
	(93.97)	(118.9)	(335.1)	(946.0)	(87.54)	(124.5)	(521.6)	(1469.1)
House is owned	0.985	0.976***	0.910	0.877	0.987	0.978***	0.844	0.831
	(0.00214)	(0.00266)	(0.0175)	(0.0217)	(0.00209)	(0.00246)	(0.0274)	(0.0278)
Sample size (all adults)	9832	29,614	1692	2995	9963	30,055	992	1987

Source: IHDS (2005) and NIDS (2008), authors' calculations.
Notes: Standard errors in parentheses. Estimates are weighted to population levels. Monetary values are expressed in 2011 US dollars, converted using PPP exchange rates (World Bank, 2014). $^{+}p < .10$, $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$ indicates that the mean differs between individuals in electrified and non-electrified households

6.1. Findings

The average treatment effects on the treated using propensity score matching using the two preferred matching methods are presented in Table 7. Employment is binary, and thus the ATT represents a difference in probability. For India, there is evidence of a small decrease in the probability of paid employment using our preferred matching algorithms, although largely among men.[12] For South Africa, the impacts of electricity access on paid employment are mostly positive, but very small. The impact is significant only for men, and only at a 10 percent level. These results are in line with the descriptive comparisons shown in the previous section.

Annual earnings and number of hours worked are estimated in their natural logarithm form, to mitigate the effects of skewness and outliers. For both measures, electricity access has a positive and significant effect in both India and South Africa. However, the difference in the wage benefit is quite stark between men and women in the two countries: the wage gain in log form is around twice as large for men as for women in India and around 40 percent larger for women than for men in South Africa. In terms of number of hours worked, in India men increase their hours more due to electricity access than women do, although the gap is not nearly as large as for earnings. In South Africa, the increase in hours worked as a result of electrification is approximately equal across genders. In both countries and for both genders, the increase in annual earnings is greater than the increase in hours worked, suggesting that access to electricity may also increase hourly earnings.

7. Panel estimation

While the PSM results presented above indicate the nature of the effect of electrification, they are unable to disentangle the effects of various contributing factors. For example, do the increases in annual earnings occur simply because electrification allows individuals to work longer hours in paid employment (for example, by providing better lighting), or is there an independent effect of electrification on earnings? Given that the PSM results present the average impact of treatment on the treated, what is the role of individual heterogeneity in response to electrification? This section exploits the time series variation in access to electricity and labor market outcomes through the analysis of matched individual-level panel data. Due to the ability to control for unobserved time-invariant heterogeneity, and to take into account some of the dynamics of household electrification, we believe that the results presented in this section are the most credible and informative estimates.

[12] An analysis of paid employment only is likely to significantly undercount the work that women do. For example, many women may be non-remunerated family workers. If they report the characteristics of their work, but not a wage, then we have included them in the estimated models by assigning them a nominal wage of one Rupee or Rand. However, neither of the datasets collects information on time spent on household duties such as cooking and childcare, and thus it is not possible to account for the effect of electrification on such activities.

Table 7
Average treatment effect on the treated (ATT) of electricity access with propensity score matching, by matching method.

	India			South Africa		
	All	Male	Female	All	Male	Female
Employment						
Kernel	−0.031***	−0.031***	−0.016**	0.013	0.028+	0.005
	(0.004)	(0.005)	(0.006)	(0.012)	(0.020)	(0.014)
Radius	−0.031***	−0.033***	−0.011+	0.002	0.029+	−0.000
	(0.004)	(0.005)	(0.007)	(0.012)	(0.021)	(0.015)
Log of annual earnings						
Kernel	0.370***	0.432***	0.212***	0.490***	0.416**	0.587***
	(0.014)	(0.015)	(0.020)	(0.117)	(0.154)	(0.153)
Radius	0.351***	0.416***	0.196***	0.455***	0.390*	0.564***
	(0.014)	(0.016)	(0.021)	(0.122)	(0.173)	(0.162)
Log of hours worked/year						
Kernel	0.168***	0.172***	0.149***	0.184***	0.182*	0.220***
	(0.009)	(0.011)	(0.017)	(0.052)	(0.077)	(0.068)
Radius	0.161***	0.166***	0.143***	0.177**	0.195*	0.190**
	(0.010)	(0.011)	(0.017)	(0.055)	(0.086)	(0.070)

Source: IHDS (2005) and NIDS (2008), authors' calculations.
Notes: Standard errors in parentheses. The covariates age, gender, education, marital status and social group were used to calculate the propensity scores. $^{+}p < .10$, $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

We matched individuals in the Indian data into a two-wave panel, which has an approximately seven-year interval between waves i.e., 2005 and 2011/12. All wave 1 households residing in the same village or urban neighborhood were re-interviewed during wave 2. When households had divided, all split households were re-interviewed if they were located in the same village/neighborhood. No panel weights were provided to correct for any bias due to attrition. However, each cross-sectional wave includes weights to adjust for differential sampling proportions and for the probability of primary units (villages or towns) being sampled. For South Africa, there are three waves of data at approximately two-year intervals. NIDS attempts to track all original respondents. The sample in subsequent waves consists of all resident household members from wave 1 and any further children of the women in these households (these are termed continuing sample members), plus any other person who resides with such individuals in later waves (temporary sample members). Panel weights, designed to correct for attrition bias and supplied with the dataset, are used in the analysis that follows, as discussed further below (Brown et al., 2012).[13]

7.1. Attrition

In panel data, the extent and nature of attrition is a major concern as it may reduce the precision of estimation through decreased sample sizes, and may bias estimates if it is non-random. Attrition may occur in a number of ways: individuals may be tracked but refuse to continue to participate in the study, may be lost to follow-up, or may die between waves. Since this paper considers only those individuals living in rural areas, anyone who moves to an urban area is also considered here to be an attritor.

Table 8 shows the extent of attrition from the two panels, based on those individuals aged 15 years and older in rural areas who were present in the wave 1 sample. For the South African data, 12 percent of individuals were lost from the panel by the second wave, and almost a further 10 percent by the third wave.[14] While these figures are not out of line with household panels in developing countries (Alderman, Behrman, Kohler, Maluccio, & Watkins, 2001), the fact that the sample size was small to begin with means that they remain something of a concern. However, although not shown here, some additional individuals also join the panel across waves. Such individuals may age into the sample, move to a rural area, or be lost to follow-up in wave 2 but tracked again in wave 3. As long as individuals are present in at least any two of the three waves, they are included in the empirical analysis for South Africa, despite not being shown in Table 8. Attrition is approximately two percentage points higher among men than among women. This is consistent with more men moving to urban areas in search of work, with women being less geographically mobile, perhaps due to childcare responsibilities. For India, around 26 percent of the individuals interviewed in wave 1 dropped out by the second wave of the survey. Similar to South Africa, some new individuals joined in wave 2, but for our panel analysis we do not consider them since they are present only in one wave. It is not surprising that the attrition rate is higher for India than for South Africa, due to the substantially larger time lag between waves. Nonetheless, the Indian dataset is sufficiently large that the loss of observations is not much of a concern, provided that attrition bias does not result. The India attrition rate is slightly higher for women than for men, but by less than two percentage points.

We use two common panel methods to determine whether the attrition was random: a probit model for the probability of attrition and the Becketti, Gould, Lillard and Welch (BGLW) test (Fitzgerald, Gottschalk, & Moffitt, 1998). Both methods use an indicator variable for whether an individual who is present in one wave will attrite in the subsequent wave. For South Africa, two such variables are defined, since attrition may occur in two stages. For each country, the tests are conducted separately for each labor market outcome.[15] For India, attrition is found to be non-random with respect to each labor market outcome, at only a five percent level for earnings but at better than a 0.1 percent level for employment status and hours worked. We therefore construct inverse probability weights to correct for attrition (Fitzgerald et al., 1998; Contoyannis, Jones, & Rice, 2004), which are applied to the models estimated in Table 12.[16] For South Africa, there is non-random attri-

[13] The NIDS datasets also contain wave-specific cross-sectional weights that can be used to analyze each wave as a cross-section of the South African population. See Brown et al. (2012) for further details.

[14] In South Africa, attrition was slightly higher among individuals without access to electricity than those with electricity, although the difference was less than three percentage points.

[15] The test results are displayed in Table B1 of the appendices.

[16] This method involves estimating probit models for non-attrition, conditional on observable characteristics which include the baseline values of the covariates. The inverse of the fitted probabilities from these models are used to weight observations in wave 1 in the subsequent estimations. The resulting standard errors produce conservative inferences (Contoyannis et al., 2004).

Table 8
Sample size and attrition of rural individuals aged 15 and older, by wave and gender.

	India			South Africa		
	All	Men	Women	All	Men	Women
Sample size						
Wave 1	90,723	45,698	45,025	9686	4070	5616
Wave 2	67,042	34,149	32,893	8492	3503	4989
Wave 3	–			7672	3124	4548
Attrition rate						
Wave 1 to Wave 2	26.10	25.27	26.95	12.34	13.93	11.16
Wave 2 to Wave 3	–			9.66	10.82	8.84

Source: IHDS (2005 and 2011/12) and NIDS (2008, 2010/11, 2012), authors' calculations.
Note: Attrition only of those individuals present in the first wave who had a minimum age of 15 years at that time. The figures are not weighted.

tion with respect only to employment status, and only from wave 1 to wave 2. Using the panel weights supplied with the NIDS data, which have been calibrated and adjusted for attrition, produces attrition test results that are random, suggesting that the weights perform well with respect to employment status. The attrition is found to be random with respect to both earnings and hours worked for both of the wave transitions.[17] We therefore apply these panel weights, but do not need to calculate further weights to correct for selective attrition for the South African data.

7.2. Transitions

In order to estimate the causal effect of access to electricity on labor market outcomes using the panel, it is necessary to have sufficient variation in electrification status within individuals across time. In addition, the extent of changes in access to electrification at the individual level is interesting in its own right. This section therefore compares transition matrices of electrification status for the two countries.

In India, around 41 percent of individuals without access to electricity continued in this state in wave 2, while almost 96 percent of those with electricity maintained their access (Table 9). Almost 60 percent of individuals gained access to electricity from one wave to the next, while less than five percent lost electricity access. The large gain in electrification in India is encouraging from a development perspective but not surprising, given the seven-year period between waves and the large roll-out of rural electrification programs over this time.

Table 10 shows the transitions for South Africa estimated separately by wave, with the top part illustrating transitions between wave 1 and wave 2, and the bottom part wave 2 to wave 3. More than 80 percent of individuals without access to electricity in 2008 remained in this state by wave 2, while 75 percent of those with electricity maintained their access across this period. Almost 20 percent of individuals gained access to electricity, while almost a quarter lost their electricity access. Between waves 2 and 3, the gain in access to electricity was much larger, at 37 percent of initially non-electrified households, while less than 14 percent lost electricity access. The gain in electrification is smaller than for India, in part due to the waves being much closer together, but losses of access to electricity are very substantial.

These transition matrices show that quite a large number of South Africans lost access to electricity, especially between 2008 and 2010/11. Many of these cases may represent disconnections due to non-payment for electricity, as South Africa experienced an economic recession in 2009 following the global financial crisis, although the reason for loss of access cannot be confirmed directly from the NIDS data. Considerable losses of electricity access in South Africa have been identified recently by Harris, Collinson, and Wittenberg (2017) using the same data, even during periods of rapid roll-outs of electrification. These have been attributed partly to processes of household formation and dissolution. The NIDS panel tracks individuals, but not households, over time. An individual's electricity access status may change over time either through the household in which the individual is living becoming electrified, or through the individual moving from a non-electrified to an electrified household, or vice versa. However, it is not possible to distinguish between these two cases in the NIDS data, since there is no consistent household identifier across waves. Disconnections were observed between 2008 and 2010 throughout the country, particularly among poor households, suggesting policy failures in the delivery of essential services (Harris et al., 2017).

We briefly explore this disturbingly large loss of access in South Africa further in Table 11, which compares the average change in labor outcomes for the two countries for four subgroups: those who maintain no access to electricity, those who retain access, those who gain access, and those who lose access. In India, employment decreases across all groups, but declines by the smallest magnitude for those who gain access to electricity. Annual earnings increase significantly for all groups. However, those individu-

Table 9
Transitions between electrification states, India.

		Wave 2	
		No electricity	Electricity
Wave 1	No electricity	40.66	59.34
	Electricity	4.43	95.57
	Total	14.54	85.46

Source: IHDS (2005 and 2011/12), authors' calculations.

Table 10
Transitions between electrification states by wave, South Africa.

		Wave 2	
		No electricity	Electricity
Wave 1	No electricity	80.25	19.75
	Electricity	24.36	75.64
	Total	43.74	56.26
		Wave 3	
		No electricity	Electricity
Wave 2	No electricity	62.92	37.08
	Electricity	13.74	86.26
	Total	34.94	65.06

Source: NIDS (2008, 2010/11, 2012), authors' calculations.

[17] If the tests for South Africa are performed at the level of the sample, without using the panel weights, most of the attrition is found to be non-random. The panel weights supplied by NIDS are therefore successful in correcting for non-random attrition with respect to the labor market outcomes examined here.

als who gain access to electricity experience the largest decrease in their average hours worked. This suggests that their labor market productivity increases substantially, while they may also be able to increase their leisure time. In contrast, the small proportion of individuals in India who lose electricity access experience no significant decline in hours worked. In South Africa, the far larger proportion of individuals who lose access to electricity experience (insignificant) decreases in employment and hours worked, while those who have access in the second period have increases in both of these outcomes. In addition, those who lose access do not experience the significant gains in wages experienced by other groups. In contrast, those who gain access to electricity have larger increases in all three outcomes than any other subgroup. Therefore, those that lose access in South Africa also appear to lose labor market benefits. However, these descriptive changes fail to account for other differences in the observed characteristics of the subgroups, or for unobserved heterogeneity, and thus we proceed to conduct panel regression estimations of the three labor outcomes.

7.3. Regression findings

We estimate fixed effects regression models for the three key labor market outcome variables, using a panel logit model for employment and panel OLS for the log of earnings and hours worked. The results are presented in Table 12, although only the coefficient of interest, on household access to electricity, from each model is reported here.[18] In the panel fixed effects formulation, the India estimation amounts to first differencing since there are only two waves, while the estimation for South Africa is quasi-differencing through time demeaning of the variables. In both cases, however, the coefficient on electricity access is interpreted as the difference in the labor market outcome between those with and without access to electricity, and is identified using variation in electrification status over time. The models were also estimated in random effects formulations, and a Hausman test was conducted to compare the estimates. However, electricity access is not orthogonal to the error term, and thus we discuss only the fixed effects results here.[19] The fixed effects OLS estimations are also performed with weights designed to correct for non-random attrition.[20] For all models, the covariates include age, marital status, education, household composition, and household wealth indicators, as shown in the descriptive statistics in Table 6. The panel OLS models among the employed also include a self-employment indicator, while the earnings model also controls for hours worked. Finally, the models for the full sample include a gender dummy.

For both countries, electrification has no significant effect on employment in the model for all individuals. However, this lack of aggregate effect conceals significant gender differences for India. Having access to electricity significantly decreases the probability of being employed for men, while Indian women become more likely to work at least 240 h in a year when their household accesses electricity. In South Africa, both men and women in households with access to electricity are more likely to work, although the effect is not large enough to be statistically significant.

Household electrification raises annual earnings for all individuals in both countries, even after controlling for changes in hours worked. The effect is insignificant only for men in South Africa. In India, earnings increase by approximately 10 log points for both genders when the household accesses electricity, while the magnitude is approximately twice as large for women in South Africa. Correcting for the potential non-randomness of attrition between waves does not alter any of these conclusions, although the standard errors of the estimates typically increase somewhat in line with the conservative nature of the weighting procedure.

In India, electrification decreases annual hours worked significantly for all groups. In contrast, in South Africa, electrification raises hours worked. The increase is significant for the full sample, but the statistical significance of this finding is driven by the result for men, with the increase not being significant for women. On the whole, the Hausman tests indicate that unobserved heterogeneity in labor market outcomes is present in both countries, which is likely to contaminate models estimated purely at a cross-sectional level or when using random effects estimation. In contrast, fixed effects estimation provides consistent estimates under such circumstances, and is thus the preferred estimation method across labor market outcomes and for both countries.

In general, the findings from the panel estimations emphasize the importance of being able to account for changes over time. The benefits of electrification accrue not only at a single point in time, but also affect the planning and behavior of individuals as time progresses. Therefore, the labor market impacts are also likely to evolve over time.

8. Discussion and conclusion

We used two key econometric strategies to estimate the impacts of having access to electricity in the rural areas of India and South Africa, two large and developing economies. Using both cross-sectional and panel data, we find that having access to electricity improves some labor market outcomes. However, the nature and extent of the impact of electricity access differs across labor market indicators, estimation method, and gender. For India, the impacts on the labor market indicators are universally statistically significant, but are not always positive. In contrast, for South Africa, there is a near-universal increase in all the indicators, but this impact is not always significant. In this section, we discuss these key findings and their implications further.

In general, we find that there are some differences in the estimated effects of electricity depending on the estimation technique, which are in line with our expectations. For example, the size and significance of the electrification impact on earnings is smaller for the panel results than for the matching results. This is consistent with unobserved individual heterogeneity playing a large role in the determination of earnings. In addition, there are larger differences by estimation technique for India than for South Africa. Given that the waves are further apart in the IHDS data than the NIDS data, this is consistent with a greater behavioral adaptation to electrification over time for India when comparing the cross-sectional matching results to the panel results. We believe that our panel fixed effects analysis offers the most convincing findings, as it accounts for both of these issues. Therefore, while we refer to the results of both identification strategies in our discussion, we focus more heavily on the panel estimates.

The first key finding of the paper is that, at a descriptive level, there is little to distinguish the two countries at the start of the study period in terms of access to electricity: approximately two thirds of rural men and women live in households that have some access to electricity. Both countries also experienced substantial expansion in electricity access over the period of the study, in line with the large-scale rural electrification programs that were in effect. However, South Africa also exhibited substantial losses of access, especially during its recessionary period.

Second, the most robust labor market result for the combined sample (both men and women) relates to earnings. Across both

[18] The full sets of estimates for all of the models for each country are presented in the appendices, in order to show the covariates.

[19] The full summary results are displayed in Table B2 in the appendices.

[20] Weighting is not supported for panel logit estimation or for random effects estimation.

Table 11
Average change in labor market outcomes, by type of electricity access transition.

	No elec – No elec	Elec – Elec	No elec – Elec	Elec – No elec
India				
Employment	−0.122***	−0.0580***	−0.0514***	−0.110***
	(0.0111)	(0.00464)	(0.00877)	(0.0192)
Log of annual earnings	0.221***	0.294***	0.215***	0.308***
	(0.0330)	(0.0152)	(0.0370)	(0.0703)
Log of hours worked	−0.0748*	−0.0922***	−0.121***	−0.0226
	(0.0335)	(0.00945)	(0.0234)	(0.0520)
South Africa				
Employment	−0.032*	0.010	0.059**	−0.021
	(0.014)	(0.0072)	(0.018)	(0.021)
Log of annual earnings	0.179+	0.187***	0.368***	0.109
	(0.100)	(0.0305)	(0.0858)	(0.190)
Log of hours worked	−0.0782	0.0737*	0.198+	−0.0277
	(0.0925)	(0.0330)	(0.113)	(0.138)

Source: IHDS (2005 and 2011/12) and NIDS (2008, 2010/11, 2012), authors' calculations.
Notes: Standard errors in parentheses. +p < .10, *p < 0.05, **p < 0.01, ***p < 0.001.

Table 12
Summary of fixed effects estimation of the effect of access to electricity on labor market outcomes, by gender.

	India			South Africa		
	All	Men	Women	All	Men	Women
Employment						
Fixed effects	−0.0813	−0.798***	0.351*	0.169	0.174	0.157
	(0.116)	(0.204)	(0.141)	(0.103)	(0.166)	(0.131)
Log of annual earnings						
Fixed effects	0.101***	0.0943**	0.103*	0.138*	0.0753	0.195*
	(0.0285)	(0.0357)	(0.0469)	(0.0629)	(0.0863)	(0.0932)
FE (attrition-corrected)	0.103***	0.0960**	0.105**	0.178+	0.150	0.183+
	(0.0272)	(0.0356)	(0.0407)	(0.0942)	(0.142)	(0.104)
Log of hours worked						
Fixed effects	−0.198***	−0.177***	−0.204**	0.177**	0.228**	0.119
	(0.0365)	(0.0431)	(0.0687)	(0.0606)	(0.0817)	(0.0905)
FE (attrition-corrected)	−0.199***	−0.180***	−0.202**	0.147*	0.273**	−0.0173
	(0.0394)	(0.0469)	(0.0721)	(0.0710)	(0.0955)	(0.103)

Source: IHDS (2005 and 2011/12) and NIDS (2008, 2010/11, 2012), authors' calculations.
Notes: Standard errors in parentheses. +p < .10, *p < .05, **p < .01, ***p < .001. All models include a complete set of control variables. Attrition-corrected fixed effects models are estimated using inverse probability weights.

countries and both estimation methods, access to electricity increases annual labor earnings. The magnitude of this increase in earnings is smaller in the panel estimations, where we control for the number of hours worked, than in the PSM results, but it remains significant and large: earnings increase by more than 10 percent. It suggests that electrification raises the annual incomes earned by those who work in paid employment.

The third key empirical finding relates to the employment effect: this labor outcome is the least affected by electrification for the full sample. The aggregate effect of electricity access on the probability of working in paid employment is negative for India, but positive for South Africa, but it is not consistently significant for either country. For India, the statistical significance of the negative impact is lost when controlling for observed characteristics and unobserved heterogeneity in the panel regressions, while the impact is not large enough to be significant for South Africa across any of the methodologies.

Finally, the effect of electrification on hours worked is consistently positive for South Africa, but the positive effect for India using the PSM analysis becomes a negative effect when using the panel methods. This suggests that unobserved heterogeneity and the time dynamics of behavioral adjustments play a larger role in India than they do in South Africa.

However, these aggregate labor market effects conceal some key gender differences in outcomes within each country. For India, electricity has different gender impacts on employment, but similar impacts on earnings and hours worked. Access to electricity significantly decreases employment for men, whereas women may benefit, based on our preferred panel estimation method. In India, female members of a household are predominantly responsible for collecting cooking fuel such as firewood. Access to modern technology via electricity therefore frees up women's time, which they may use for income generating activities either within or outside the home. Interestingly, other research suggests that it also leads to redistribution of household chores. Men may drop out of the labor force, relying more on female members to earn an income or contribute to the family business (Walle, 2013). Another explanation for men dropping out of the paid labor force could be that access to electricity provides cheaper and improved methods of irrigation, such as electric pump sets, which raises the productivity of crops, especially water-intensive crops such as rice (Rud, 2012). Farmers who worked on other jobs to support their farm income may therefore withdraw from those secondary jobs as their crop yield improves.

There is a pronounced impact of household electrification on raising annual earnings while decreasing hours worked for both men and women in India. Household electrification may have improved the productivity of home businesses by facilitating time efficient technologies (such as electric irons and sewing machines). Improved productivity for home businesses and extra hours of light in the evening results in higher earnings for both men and women. Given the use of productive resources, men and women spend less time doing the same or a greater amount of work. Given the higher earning potential due to electrification, men also tend to spend the extra hours on leisure activities like watching television – facilitated by electricity – at home (Walle, 2013).

For South Africa, the positive effect of electrification on earnings occurs to a greater extent among women than among men. Therefore, although women are no more likely to access paid employment after electrification, those who do hold such jobs enjoy higher wages, perhaps because their labor market productivity increases when electrification reduces the intensity required to carry out home production tasks. This would be consistent with gender norms in rural South Africa. Time use data show that individuals who collect firewood spend more than two hours per day on this activity, but that women are twice as likely as men to engage in this task (Charmes, 2006). Therefore a likely mechanism for the impact of having access to electricity is that it reduces the hours devoted to this type of physical duty, thus allowing women to perform their labor market tasks more productively. Women may also devote more hours to paid work, although the effect is not significant consistently. Women therefore experience welfare gains across several dimensions: they are required to do less unpaid physical labor and earn larger incomes. The latter is likely to improve their bargaining power within the household, as well as raising wellbeing directly. However, these benefits are only realized by those who can access jobs.

In contrast, the main impact of electrification for men in South Africa is that they spend significantly longer hours working in paid employment. They are also slightly more likely to hold such jobs when their household has access to electricity, although the effect is not large enough to be significant consistently. Their annual incomes are also greater, but this increase in earnings is not independently statistically significant after accounting for their hours worked. Therefore, access to electricity may change the nature of the work that men do. Although the NIDS sample size becomes very small when disaggregating by job type, there is some evidence that among those who access electricity, men in particular are more likely to take up self-employment. This type of work is typically associated with longer working hours for men, and although it may not bring immediate earnings benefits, it may enable them to generate higher business incomes in the longer term.

In general, we find that the impact of electrification on labor market outcomes is more muted for South Africa than for India. There are several plausible explanations for this result: first, there are extremely high levels of unemployment in the rural areas of South Africa, as outlined in Section 2. This suggests that even if the labor-saving impacts of electrification result in individuals having more time available to search for or engage in paid employment, as some previous authors have suggested (Dinkelman, 2011), these do not translate into significant increases in employment due to the economy's lack of labor absorptive capacity. Therefore, we see larger impacts among those who can access paid work, in terms of their earnings and hours worked, than at the extensive margin. Policies that enhance labor demand and support local business development may thus be effective in improving the labor market effects of electrification. Second, the sizes of the datasets are very different, with the sample for India being approximately 10 times the size of the South Africa sample. The number of observations in the South African data may thus be too small to estimate the effect of household electrification precisely enough for the results to be statistically significant, especially if the effect is quantitatively quite small.

In general, the potential benefits of electrification will be underrealized if households cannot consistently access it. This is a major concern for policy-makers: the rollout of rural electrification is unlikely to achieve the desired improvements in welfare if households subsequently become disconnected from the electricity grid or combine the use of electricity with more traditional power sources, due to lack of payment or technical issues with the electricity supply. If some of the benefits of electrification can only be gained in the medium term, once individuals have adapted their behavior, then a lack of consistent access to electricity is likely to dampen the findings. A notable result from the transition matrices for the South African data is that there is considerable 'churning' in access to electricity. Nearly a quarter of individuals lost access to electricity between the first two waves of the panel. This may be a further reason why the results for South Africa are less statistically significant than those for India. The reliability of the electricity supply is a major issue in India: in order to attain the full benefits of electrification, households must be able to access the power supply continuously. However, according to the IHDS-I (Desai et al., 2007), only six percent of all the surveyed rural households had a steady 24 h supply, and a quarter had only 12 h or fewer per day. This issue has received considerable policy attention in recent years, and is the focus of the current national electrification policy in India.

While it is clear that rural electrification does have welfare impacts, especially through reducing the burden of gathering fuel sources which falls mainly on women, and raising the productivity of market work, it cannot be used as a masterstroke for all development problems. We show in this cross-country study that the benefits of electrification aren't necessarily universal. Instead, policy makers need to consider the local social and political structures, gender roles and labor absorptive capacity in order to realize the full benefits of rural electricity programs.

9. Conflict of interest statement

The authors have no conflict of interest to declare.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.worlddev.2018.05.016.

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