EMPLOYMENT IMPACTS OF CLEAN ENERGY INVESTMENTS IN EMERGING MARKET ECONOMIES

A Review of the Literature and Methodologies Used in Assessment
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Aurélien Saussay, Zuzana Dobrotková, and Sheoli Pargal
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About this Report

This literature review was undertaken under a program of analytical work that investigates the impacts of the global transition to clean energy on the quantity and quality of jobs in low- and middle-income countries. Under the program, entitled “Estimating the Job Creation Potential of the Clean Energy Transition,” the World Bank’s Energy Sector Management Assistance Program (ESMAP) undertook multiple streams of analysis:

- Modeling of economywide job impacts of policies supporting the clean energy transition in selected countries in Sub-Saharan Africa
- Case studies of the effects on employment of selected World Bank clean energy projects
- Deep dives into the impact on jobs of closure of coal-fired power plants; of productive uses of electricity associated with mini grids in Nigeria; and of the Rusumo Falls Hydropower Project.

Building on the above-mentioned steams of analysis, the program has also produced a high-level report summarizing its findings and conclusions “Jobs for a Livable Planet: Job Creation Potential of the Clean Energy Transition” and a discussion paper to support project design “Tracking Jobs in Projects Focused on Clean Energy and Productive Uses of Electricity”, providing strategies for tracking and enhancing job creation that can be used in the clean energy projects.

The reports developed under this program together aim to support low- and middle-income countries in reaping greater socioeconomic benefits from the energy transition by supporting them in increasing the number and quality of local jobs generated while implementing clean energy projects. Realizing the benefits of the jobs created by clean energy interventions will depend on effective planning and preparation in the early stages of projects and sustained support during their implementation.

The reports target multiple audiences, from policy makers to development practitioners and academics. They also aim to familiarize energy specialists with the effects of energy projects on jobs and give them tools that enable them to take account of—and, where possible, maximize—the socioeconomic benefits of the clean energy transition.

The reports can be found at https://www.esmap.org/publications.
Abbreviations

ARRA American Recovery and Reinvestment Act
BAU business-as-usual
CGE computable general equilibrium
CSP concentrating solar power
DRE decentralized renewable energy
EU European Union
FTE full-time equivalent
IEA International Energy Agency
IO input–output
IOT input–output table
IRENA International Renewable Energy Agency
IV instrumental variable
LATE local average treatment effect
NDC Nationally Determined Contribution
O&M operation and maintenance
PV photovoltaic
RCT randomized controlled trial
RD regression discontinuity

All currency is in United States dollars (US$, USD), unless otherwise indicated.
Executive Summary

This literature review is based on more than a hundred articles, working papers, and reports on the employment impacts of clean energy investments. Most of the references are highly cited studies published between 2010 and 2022 in leading international academic journals; policy reports were included only when of particular relevance.

The review identifies the best practices in assessing the employment impacts of clean energy in developing and emerging economies, with a view to informing the World Bank's investments in this respect.

Clean energy investments create employment via multiple channels:

- **Direct jobs** created in the installation, operation, and maintenance of clean energy projects
- **Indirect jobs** in those projects' manufacturing and corresponding upstream supply chains
- **Induced jobs** created due to the increase in economic activity spurred by energy investments
- **Productive use jobs**, a specific subset of induced jobs resulting from electrification or improved electricity access

Job creation via some or all of these channels can be estimated using five approaches: bottom-up engineering models, input–output (IO) models, computable general equilibrium (CGE) models, macroeconometric models and econometric assessments.

This review of the recent literature yields the following key findings:

- More research is required to better understand the impacts of clean energy investments in generating employment, especially, the impact of electrification on local economic activity (e.g., firms' entry, productivity, and employment levels).
- Even though energy efficiency and renewable energy technologies tend to be more labor intensive than their fossil fuel counterparts, clean energy investments still create relatively few direct jobs, either in developed or emerging economies.
- Given that a few middle- and high-income countries control much of the manufacturing supply chain for energy efficiency equipment and renewable energy systems, most developing economies would not capture a lot of upstream jobs either.
- Clean electrification can create productive use jobs in developing countries if—and only if—the newly available power can be taken advantage of. Otherwise, its impact on productive use jobs appears close to zero according to the first *ex-post* assessments reported in the literature.

This review shows that methodological complexity cannot compensate for a lack of quality data. This is particularly relevant in data-poor environments such as developing countries, where neither IO nor household- or firm-level microdata are generally available.
Evaluating the causal impact of a given clean energy investment on employment requires an ex post econometric assessment. This is especially the case for induced jobs, which are significantly more difficult to measure than direct or indirect jobs. However, such evaluation requires specific microdata, the collection of which needs to be included in from the design stage of clean energy projects. Some projects have specific geographical or regulatory features that lend themselves to quasi-experimental designs. In these very specific cases, ex post evaluation remains possible after project completion even if it was not envisioned at inception.

When econometric evaluation is not possible, the literature suggests that it is preferable to adopt an approach that avoids unnecessary complexity. In particular, the marginal benefits of CGE models would almost never justify their added complexity, data requirements, implementation time, and cost when evaluating a discrete clean energy investment representing much less than 1 percent of gross domestic product.

Conversely, a review of IO models used in the evaluation of clean energy investment suggests that they might be necessary if it is important to understand the impacts of the structure of supply chains away from investments’ location. Yet, a simple assessment building on bottom-up technological assumptions should already provide a good first approximation. This can then be usefully complemented by an ex post field survey of investment recipients.

The majority of literature so far, particularly on emerging and developing economies, has focused on ex ante assessments. More comprehensive microdata collection, covering both households and the local businesses affected by increased availability of clean energy, will be needed to obtain causal identification in econometric assessments. In that regard, randomized controlled trials of clean electrification impacts would provide a major contribution.
ONE

INTRODUCTION
Significant scale-up of clean energy, such as renewable energy and energy efficiency, is the most important component of worldwide efforts to address climate change and increase energy access. As clean energy makes a growing contribution to the total energy supply, as countries undertake their energy transitions, it is also expected to create millions of jobs.

This review is part of an investigation into how the global energy transition—the move away from fossil fuels, which involves the adoption of new technologies and new service delivery models in the sector—can contribute to job creation and support economic activity while advancing the global decarbonization agenda. Many aspects of the energy transition, including investment in renewable energy; grid strengthening to absorb variable renewable power; distributed generation, including for energy access; and improvements in energy efficiency in buildings, industry, and transport, have significant potential to create employment. Moreover, the provision of expanded and improved energy services can boost economic activity and job creation in the broader economy in addition to jobs creation in the energy sector. The impact of energy sector policies and energy-transition-related investments on job creation and economic growth thus links to the literature on the relationship between the development of infrastructure and economic growth. An additional motivation for this investigation is to identify ways to support a “green” recovery from the global crises caused by COVID-19 and the war in Ukraine, which have significantly affected global energy markets and global supply chains.

The objective of this literature review is to understand how existing academic and policy work has assessed the impact of energy-transition-related policies, regulations, and investments on job creation, wages, and other employment-related outcomes. This review covers studies of energy sector jobs as well as jobs created in upstream sectors resulting from energy-transition-related investments and policy changes. The review also includes studies of wider, often economywide, “induced” employment effects. In particular it focuses on the impact of electrification programs using distributed renewable generation, since such programs make it possible to establish causality in job creation more clearly than clean energy projects contributing additional power to existing grids. The aim of better understanding the causal chain has led to particular attention being devoted to the methodologies for assessing job creation. The literature review also serves as a point of reference and comparison for findings from a set of case studies of World Bank projects being undertaken as part of this same investigation.

This review of literature is based on nearly a hundred articles, working papers, and reports on the employment impacts of clean energy investments (selection criteria for inclusion of articles in the review are provided in box 1.1). While the majority of the references are highly cited studies published between 2010 and 2022 in leading international academic journals, policy reports were included when particularly relevant. Given the relative lack of data on job creation resulting from energy efficiency interventions, this review primarily focuses on job creation resulting from renewable energy deployment.

This review is organized as follows: chapter 2 provides statistics on global clean energy jobs as reported by global energy agencies, describes the basic mechanisms of direct and indirect job creation, and explains potential paths through which induced jobs can occur,
SELECTION CRITERIA FOR ARTICLES STUDIED FOR THIS LITERATURE REVIEW

The present report results from a review of nearly a hundred articles, working papers, and reports on the employment impacts of clean energy investments. The selection was focused on studies examining developing and emerging economies. However, articles examining developed countries were included for illustration purposes when relevant.

Publications were selected for inclusion of combinations based on variations and combinations of the following phrases: “renewable energy” (“solar,” “photovoltaic,” “wind power”), “employment impacts” (“evaluation,” “assessment”), “input–output,” “computable general equilibrium,” “econometric.”

The majority of the cited references are the most highly cited studies published between 2010 and 2022 in leading international academic journals. Policy reports were included when particularly relevant. It should be noted that ex ante analyses dominate in the existing literature, which explains their overrepresentation in the bibliographic references in the present report.

The full list of literature reviewed is provided in References.

particularly in developing countries. It also provides an overview of the different modeling approaches used in the literature to assess job creation resulting from clean energy deployment. Chapter 3 discusses the results of studies using ex ante modeling approaches, while chapter 4 discusses the results of studies using ex post modeling approaches. Chapter 5 concludes the review and suggests avenues for further research.
TWO
GLOBAL CLEAN ENERGY EMPLOYMENT
Investment projects generate employment across multiple dimensions. Jobs creation attributable to investment projects typically includes direct, indirect, and induced jobs (Sustainable Energy Jobs Platform, 2022). Furthermore, certain types of investments that have wide-ranging productive applications create so-called productive use jobs, which are considered to be a subset of induced jobs in this literature review. Such types of investments include, for example, investments in clean energy provision and electrification in developing countries. We discuss each job category below with a focus on clean energy investments.

Direct jobs include all jobs directly related to the installation, operation, and maintenance of energy projects. For off-grid solar projects, for example, the distribution, marketing, and sales of solar equipment will give rise to additional direct jobs.

Deployment of clean energy also creates additional, indirect, jobs in other sectors that supply inputs to the energy sector. The indirect effects of renewable energy investments can percolate quite widely. For example, additional employment effects can be expected in the steel industry, which produces components for wind turbines, or in the semiconductor industry, which furnishes materials to build solar cells, as well as in their respective upstream sectors (e.g., mining). The degree of indirect employment will depend on the volume of inputs from upstream sectors that is required by new renewable energy projects and the employment factors in these sectors (i.e., the number of employees required per unit of output in these sectors).

The consumption (spending) of people in direct or indirect jobs results in further economic growth, in turn creating induced jobs. Induced jobs can also stem from increased spending using consumer savings achieved thanks to energy efficiency or the cost competitiveness of renewables. As opposed to indirect jobs, induced jobs are found in all sectors of an economy, since they stem from the final demand for goods and services. Induced jobs are especially important in the context of large-scale governmental stimulus/investment programs. The magnitude of induced effects may be lower for more narrowly defined projects, even though they should not be dismissed entirely. The creation of medium-skill jobs is likely to have strong induced effects especially in poorer countries, where households have a high marginal propensity to consume and where spending is mostly local. Such strong induced effects are likely to benefit local communities.

International energy think tanks such as the International Energy Agency (IEA) and International Renewable Energy Agency (IRENA) routinely estimate global energy sector employment, especially employment in new and renewable technologies.

The IEA builds its employment estimates based on its comprehensive global investment, energy production, and demand data. Its assessments are also calibrated to national labor statistics, data from corporate filings, company interviews, international organizations, and the academic literature. In the IEA’s accounting, energy employment encompasses all jobs directly related to the construction and operation of energy facilities as well as indirect jobs in the manufacturing of direct inputs specific to the energy industry. Indirect jobs associated with the production of general goods such as cement are not considered, nor are induced jobs (i.e., jobs resulting from the increase in economic activity spurred by energy investments). Jobs are normalized to full-time equivalent (FTE) employment for consistent accounting. Numbers include informal workers in order to better reflect the impacts of energy policy on the labor force.
IRENA’s original calculations draw on a wide range of studies and reports by government agencies, industry associations, nongovernmental organizations, and academic researchers. As such, the numbers presented result in part from extrapolations both at the national and technology levels—in particular, the employment factors used to obtain these statistics are calculated based on data from developed countries, which may not be representative of developing and emerging market economies. Accurate estimation of these factors would certainly benefit from more consistent coverage of microlevel employment data. Yet, IRENA’s annual reports still represent the most comprehensive and detailed data sources for renewable energy employment at the global level.

This review of the academic and policy literature complements the work of the IEA, IRENA, and others by shedding light on our understanding of the causal chain between clean energy investments and jobs, and, specifically, by focusing on developing countries and emerging market economies, where data are often limited, but which are likely to see the bulk of new energy investment.

### 2.1 Global Clean Energy Employment Estimates

According to IEA employment estimates for both renewable energy and energy efficiency, as presented in the recent *World Energy Employment* report (IEA 2022), the number of jobs in “new sectors” driving the energy transition (such as renewable energy and energy efficiency, but also jobs attributed to investments in modern grids capable of accommodating variable renewable energy and jobs in the rapidly growing electric vehicles sector) already rivaled the number of jobs in conventional energy globally in 2019 (figure 2.1).

The IEA estimates that 10.9 million people were employed in improving energy efficiency in buildings and industry in 2019. Nearly half of all energy efficiency jobs worldwide were in the construction sector and, geographically, China accounted for nearly one-third of global efficiency-related employment. For renewable energy in power generation, the IEA estimated 6.9 million jobs in 2019, encompassing manufacturing and construction (60 percent of the total), and operation and maintenance (O&M) (40 percent). China had the highest number of solar and wind jobs not only because of its large number of installations, but also due to its global dominance in solar and wind equipment manufacturing.

A more comprehensive view of renewable energy employment is provided in IRENA’s annual jobs review. In its 2022 report, IRENA reports that global renewable energy employment grew 74 percent from 7.3 million to 12.7 million between 2012 and 2021 (figure 2.2). Non-hydro, renewable energy saw an even stronger growth in employment, at around 83 percent, over
FIGURE 2.1
Global Employment in Selected Energy Subsectors, 2019

![Graph showing global employment in selected energy subsectors, 2019.](image)

Source: IEA 2022.
Note: ICE = internal combustion engine.

FIGURE 2.2

![Graph showing global renewable energy employment by technology, 2012–20.](image)

Source: Based on IRENA (2022a).
the same period. Employment in solar photovoltaic (PV) tripled in eight years and was the primary driver of employment growth. In 2021, solar represented more than one-third of the global renewable energy workforce, with a total of 4.29 million jobs. The second-largest renewable energy employer, hydropower, saw only minor employment growth, which is likely due to the diminishing number of suitable locations to build new hydropower plants. This trend restricts hydropower jobs mainly to O&M rather than manufacturing and construction.

Finally, the wind energy sector also saw 83 percent growth in employment between 2012 and 2021, despite remaining largely constant in terms of employment in more recent years. The level of employment in the sector remains relatively low, however, at 1.37 million jobs. Today, onshore wind installations account for the majority of wind energy jobs. This picture is likely to change over the coming decade amid an expected surge in offshore wind power.

The job numbers presented by IRENA include the entire production chain for each renewable technology, from manufacturing, installation, and O&M to employment in upstream sectors in the renewables supply chain.

IRENA finds that renewable energy jobs are largely concentrated in a handful of countries, most of them developed or emerging market economies. In terms of total renewable energy employment, China is followed by the European Union, Brazil, India, and the United States. These five economies account for nearly three-quarters of global renewable energy employment. Renewables have also experienced rapid growth in other parts of Asia—in aggregate, the entire continent, including China and India, accounted for 64 percent of global jobs in 2020.

Table 2.1 shows a breakdown of renewable energy employment by country and technology. In addition to China, India also has a sizeable solar labor force, which is yet far below its potential given the country’s market size. Onshore wind accounts for a larger relative share of green jobs in the United States and European Union than in China or India, confirming the more advanced deployment of wind power in developed countries.

Decentralized renewable energy (DRE) solutions are especially relevant in developing countries, where mini grids, home solar systems, or solar lanterns present an opportunity to cost-effectively provide electricity access, including to the most remote communities that cannot be easily connected to the traditional electric grid. Much like the utility power sector, DRE creates jobs in the assembly, installation, and O&M of such power systems. In addition, certain products such as solar lanterns and other pico-solar appliances can be sold as regular consumer goods, in turn creating additional business and job opportunities in product distribution and sales. Power for All (2022) estimates that in 2021, DRE for energy access directly and indirectly employed approximately 80,000 workers in India, 50,000 in Kenya and Nigeria, 30,000 in Uganda, and 14,000 in Ethiopia. It should be noted that the majority of these are now formal jobs in all these countries, with the exception of Kenya. This trend may have resulted from the COVID-19 pandemic, which adversely impacted informal workers, leading companies to become more reliant independent contractors to gain flexibility (Power for All 2022).
### TABLE 2.1
Estimated Direct and Indirect Jobs in Renewable Energy Worldwide, 2019–20

<table>
<thead>
<tr>
<th></th>
<th>WORLD</th>
<th>CHINA</th>
<th>BRAZIL</th>
<th>INDIA</th>
<th>UNITED STATES</th>
<th>EUROPEAN UNION</th>
</tr>
</thead>
<tbody>
<tr>
<td>Solar photovoltaics</td>
<td>4,291</td>
<td>2,682</td>
<td>115.2</td>
<td>217</td>
<td>259</td>
<td>235</td>
</tr>
<tr>
<td>Liquid biofuels</td>
<td>2,421</td>
<td>51</td>
<td>176.9</td>
<td>35</td>
<td>322.6</td>
<td>142</td>
</tr>
<tr>
<td>Hydropower*</td>
<td>2,370</td>
<td>872.3</td>
<td>63.8</td>
<td>414</td>
<td>72.4</td>
<td>89</td>
</tr>
<tr>
<td>Wind power</td>
<td>1,371</td>
<td>654</td>
<td>42</td>
<td>35</td>
<td>120.2</td>
<td>298</td>
</tr>
<tr>
<td>Solar heating and cooling</td>
<td>769</td>
<td>636</td>
<td>42</td>
<td>35</td>
<td>120.2</td>
<td>298</td>
</tr>
<tr>
<td>Solid biomassb,c</td>
<td>716</td>
<td>190</td>
<td>58</td>
<td>46.3</td>
<td>314</td>
<td></td>
</tr>
<tr>
<td>Biogas</td>
<td>307</td>
<td>145</td>
<td>85</td>
<td>64</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Geothermal energyadf</td>
<td>196</td>
<td>78.9</td>
<td>8&quot;</td>
<td>60&quot;</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Concentrating solar power</td>
<td>79</td>
<td>59.2</td>
<td></td>
<td>5.2</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>TOTAL</strong></td>
<td>12,677</td>
<td>5,368</td>
<td>1,272</td>
<td>863</td>
<td>923</td>
<td>1,242</td>
</tr>
</tbody>
</table>

**Source:** Based on IRENA (2022a).

**Note:** The figures presented here are the result of a comprehensive review of primary national entities, such as ministries and statistical agencies, and secondary data sources, such as regional and global studies. Empty cells indicate that no estimate is available. Columns may not add up to totals due to rounding.

- Direct jobs only.
- Power and heat applications.
- Traditional biomass not included.
- Includes 7 400 jobs for ground-based heat pumps in EU countries.
- Includes an estimate of 342 000 jobs in off-grid solar PV in South Asia and East, West and Central Africa.
- Includes 39 000 jobs in waste-to-energy.
- Includes about 168 400 jobs in sugarcane cultivation and 167 800 in alcohol/ethanol processing in 2020, the most recent year for which the data are available. The figure also includes a rough estimate of 200 000 indirect jobs in equipment manufacturing and 326 900 jobs in biodiesel in 2021.
- Includes 137 000 jobs in grid-connected and 80 400 in off-grid solar PV. Also see note e.
- Includes jobs in all solar technologies, principally PV but also solar heating and cooling and concentrating solar power.
- Includes 258 700 for ethanol and approximately 63 900 jobs for biodiesel in 2021.
- US DOE estimate, including 53 029 jobs in traditional hydro and 11 485 jobs in low-impact hydro. An estimated 7 901 jobs in pumped hydro (energy storage) are not included in the US total.
- Includes woody biomass fuels (33 898 jobs) and biomass power (12 388 jobs).
- The figure is for direct geothermal power employment.
- Includes 98 932 jobs in technologies not separately broken down in the table, such as solar heating and cooling, geothermal heat, heat pumps, and others. Solar heating and cooling are also included (but not reported separately) in the Solar Foundation estimate for all solar technologies, so there is a small amount of double counting.
- Solar PV and wind jobs are for 2021, hydropower figures are for 2020 and 2021, and the figures are for 2020 for other technologies.
2.2 Job Creation and Clean Energy Investments

Most global clean energy employment figures reported in the literature (such as those of the IEA and IRENA) typically include manufacturing of clean energy equipment, construction, and O&M figures. Hence, they aggregate the largest direct and indirect job categories. Detailed reports on the composition of value chains, such as reports by IRENA (2017a, 2017b) that have examined employment impacts along the solar PV and onshore wind value chains, include additional categories such as planning and decommissioning. These reports show that planning and decommissioning represent a very small fraction of overall jobs (table 2.2). A comparison of solar PV and wind jobs also shows a significant difference in job creation at different stages of their respective value chains. Wind power is significantly less labor intensive than solar PV: from project planning to decommissioning, a 50 megawatt (MW) wind power plant will require 71 percent fewer person-days than its solar PV equivalent.

It is important to note that not all the above job types may materialize on an individual country level given that the manufacturing of renewable energy equipment is concentrated in a handful of countries. Also, depending on the capabilities of the local labor force, foreign nationals may perform a part of jobs across all the above categories, thus not contributing to local job creation.

TABLE 2.2
Activity-Based Distribution of Human Resources Along the Value Chain for Development of a Solar PV Plant and a Wind Farm (50 MW Each)

<table>
<thead>
<tr>
<th>PERCENTAGE OF JOBS</th>
<th>SOLAR PV VALUE CHAIN</th>
<th>ONSHORE WIND VALUE CHAIN</th>
</tr>
</thead>
<tbody>
<tr>
<td>Project planning</td>
<td>1%</td>
<td>2%</td>
</tr>
<tr>
<td>Manufacturing and procurement</td>
<td>22%</td>
<td>17%</td>
</tr>
<tr>
<td>Transport</td>
<td>2%</td>
<td>1%</td>
</tr>
<tr>
<td>Installation and grid connection</td>
<td>17%</td>
<td>30%</td>
</tr>
<tr>
<td>Operation and maintenance</td>
<td>56%</td>
<td>43%</td>
</tr>
<tr>
<td>Decommissioning</td>
<td>2%</td>
<td>7%</td>
</tr>
<tr>
<td>Total person-days</td>
<td>229,055</td>
<td>144,420</td>
</tr>
</tbody>
</table>

Source: IRENA 2017a, 2017b.
Note: MW = megawatt; PV = photovoltaics.
The renewables sector is often hailed as a provider of stable, middle-class jobs. This is especially true for developing countries, where the skill and compensation levels of the clean energy workforce are higher on average than for other energy sources (IRENA 2020).

DRE for energy access has the potential to generate significant employment through productive use of electricity, given its primary purpose of providing electricity to remote areas at relatively low cost. This will crucially depend on DRE systems’ ability to deliver sufficient capacity to sustain productive activities, as well as affordable and reliable power connections. Power for All (2022) estimated that in 2021, productive use jobs attributed to DRE outnumbered DRE-related direct and indirect (formal) jobs by more than four times.

According to Power for All (2019), electrification can give rise to productive use jobs through a variety of mechanisms:

1. **Increased farm and nonfarm productivity:** In rural areas, electricity might increase agricultural productivity and output, for example, through access to electrified water pumps and irrigation systems. Other non-agriculture-based firms may also experience efficiency gains by substituting the direct use of fossil energy sources with electricity, prompting investments in new machinery, lighting, refrigeration, and information technology. While some of these investments may also replace labor, it appears more likely that productivity gains will boost firm growth, increase incomes, and create more direct and indirect employment across sectors.

2. **Business creation:** Access to electricity allows the operation of new industries and services that use electricity as an input. Similarly, in both the manufacturing and the services sectors, electricity access may lead to the creation of firms whose offerings range in scale from industrial activities to home-based services.

3. **Labor supply:** An electric connection can enable a household to save substantial time in performing domestic labor (e.g., through the availability of electric cooking stoves and other appliances). As a result, women often account for a larger share of employment gains, since they can reallocate time toward labor market participation.

4. **Education:** In the longer run, electrification and particularly improvements in lighting in schools and at home are likely to improve children’s educational outcomes. This can allow them to access better jobs, thereby helping local economies to expand.

This literature review examines a variety of econometric studies on jobs stemming from the productive use of electricity in chapter 4 and discusses their methodologies and results in more detail. An important finding of the review is that the effects of electrification on productive use job creation are highly context dependent. While the above mechanisms have all been confirmed in different studies, they do not hold in all situations. Policy makers, as well as all stakeholders in renewable energy investments, will need to consider complementary policies and measures as well as capacity building and training that ensure the creation of more productive use jobs linked to electrification.
2.3 Classification of Modelling Approaches

In this section, we examine the different potential approaches to modelling employment impacts from investing in clean energy. We distinguish five broad categories:

- Engineering bottom-up models
- Input–output (IO) models
- Computable general equilibrium (CGE) models
- Macroeconometric models
- Econometric estimations

The first four approaches provide ex ante evaluations of the impact potential of projected investments, while econometric estimations can provide ex post assessments of completed projects. Given that distinction, econometric techniques are examined separately in the next section. However, in specific cases, engineering bottom-up models can also provide ex post assessments.

Each of these methodologies presents a different arbitrage option between technical complexity, data requirements, ease of implementation, and scope of results. Table 2.3 provides a synthetic overview of the characteristics of each methodology, along with an assessment of its suitability for evaluating the employment impacts of clean energy investments in a developing economy context.

It should be noted that jobs modeling is a rapidly evolving field with new models and methods constantly being developed. Macroeconometric models have gained attention relatively recently and therefore their treatment in this paper is brief. These models are grounded in empirical analysis and data and allow for market imperfections, path dependence and rigidities. For instance, IRENA has used macroeconomic models of renewable energy employment as part of their work on clean energy development (IRENA 2022b and IRENA 2022c). The World Bank has also strengthened its expertise in non-neoclassical, non-equilibrium model development, to provide further insights into the labor market effects of clean energy and climate policies. Notably, the World Bank has adopted and further developed the MINDSET model, a price endogenous multi-region IO model, which has been extended to a macroeconomic model (World Bank, forthcoming). This model has increasingly been incorporated into Country Climate Diagnostic Reports, such as for the Philippines and Pakistan. The model has also been utilized to assess the job impacts of the EU's carbon border tax adjustment mechanism in Bosnia and Herzegovina and provides projections of clean energy job impacts under Paris aligned scenarios for ongoing World Bank analyses. Other available models are E3ME by Cambridge Econometrics, a macroeconomic model designed to assess global policy challenges, widely used for policy assessment, forecasting and research purposes (Cambridge Econometrics 2023), and GINFORS_E model by Joint Research Center of European Commission, a macroeconomic model designed for assessments of economic, energy, climate and environmental policies up to the year 2050 (JRC 2023).
### TABLE 2.3
Comparative Characteristics of Employment Impact Assessment Methodologies for Clean Energy Investments

<table>
<thead>
<tr>
<th>Methodology</th>
<th>Data Requirements</th>
<th>Technical Complexity</th>
<th>Temporality</th>
<th>Job Creation Scope</th>
<th>Implementation in a Developing Economy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bottom-up engineering</td>
<td>Moderate</td>
<td>Moderate</td>
<td>Low</td>
<td>Yes</td>
<td>Adapted</td>
</tr>
<tr>
<td>Engineering assessments rely on technology assumptions that are mostly common across the world and widely available.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bottom-up engineering</td>
<td>Low</td>
<td>Static or dynamic</td>
<td>Yes</td>
<td>Sometimes</td>
<td>Gross estimate</td>
</tr>
<tr>
<td>Engineering assessments rely on technology assumptions that are mostly common across the world and widely available. This makes these models very useful in data-poor environments. This approach can yield results from simple investment figures with a limited number of assumptions. The scope of job creation considered is correspondingly limited, although it can include, in some limited capacity, productive jobs.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Input-output (IO)</td>
<td>High</td>
<td>Moderate</td>
<td>Static</td>
<td>Yes</td>
<td>Requires extensions</td>
</tr>
<tr>
<td>Getting relevant results on renewable technologies requires the corresponding sectors to be identified in the IO table. This entails a high level of sectoral disaggregation.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Input-output (IO)</td>
<td>Moderate</td>
<td>Static</td>
<td>Yes</td>
<td>Yes</td>
<td>Requires extensions</td>
</tr>
<tr>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Input-output (IO)</td>
<td>High</td>
<td>Dynamic</td>
<td>Yes</td>
<td>Yes</td>
<td>Requires extensions</td>
</tr>
<tr>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Computable general equilibrium (CGE)</td>
<td>Very high</td>
<td>High</td>
<td>Dynamic</td>
<td>Yes</td>
<td>Requires extensions</td>
</tr>
<tr>
<td>CGE models extend the data requirements of IO models with a complete parametrization of elasticities of substitution among different factors of production, imported and domestic goods, and potentially intermediate consumptions.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Computable general equilibrium (CGE)</td>
<td>High</td>
<td>Dynamic</td>
<td>Yes</td>
<td>Yes</td>
<td>Requires extensions</td>
</tr>
<tr>
<td>CGE models extend the data requirements of IO models with a complete parametrization of elasticities of substitution among different factors of production, imported and domestic goods, and potentially intermediate consumptions.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Computable general equilibrium (CGE)</td>
<td>Very high</td>
<td>High</td>
<td>Dynamic</td>
<td>Yes</td>
<td>Requires extensions</td>
</tr>
<tr>
<td>CGE models extend the data requirements of IO models with a complete parametrization of elasticities of substitution among different factors of production, imported and domestic goods, and potentially intermediate consumptions.</td>
<td></td>
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<td></td>
</tr>
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<td>Very high</td>
<td>High</td>
<td>Dynamic</td>
<td>Yes</td>
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</tr>
<tr>
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<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
</tbody>
</table>

(continues)
### Table 2.3
Comparative Characteristics of Employment Impact Assessment Methodologies for Clean Energy Investments (Continued)

<table>
<thead>
<tr>
<th></th>
<th>DATA REQUIREMENTS</th>
<th>TECHNICAL COMPLEXITY</th>
<th>TEMPORALITY</th>
<th>JOB CREATION SCOPE</th>
<th>IMPLEMENTATION IN A DEVELOPING ECONOMY</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>DIRECT</td>
<td>INDIRECT</td>
</tr>
<tr>
<td><strong>Macroeconometric models</strong></td>
<td>High</td>
<td>Moderate</td>
<td>Dynamic</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td></td>
<td>High. Typically have IO tables at the core. Single country models can be based on country data and data from international institutions. Global models require consistent IO data sets.</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Econometric models</strong></td>
<td>High</td>
<td>Variable</td>
<td>Static</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td></td>
<td>Econometric assessments rely on the availability of high-quality microdata. Even though econometric assessments allow for ex post assessments, data collection generally needs to be thought out before making an investment into a project or program to be assessed, in order to improve results' quality.</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
THREE
EX ANTE
ESTIMATION OF
EMPLOYMENT
IMPACTS OF
CLEAN ENERGY
DEPLOYMENT
3.1 Engineering Bottom-Up Models

Engineering models, also called “bottom-up models,” are often used in the analysis of investments related to energy infrastructure and environmental concerns. Indeed, unlike traditional goods, the energy market tends to be closely linked to the technological characteristics of energy production and consumption. Engineering models thus prioritize the accurate modelling of the technology employed in energy consumption and supply, while drastically simplifying the representation of economic mechanisms. This is particularly manifested in the modelling of energy demand.

A bottom-up assessment can be a simple field survey to estimate the number of jobs directly created by the economic actors that implemented a clean energy investment. Alternatively, technology assumptions and labor intensity estimates from the literature can suffice to obtain a gross estimate of direct employment impacts.

Bottom-up energy infrastructure models can be complex, and they represent substitution patterns between energy carriers (e.g., clean electricity versus diesel) while factoring in realistic technological constraints. This is in contrast with macroeconomic models, where the final energy demand typically follows a classical demand function, and agents adjust their energy consumption based on the relative prices of available energy sources. Firms and households optimize their energy demand under a budget constraint but ignore technological constraints—this can lead to unrealistic substitution patterns between energy carriers.

The two models will reach different conclusions if we consider, for example, a decrease in electricity prices due to an investment in additional generation capacity. In a macroeconomic model, the effect will propagate through elasticities of substitution between several energy sources, or between energy and other goods. Such models generally consider all energy sources uniformly, without consideration for the technological realism of the potential substitution between two sources. However, by modelling the substitutability between different technologies explicitly—thus ruling out some substitutions—an engineer’s model would predict a much smaller effect on the final energy demand.

This would substantially change the resulting estimated employment impacts, notably, productive use jobs. The lack of technological constraints in most macroeconomic models could lead to an overestimation of the increase in electricity use due to falling electricity costs, including increased electricity consumption by sectors or households without the required machinery or appliances to make use of it.

Example Applications

This section presents multiple examples of bottom-up models applied to particular countries or regions. Box 3.1 presents an application of the modelling approach at the global level.
Local Impact of Renewables on Employment: Assessment Methodology and Case Study (Sastresa et al. 2010)

Sastresa et al. (2010) use a bottom-up analysis to estimate the economic impact of a regional-level deployment of renewable energy, notably in terms of the number of direct jobs created in the autonomous community of Aragon (Spain). To this end, they apply an employment factor that is defined as the number of jobs generated by megawatts installed. The employment factor is complemented by a ratio measuring the quality of the jobs created, which they call the quality factor.

The above analysis considered three stages of development of renewable energy activities: design stage (F1), installation/uninstallation (F2), and O&M (F3). The stages are quantified in terms of employment creation (number of jobs generated by megawatts installed) as well as the quality of the jobs created (measured in terms of the jobs' location [local or outside the community], nature [temporary or stable jobs], and degree of professional specialization). All of these metrics were measured for a sample group of 126 companies, of which approximately 50 percent were in solar thermal and 15 percent in the wind sector. The results show that the renewable energy companies provided 2,500 stable and direct jobs in 2007. The number of jobs-per-megawatt ratio ranged from 1.28 to 5.54 between 1998 and 2007, with the most recent estimate being on the lower end, at 1.43.

Sastresa et al. (2010) also considered the jobs/MW installed for each of the abovementioned stages. They showed a high rate of employment intensity in the technological development stage for wind and a concentration of job creation due to installations of solar thermal and solar PV. More than half of the workers in renewable energy require highly specialized skills. When comparing employment intensity, renewable energy generates between 1.8 and 4 times as many jobs/MW installed as conventional energy sectors.

Potential for Renewable Energy Jobs in the Middle East (Van der Zwaan, Cameron, and Kober 2013)

Van der Zwaan, Cameron, and Kober (2013) also used a bottom-up method to evaluate renewable energy jobs in the Middle East. However, unlike Sastresa et al. (2010), they first implemented an energy systems model to determine the necessary energy mix to achieve a greenhouse gas (GHG) emissions target compatible with the 2°C objective. In that scenario, their model predicts that wind and solar power will together have to account for approximately 60 percent of the electricity supply by 2050.

The study then considers wind, solar PV, and concentrating solar power (CSP), and estimates an employment factor for each technology based on a review of 22 publications (for a comprehensive review of the literature on employment factors, see Cameron and Van der Zwaan [2015]). Specifically, this review identifies distinct employment factors for the manufacturing and installation stages of projects. For each technology that is considered, Van der Zwaan,
Solar has greater technoeconomic resource suitability than wind for replacing coal mining jobs (Pai et al. 2021).

Pai et al. (2021) analyze the impact that a transition to a “greener” economy has on global employment. Their work relies on a new global dataset of employment factors in 50 countries for 11 energy technologies and 5 job categories (construction and installation, operations and maintenance, manufacturing, fuel production, and refining). This dataset was used to calibrate an integrated assessment model (IAM) for studying the impact of keeping global warming well below 2°C (WB2C) on direct energy sector employment and for comparing those results with current policy scenarios.4

This is study on the global employment impacts of staying below 2°C especially because Pai et al. estimate specific employment factors for developing countries such as Brazil, China, India, and Mexico and, unlike previous studies. They find that implementing a WB2C scenario would increase the number of energy sector jobs from 18 million to 26 million, compared with an increase to 21 million jobs under the current policy scenario. And even though employment related to fossil fuels would decrease considerably, from 12.6 million jobs currently to 3.1 million, those losses would be more than compensated through gains in renewable energy jobs, from 4.6 million to 22 million, most of which would be concentrated in solar and wind (accounting for over 85 percent of those gains).

To evaluate the robustness of their results, Pai et al. consider three standard shared socioeconomic pathways (SSPs) aligned with the Intergovernmental Panel on Climate Change Assessment Report 6. The above results correspond to the middle-of-the-road scenario (SSP2), wherein socioeconomic and technological trends follow historical patterns. The other scenarios are under a fossil-rich world (SSP3) and under a sustainable world (SSP1).5

Although global results are promising, some fossil-fuel-exporting regions, such as Mexico, Australia, Canada, and South Africa, experience negative employment impacts under the WB2C scenario, since the majority of the current energy employment in these countries is in extractive sectors, and losses would not be (continues)
compensated by gains in renewable energy jobs. For other emerging economies and regions, such as Indonesia, Southeast Asia, Brazil, India, and South Asia, increases in energy demand still result in an overall increase in employment under the WB2C scenario. Conversely, China would lose jobs compared with the current scenario due to losses in the coal mining industries.

In summary, Pai et al. (2021) find that while the majority of fossil fuel employment would disappear under the WB2C scenario, these losses would be offset by gains in renewable energy jobs at the global level, with only China and fossil-fuel-exporting countries facing net job losses, while other regions would experience net job gains, thanks to increased renewable energy employment.

Meanwhile, the limitations inherent to ex ante impact assessments are a challenge for studies of this type. Evaluating clean energy investments, especially in the developing world, is difficult and this is especially true for ex post assessments, which require both an extensive data collection that ideally reflects significant period of climate policy implementation. Both of these features are rare in developing economies.

Cameron, and Kober (2013) also estimate the proportion of manufacturing that is performed locally in the Middle East region. They do so based on a conservative estimate of the number of components that could be produced for each technology in the region.

Van der Zwaan, Cameron, and Kober (2013) considered two scenarios to estimate the volume of direct employment until 2050: (1) the manufacturing process is entirely local in the region, and (2) 49 percent, 46 percent, and 50 percent of wind, PV, and CSP components, respectively, are manufactured locally. In both scenarios, installation and O&M create jobs locally. Based on the median values of employment factors, in scenario (2), approximately 155,000 jobs can be created in the Middle East by 2050, whereas in scenario (1), there would be 180,000 jobs by that time. Meanwhile, based on the maximum values of the employment factors, approximately 400,000 jobs are created in 2050 in scenario (1), but only 350,000 under (2).

Renewable Energy Jobs and Sector Skills Mapping for Pakistan (World Bank 2022a)

Another recent analysis of clean energy’s employment effects was produced by the World Bank (2022). It forecasts employment impacts resulting from the projected development of
renewable energy in Pakistan under the recently adopted government targets for 2030. Specifically, the report assesses direct formal job creation using an employment factor approach and estimates indirect employment impacts in aggregate using employment multipliers sourced from the research literature.

The authors find that under the more ambitious renewable energy policy scenario, deployment of renewable energy will lead to the creation of more than 190,000 direct jobs in the sector and an additional 137,000 indirect jobs in related sectors. Although most direct jobs would be temporary, lasting only through implementation period of projects, the renewable energy industry could provide more than 14,000 permanent jobs between 2021 and 2030.

The above results highlight the importance of employment-factor-related uncertainty and supply-chain-localization-related uncertainty when estimating direct employment impacts in the renewable energy sector. Yet, the above three papers also provide examples of straightforward methodologies to estimate the employment impacts of renewable energy investments, particularly in regions where data may not be easily available, for example, the Middle East and South Asia. As such, the methodological approach showcased is readily replicable in the context of evaluating the employment impacts of specific policies and projects.

In conclusion, engineering models typically have the benefit of specifying the technological constraints affecting both demand and supply sides of energy markets. They also contain more information on the effects of policies targeting energy infrastructure. However, these models cannot capture the macroeconomic effects of energy sector investments stemming from interactions between energy markets and other goods. They are, therefore, better suited for estimating direct job creation, along with productive use jobs to the extent that they represent a detailed pattern of energy use substitution between electricity and other energy carriers (including manual labor).

Advancing Inclusion Through Clean Energy Jobs (Muro et al. 2019)

Muro et al. (2019) provide an important analysis of the employment impacts of energy transition in the United States. While focused on a developed economy, it provides a good reference point regarding what can be expected from an ex ante assessment. The report combines federal datasets with industrial classifications from the existing clean energy investment literature to assess the skills, demographics, and education profiles that workers will have to present for the United States to successfully transition to a clean energy economy.

Since the analysis is conducted ex ante, it relies on data obtained from the Bureau of Labor Statistics and O*NET to characterize individuals who are currently employed in the clean energy sector. These positions are defined as the most relevant in the transition to a clean energy economy within a predefined set of clean energy sectors, namely, clean energy production, energy efficiency, and environmental management.

Muro et al. (2019) find that the average wage in clean energy jobs exceeds the national average by approximately 10 percent, with a peak of 20 percent in clean energy production.
The report also highlights that clean energy provides a wide range of middle-income jobs paying between $20 and $35 per hour in the United States. Regarding the levels of educational attainment, high school graduates occupy approximately 45 percent of clean energy occupations. This is an important result, since this relatively large share of low-skill jobs can facilitate the transition of workers from high-carbon sectors of the economy, yet it may also reduce their long-term income prospects and the wage premium they currently enjoy.

### 3.2 Input–Output Models

Input–output models are organized based on an input–output table (IOT). An IOT is first used to record interindustry trade, that is, the proportion of the output of one sector of an economy that is used by another sector as input for production. For example, the agricultural sector requires fertilizers produced by industry, which in turn uses the goods produced by other sectors. This sectoral analysis can be conducted at a three-sector level (agriculture, industry, and services) at the very least, although it can also follow a more detailed typology of the goods produced in the economy. Specifically, it can represent the production and consumption of energy and electricity at a fairly disaggregated level.

An IOT thus contains a wealth of income- and expenditure-flow-related information over a given period of time (typically a year) between the different components of an economy. The construction of an IOT follows certain simple principles. Column accounts correspond to the demand side of an economy and row accounts correspond to the supply side. Each cell, therefore, records a payment flow from a column to a row. The sum of the values in each row corresponds to income and the sum of the values in each column corresponds to expenditures. The values in an IOT are expressed in monetary units (i.e., value). In the simplified IOT example (figure 3.1), the top left section (the figures in nonbold font) describes interindustry trade.

**FIGURE 3.1**
An Example of an IOT

<table>
<thead>
<tr>
<th>AGRICULTURE</th>
<th>INDUSTRY</th>
<th>SERVICES</th>
<th>TOTAL INTERMEDIATE CONSUMPTION</th>
<th>TOTAL FINAL CONSUMPTION</th>
<th>TOTAL OUTPUT (DEMAND)</th>
</tr>
</thead>
<tbody>
<tr>
<td>AGRICULTURE</td>
<td>100</td>
<td>300</td>
<td>20</td>
<td>420</td>
<td>580</td>
</tr>
<tr>
<td>INDUSTRY</td>
<td>300</td>
<td>400</td>
<td>100</td>
<td>800</td>
<td>3,200</td>
</tr>
<tr>
<td>SERVICES</td>
<td>50</td>
<td>50</td>
<td>200</td>
<td>300</td>
<td>2,700</td>
</tr>
<tr>
<td>TOTAL</td>
<td>450</td>
<td>750</td>
<td>320</td>
<td>1,490</td>
<td></td>
</tr>
<tr>
<td>VALUE ADDED</td>
<td>550</td>
<td>3,250</td>
<td>2,680</td>
<td></td>
<td>6,510</td>
</tr>
<tr>
<td>TOTAL OUTPUT (SUPPLY)</td>
<td>1,000</td>
<td>4,000</td>
<td>3,000</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
For example, the agricultural sector (column 1) buys 100 units of agricultural goods, 300 of industrial goods, and 50 of services (a total of 450 units) for use in production. The total for the first column therefore includes the values of the inputs to the agricultural sector, which will then be consumed or transformed during production. It corresponds to the sum of the intermediate consumption for this sector.

The total value for agricultural production can then be broken down into the intermediate consumption values and the value added. The value added for the agricultural sector is thus the difference between the total production value (1,000) and the intermediate consumption value (450). The value added is a measure of the wealth produced by the agricultural sector. The sum of the value added for each sector of an economy gives the gross domestic product (GDP).

The above IOT also breaks down demand into two components: intermediate and final demand. For the agricultural sector, intermediate demand (line 1) is the sum of the agricultural goods consumed by all sectors of the economy (in this example, 420 units). Thus, all agricultural production that is not consumed as input by another sector is used for final consumption (580 units).

In sum, supply (last row) must always equal demand (last column) for each sector.

IOTs provide a snapshot of all the transactions between the different accounts in the economic system. In this way, they enable us to visualize the interdependence of the different sectors of activity. Unlike partial equilibrium models, IO models do provide some general equilibrium features. Using matrix calculus, it is possible to calculate the level of production that must be assured for a given level of final consumption (by inverting the well-known “Leontief matrix”).

Example Applications

This section presents multiple examples of input–output models applied at country level. Box 3.2 presents a special class of models lying between the static input–output and full-fledged computable general equilibrium models: macroeconometric models.

Assessing Employment in Renewable Energy Technologies: A Case Study for Wind Power in Brazil (Simas and Pacca 2014)

Simas and Pacca (2014) use an IOT to estimate the number of direct jobs in manufacturing, construction, and O&M, as well as the number of indirect upstream jobs in the supply chain for materials and inputs for building wind turbines and wind farms in Brazil. Unlike Sastresa et al. (2010) and Van der Zwaan, Cameron, and Kober (2013), Simas and Pacca
Another class of models representing an entire economy lies between the static input–output and full-fledged computable general equilibrium models: these are called macroeconometric models. Their methodology has deep historical roots, reaching all the way back to the Cowles Commission of the 1930s in the United States. It purports to represent an economy as a system of dynamic equations relating to macroeconomic and sectoral quantities and prices. This system is then estimated based on historical data over long time horizons often cumulating 20–30 years of observations.

The main benefit of macroeconometric models is that they are completely empirically grounded: every single parameter is estimated econometrically from observed data. The models thus require substantial quantities of data to produce reliable estimates—particularly since the level of sectoral disaggregation in the models increases. As such, these models can prove difficult to adapt to countries for which detailed economic statistics may not yet be available over long time horizons.

In the field of environmental and energy economics, macroeconometric models have been successfully extended to account for physical emissions and energy quantities. Leading examples include the E3ME model (Cambridge Econometrics 2019) and GINFORS (Lutz and Giljum 2017). It should be noted that both are closed-source and proprietary models.

(2014) consider separate employment intensities for each component of the activities considered. This provides a more granular analysis of the local employment impact. Their study also uses employment factors associated with production capacity instead of rated installed capacity for each type of renewable energy infrastructure considered. Indeed, adopting rated capacity-based factors, as in Sastresa et al. (2010) and Van der Zwaan, Cameron, and Kober (2013), can lead to an overestimation of the number of job-years/MW.

In the wind power sector, over 55 percent of direct jobs and 40 percent of total jobs were created in construction, with a low impact in jobs in O&M. Interestingly, this article contrasts the number of direct jobs estimated when using employment factors defined in terms of job-years/production with those defined using job-years/installed capacity—and confirms that the latter metric tends to overestimate job creation.
Garrett-Peltier (2017) also uses an IOT approach to evaluate the short-term employment impacts of clean energy spending. The paper compares the employment impacts of investments in energy efficiency and renewable energy with fossil fuel investments. From a methodological standpoint, this paper illustrates a useful approach to introduce renewable energy sectors (e.g., wind, solar, bioenergy, hydro, and geothermal) and energy-efficiency sectors (e.g., building weatherization, mass transit and freight rail, industrial energy efficiency, and electrical grids upgrades) in a standard IOT that lacks these sectors. This is often the case even in developed countries with sophisticated national accounts statistics collection—as such, this type of approach is especially ambitious for developing economies.

The method described involves treating clean energy spending as a demand shock and then creating demand vectors that target the intermediary consumption required by clean energy industries in manufacturing, construction, and other services. Using a 71-sector industry-by-industry IOT obtained for the US economy, Garrett-Peltier (2017) identifies the corresponding technical coefficients for the aforementioned 9 clean energy industries as well as 2 fossil fuel industries (e.g., oil and gas, and coal). The industry-wise employment requirements to deliver $1 million of final demand for a specific product or service are then estimated for direct as well as indirect jobs using the full-time equivalent (FTE). The paper finds that, on average, $1 million of demand for renewable energy generates 7.5 FTE jobs (4.5 direct + 3 indirect), with the same amount generating 7.7 FTE jobs in energy efficiency (4.6 direct + 3.1 indirect). On the fossil-fuel industry side, $1 million of final demand creates 2.7 FTE jobs (1 direct + 1.7 indirect). Shifting a $1 billion investment from fossil fuels to renewable energy or energy efficiency would generate a net balance of 5,000 FTE jobs.

In practice, the IO approach discussed above allows to go beyond the jobs created by the sector(s) implementing clean energy investments themselves (direct jobs) and include employment impacts along the entire supply chain of those sectors (indirect jobs). In particular, IO models can be amenable to the disaggregation of sectors relevant to the project under consideration. For example, IO models can be useful for disaggregating the construction sector into multiple infrastructure subsectors to analyze the employment impacts of large-scale infrastructure projects (see World Bank [2021] for a recent example) or disaggregating clean energy sector into subsectors to analyze their impacts (see World Bank [2022b, 2022c]).

However, the IO approach does not adequately factor in the general equilibrium effects stemming from the increased economic activity resulting from a clean energy investment (notably through increased demand from increased employment). In particular, price mechanisms such as the potential inflationary pressures or competitiveness impacts of a surge in public investments are completely ignored, even though they form an important part of an accurate assessment of induced jobs response. Further, IOTs provide a static representation of an economy, which fails to capture sectoral shifts over time. Modeling these sectoral shifts requires a more sophisticated framework: CGE modelling.
Turning back to emerging and developing economies, Grafakos et al. (2020) assess the macroeconomic impacts of decarbonization pathways in Mexico, Indonesia, and Rwanda under their respective Nationally Determined Contributions (NDCs), with a particular focus on renewable energy employment. The report uses an IO matrix to mainly evaluate the direct employment effects of renewable energy technologies as well as indirect renewable energy jobs in the above countries. In general terms, the report finds that overall employment impacts grow with the ambition of climate change mitigation policies.

In Mexico, the additional renewable energy capacity required by 2030 to meet the NDC targets would result in approximately 830,000 direct jobs, 440,000 indirect jobs, and 250,000 induced jobs. At the peak of renewable energy deployment, this would grow total employment by 600,000 jobs compared with the business-as-usual (BAU) scenario. Achieving these results would require $31 billion of direct domestic investment in onshore wind and solar PV, $13 billion more than the reference case.

Indonesia’s NDC targets a 29 percent reduction in GHG emissions by 2030 compared with its BAU scenario. Grafakos et al. (2020) focus on scenarios where the entire Indonesian population has access to electricity by 2030, with a projected electricity mix of 26 percent renewable energy and 74 percent fossil-fuel-based energy. In the Indonesian context, the relevant technologies are hydro (small and large), solar PV, and geothermal. Large hydro would account for the highest number of renewable energy jobs in Indonesia (approximately 4.6 million job-years), followed by geothermal (with 1 million jobs), small hydro (with 0.9 million jobs), and solar PV (with 0.7 million jobs). The corresponding total investment is $49 billion. Construction and installation, along with project management, would see the majority of job creation.

For Rwanda, Grafakos et al. (2020) consider a high-ambition scenario based on governmental policy documents. The scenario proposes to increase the renewable energy share in the Rwandan electricity mix to 66 percent by 2030. The state of electricity access is assumed to follow current governmental projections in all scenarios, increasing from 53 percent of households in 2019 to universal electricity access by 2024. Implementing this scenario would result in an employment impact of 31,000 direct job-years for a direct investment of $645 million in large hydro and solar PV. As in Mexico and Indonesia, the majority of the jobs would be created in construction and installation, with more than 75 percent of the direct job-years from solar PV relating to careers requiring medium- and low-skills.

This growing literature points to the significant potential of clean energy investments to create jobs across a wide range of economies, thereby improving local outcomes and development prospects.
3.3 Computable General Equilibrium Models

An economic model is a set of structural and behavioral relationships in the form of a system of equations giving rise to a unique solution. While structural relationships often include market equilibrium conditions representing constraints for individuals, behavioral relationships include, for example, the production and utility functions that describe a producer's technologies or a consumer's preferences. The equations of an economic model connect all its endogenous and exogenous variables. Compared with IO models, CGE models contain more information about the behavior of economic agents and the relationships between economic variables. In particular, CGE models explicitly model the structure of the final demand and production factors and can account for the evolution of that structure in a growing economy.

All economic models are based on the optimization behavior of economic agents. Consumers seek to maximize their utility (derived from the consumption of goods) under budget constraints, while producers seek to maximize their profits (the difference between their income and costs). The utility and production functions are typically multivariate. The utility function relates to goods that provide utility (consumer goods, or also leisure). It describes the preferences of an economic agent, or the proportion of utility they derive from one good when compared with another. In the case of the production function, the input variables are the factors of production (capital, labor, and sometimes energy). The production function indicates the level of production (output) associated with a combination of factors of production (inputs). It describes the technological relationship between inputs and output.

Different consumer preferences or production technologies can be represented using a variety of utility or production functions. The majority of the functions used are concave (to find a solution to the maximization program) and assume a constant elasticity of substitution, which is independent of the absolute level of production achieved.

The term “general equilibrium” refers precisely to the fact that this class of models recognizes the interdependence among different markets. CGE models thus constitute a coherent framework in which the prices and quantities of all markets are determined endogenously and simultaneously through the interaction between multiple markets. The “calculable” attribute of CGE models stems from the fact that they are based on real numerical data and result from the use of simple mathematical functions whose properties (continuity, derivability) facilitate the calculations. The numerical resolution made possible by CGE models is particularly useful for the quantitative analysis of the impact of economic policies or investment stimuli, as the evolution of the economic equilibrium following an exogenous shock becomes easily calculable.

Historically, CGE models emerged as a generalization of the IO models introduced by Wassily Leontief (1936). This extension proved necessary since the economic system cannot be reduced to interindustry trade: there is a broader set of flows in the economy to model. Within an economy, the main income and expenditure flows stem from the value added from production activities. The value added is used to pay for production factors,
which in turn allows the distribution of income to economic agents and, ultimately, the consumption of output by economic agents.

Finally, another essential contribution of CGE models compared with IO models is that they allow price-based adjustment of market equilibrium. By contrast, IO models operate under a fully exogenous pricing assumption, which is not very realistic considering the constraints of a producer. Only in rare cases can a producer produce any quantity of a good at a constant price, because an increase in production would cause production costs to explode. Supply is generally inelastic in the short run. Given these short-term rigidities, increasing output would raise the price of the final good, and of the intermediate goods used in production, to restore market equilibrium.

If we consider that the market equilibrium adjusts through prices, as in CGE, we implicitly also consider substitution effects between several consumer goods, or between production factors, when prices change. For example, if an increase in the demand of a domestically produced good increased its price, consumers might want to substitute that good with a substitutable good produced abroad. Also, an increase in demand would increase firms’ demand for labor to increase production in order to address the higher demand for their products. The aggregate increase in the demand for workers would, at least temporarily, increase wages. A firm could thus consider substituting part of its labor force by investing in machines (capital) that make the existing labor force more productive. The issue with IO models is that an IOT specifies exactly the combination of inputs required to produce a final good: the inputs here are perfect complements and nonsubstitutes. The corresponding production function is of the Leontief type with zero elasticity of substitution. CGEs therefore use nonlinear production and utility functions (generally constant elasticity of substitution or Cobb–Douglas functions) where elasticity of substitution is positive and noninfinite. Through different elasticities, CGEs capture the behavioral adjustments of economic agents. Apart from elasticities of substitution, three other elasticities are relevant for modeling:

- **Price elasticity:** The change in demand for a good following a 1 percent increase in its price.
- **Income elasticity:** The change in demand for a good following a 1 percent increase in income.
- **Armington elasticity:** The elasticity of substitution between a domestically produced good and an imported good, when foreign trade is taken into account. It may, for example, depend on differences in quality between domestic and imported goods.

### Example Applications

**Green Growth: The Economic Impacts of Large-Scale Renewable Energy Development in China (Dai et al. 2016)**

Dai et al. (2016) use a general equilibrium model with 41 commodities and their corresponding producing sectors, along with eight power generation technologies (coal, oil, gas, hydro, nuclear, wind, biomass, and solar), to assess the impacts of renewable energy in China by 2050. The authors compare two scenarios: a reference scenario assuming conventional
development of renewable energy and a ReMax scenario hypothesizing significant penetration of renewable energy up to 2050 (i.e., renewable energy and non-fossil-based energy would have 74 percent and 78 percent shares in power generation in 2050, which accounts for 56 percent and 60 percent of the total primary energy, respectively).

The results illustrate the level of detail achievable with a CGE model both in terms of metrics produced (GDP, employment) and sectoral coverage—both of which come at a significant implementation cost. In the reference scenario, China reaches the GDP per capita of a moderately developed country ($27,000), with a share of household consumption/GDP of approximately 68 percent by 2050 and a shift from a secondary to a service-driven economy (with services accounting for 65 percent of the overall economy by 2050). Renewable-energy-related activities would represent approximately 2 percent of China’s GDP by 2050. By comparison, renewable-energy-related activities would account for 3.4 percent of GDP in the ReMax scenario, which would be comparable to other important economic sectors, such as agriculture (2.5 percent), iron and steel (3.3 percent), and construction (2.1 percent). Moreover, under the more aggressive ReMax scenario, China would be able to create 4.12 million jobs in 2050, with most benefits going to machinery, transport, service, and electronic equipment. It should be noted that China’s dominant role in the manufacturing of key renewable energy technologies (especially solar PV panels) plays an important part in these results.

CGE models also allow assessment of aggregate macroeconomic impacts. Gains in the renewable energy sector do not compensate the substantial employment and output losses in the coal sector. Thus, these two scenarios would result in small negative effects in terms of GDP and welfare (0.3 percent and 1.6 percent reduction, respectively) across the entire economy.

Employment Creation in European Union Related to Renewables Expansion (Fragkos and Paroussos 2018)

Fragkos and Paroussos (2018) also implement a CGE model to evaluate the employment impacts from the expansion of renewable energy technologies necessary to achieve a low-carbon transition by 2050 in the European Union (EU). Interestingly, unlike the previous contribution, this paper combines employment factors (bottom-up analysis) with general equilibrium modeling. Employment factors are used to estimate the labor intensity of the different renewable energy technologies (i.e., solar, wind, and hydro) as well as that of the fossil fuel sector.

The authors model a scenario targeting a 40 percent reduction in GHG emissions and a 27 percent share of renewables in the gross final energy demand, and an energy efficiency target of 30 percent by 2030. The scenario includes a further target that renewable energy should account for 53 percent of the gross final energy demand by 2050. They find that this would shift approximately 1.85 million jobs (corresponding to 1 percent of the EU workforce) from the fossil fuel to the renewable energy sector. The majority of job creation is concentrated in solar PV, advanced biofuels, and wind, with 1.5 million more jobs in 2050. By contrast,
fossil fuel jobs are reduced by 1.1 million from 2015 levels, with coal mining being particularly affected. It should be noted that the perimeters are not strictly comparable, since a significant proportion of upstream employment in renewable energy (manufacturing in particular) is not located in Europe. Yet, overall, since renewable energy requires more employees than fossil-fuel-based industries, the low-carbon transition is expected to have positive impacts on the EU labor markets, with an increase in aggregate employment of 200,000 additional jobs by 2050.

In an emerging country context, Yahoo and Othman (2017) also apply CGE modeling to evaluate the impacts of a CO2 intensity reduction of 40% from the 2005 levels in Malaysia by 2020. They use two mechanisms: a market-based mechanism (carbon tax with a compensating scheme) and a command-and-control mechanism (sectoral emissions standards). Under both policy tools, GHG emissions shrink by 6.7 percent. This is accompanied by a 0.60 percent increase in real GDP in the market-based mechanism, since the redistribution of carbon tax receipts to households increases consumption and investment.

Conversely, command and control reduces real GDP by 0.35 percent, since in the modelling framework used, such a mechanism creates distortions in the economy. It should be noted that this outcome is quite sensitive to the modelling choices made while designing the CGE model. When employing market-based mechanisms, the demand increase resulting from the redistribution of the carbon tax leads to an increase in production and, subsequently, employment. In this case, employment increase would reach 1.55 percent across the economy, whereas employment would decrease by about 0.75 percent under command and control.

While CGE models provide the most comprehensive account of economies and their macroeconomic mechanisms, they are also complex to implement and require large volumes of data to calibrate. This increase in complexity is justified when evaluating the impact of broad climate change mitigation policies, such as economywide energy transition scenarios or carbon pricing. However, this would generally prove unnecessary when assessing the employment impacts of discrete clean energy investments. Capturing general equilibrium effects allows analysts to evaluate induced jobs, which would be difficult to do with an IO model given the lack of price and wage effects. Yet, for small projects well below the 1 percent GDP threshold, these second-order effects are likely to be negligible—capturing them does not justify the added cost, development time, and complexity incurred by a CGE model.

**Effect of Climate Policies on Labor Markets in Developing Countries: Review of the Evidence and Directions for Future Research (Hafstead et al. 2018)**

Hafstead et al. (2018) use a general equilibrium model called Environmental Impact and Sustainability Applied General Equilibrium (ENVISAGE) to estimate the effects of a global carbon tax increasing to $160 by 2050. The model includes 26 sectors, three regions (large emitters, swing emitters, and carbon-dependent countries), and two types of labor (skilled and unskilled). Their results suggest that job losses in carbon-intensive industries such as
coal, natural gas, coal-based power, gas-based power, and refined oil products will represent an important component of employment impacts. However, since fossil-fuel-related sectors represent only a small fraction of employment in most countries (e.g., approximately 1 percent on average and less than 5 percent even in the major fossil-fuel-producing countries), employment gains in less carbon-intensive industries offset those losses.

It is important to note that these results are derived from two important assumptions: first, perfect (frictionless) labor markets and, second, similar labor markets in developed and developing economies (even though the latter are often characterized by a surplus of labor and a relatively rigid labor market where workers experience limited mobility between employers and/or geographies). Yet, even under additional assumptions such as labor-leisure decisions, wage rigidities, sector-specific labor, and search frictions, Hafstead et al. (2018) still find job gains in relatively less polluting industries. In the same general equilibrium modeling literature, Guivarch et al. (2011) show that more rigid labor markets (i.e., exhibiting higher wage rigidity) experience larger GDP losses under climate mitigation policies. Decarbonization involves shifts of activity and employment between sectors of activity—labor market rigidities that impede these movements lead to adverse macroeconomic consequences. This is an important result in the context of developing nations.

The literature on current general equilibrium modeling finds that, in aggregate, the impacts of the energy transition on employment are relatively small. However, the effects on specific regions and workers can be much larger—especially those employed in fossil-fuel-intensive sectors that will be negatively affected by the transition to cleaner energy. Further, in developing economies, a large informal sector and segmented labor markets can lead to a large share of low-skilled, low-productivity workers in the labor force, which could slow down the transition to a greener economy.

Endnotes

1. This region was chosen because its electricity production levels are higher than the rest of the European Union and because of the high volume of exports of electricity generated. According to the data collected by Sastresa et al. (2010), renewable-based electricity production in Aragon was 36.8 percent in 2007, whereas the same variable for the European Union was 14.9 percent. Moreover, Aragon exported 60 percent of the electricity produced at that time—which is important in order to analyze whether the jobs created are local or are primarily being generated outside the region.

2. This finding can be further compounded by the difference in capacity factor between renewable energy and fossil-fuel-based power plants. Since renewable energy has a much lower capacity factor, many more megawatts of installed renewable energy capacity are needed to achieve a given level of electric energy output—which in turn increases the volume of job creation further.

3. IAMs are a class of models that combine socioeconomic and geophysical (typically climate) modeling to assess the interplay between human activity and environmental externalities in a single cohesive framework.
4. Their dataset covers 80 percent of the total estimated global jobs from energy production. For each job category, they evaluate whether each of the 11 technologies is possible (coal, gas, oil, nuclear, hydropower, solar PV, solar CSP, traditional biofuels, onshore wind, offshore wind, and solid biomass), allowing them to have 36 technology–category combinations. After building the dataset, they use the IAM to project future energy jobs under the WB2C scenario as well as under current policies. To build the reference scenario, they use the currently implemented policies (until 2020) and extrapolate the implied emission intensity afterwards. The W2BC scenario is built by estimating the peak carbon budget (742 gigatonnes of CO₂ for the period 2011–2050). More details can be found in Pai et al. (2021).

5. The labor productivity improvements are assumed in such a manner that the employment factors for non-OECD (Organisation for Economic Co-operation and Development) countries converge toward the mean for the OECD countries by 2050. The main results are qualitatively similar for the other socioeconomic pathways considered.

6. The NDCs refer to the voluntary long-term commitments of countries to reduce national emissions and mitigate the effects of climate change. The Paris Agreement requires that each ratified member (currently 189 countries) be able to prepare, communicate, maintain, and refresh successive NDCs that they intend to achieve.

7. The renewable energy technologies evaluated are utility-scale solar PV, solar PV, and onshore wind.

8. Energy efficiency is modelled in terms of the average energy intensity of GDP in Fragkos and Paroussos (2018).
FOUR EX POST EMPLOYMENT IMPACT ASSESSMENT OF CLEAN ELECTRIFICATION
Adoption of clean energy in emerging economies can potentially provide millions of households, especially in rural areas, with access to clean electricity. This can materialize through investment in renewable energy sources and the related transmission and distribution infrastructure, but also through improved energy efficiency. Access to electricity benefits firms, for example, by enabling them to power machinery, thereby boosting productivity. Further, clean energy access can potentially improve education and health outcomes, as well as the overall quality of life, in emerging economies by electrifying public buildings such as schools and health facilities, and by replacing polluting diesel- or heavy fuel oil-powered generators or kerosene.

Electrification using renewable energy sources also has a strong job creation potential. Clean electricity jobs stem directly from the installation, operation, and maintenance of new energy systems and indirectly from the related upstream industries along the value chain (e.g., component manufacturing and mineral mining). These new jobs increase activity levels across the wider economy, in turn increasing employment further. These jobs relate to the direct, indirect, and induced employment impacts described earlier in this paper.

Yet, increased access to clean electricity itself can augment employment opportunities. These additional jobs are commonly referred to as “productive use” jobs. Improved electricity access opens more opportunities for businesses, allows households to invest in labor-saving devices at home, and increases the potential for both formal and informal income-generating activities. For example, electricity access at low cost may enable more women to participate in the labor market by reducing the time spent in nonmarket activities at home, or it may spur the creation of small businesses.

In the context of the present analysis, productive use jobs should not be confused with induced jobs. The latter result from the spending of income generated through the construction, installation, operation, or maintenance of clean energy infrastructure, while the former are made possible through the increased availability of (clean) energy. Any analysis studying the employment impacts of clean energy in developing countries will thus have to factor in all potential channels through which electrification itself creates jobs and generates income.

While electricity access yields undeniable benefits in terms of quality of life, investments in electrification, use of renewables, or expansion of existing grids may also entail significant opportunity costs. In fact, the costs of electrification may well outweigh its economic benefits if the latter are not significant enough—even for off-grid developments. Governments might then be tempted to allocate funds to other areas that might generate higher net economic returns. This highlights the crucial role of evaluating the economic impacts of electrification, especially on job creation, using rigorous methods.

Jobs attributable to productive use of electricity are difficult to estimate using ex ante evaluations. IOTs generally fail to account for the effects of electrification unless augmented with specific models relating technology adoption to household and firm behavior. In addition, households and firms need financial resources and access to markets to acquire appliances and knowledge to operate appliances and machinery that can enable productive use of the newly available electrical power. This is not captured at all by traditional IO frameworks.
Direct measurement via household and firm surveys is possible but would be very costly given the need to achieve a sufficiently large sample size.

Overcoming these obstacles requires using quasi-experimental ex post assessment methodologies. Quasi-natural experiments in economics refer to serendipitous situations in which economic agents (e.g., individuals, households, firms) are assigned randomly to a treatment and a control group. As such, they “approximate” the randomized design of a well-controlled experiment, which allows causal inference.

These methodologies allow us to estimate the causal effect of electricity access on the level of employment and economic activity across multiple levels of aggregation, from households to regions. Although these observational studies are typically less costly to run than randomized controlled trials, they need large quantities of data, since they require simultaneous measurement of electrification status and economic outcomes.

Over the past decade, a growing economics literature analyzing the effects of electrification on income, education, employment, and health in developing countries and using microeconometric evaluation methods has emerged. This literature allows ex post estimations of job creation induced by the expansion of electricity access, as opposed to ex ante methods involving employment factors, IOTs, and CGE models. However, it should also be noted that in terms of implementation, ex post evaluations require data collection before a project or investment is undertaken, just like ex ante approaches.

In more recent years, the literature has also started to pay closer attention to renewables, particularly, the deployment of solar-powered mini grids in remote rural communities, or the distribution of solar home systems and solar-powered appliances to households. Nevertheless, it is important to note that the effect of electrification in generating productive use jobs is largely independent of the technology used to produce power. Thus, in what follows, we consider studies assessing the economic effects of fossil-fuel-based and renewable-energy-based electrification.

The literature considered in this chapter offers a causal assessment of the economic impacts of clean energy investments in emerging economies, an exception is box 4.1 presenting examples of ex post assessments in developed economies. In practice, the literature has almost exclusively centered on evaluating the economic effects of electrification in developing countries, including the employment effect of increased electricity access—thus productive use jobs, particularly in rural contexts. This focus is reflected in the remainder of the present literature review.

The projects assessed in the reviewed articles cover both “traditional” grid connections (e.g., power lines extensions) and more recent decentralized energy access approaches using clean energy sources. We present the different methodological approaches and discuss their respective advantages and disadvantages, especially regarding the feasibility of implementation. We also detail the main econometric challenges posed by each approach and provide examples related to specific context of electrification, especially using renewables. Finally, we address why different methodological approaches can yield different results. A summary of the literature reviewed in this chapter is provided in Table 4.1, at the end of the chapter.
The employment impact of a green fiscal push: Evidence from the American Recovery Act (Popp et al. 2020)

Popp et al. (2020) provide an example of an ex post assessment of a climate-related policy in the United States. In particular, this is an econometric assessment of the employment effects of the green component of the 2009 American Recovery and Reinvestment Act (ARRA)—one of the largest fiscal stimuli in recent history. The full stimulus package included over $350 billion of direct government spending along with an additional $260 billion in tax reduction, with the green component corresponding to approximately 17 percent of all direct government spending. This spending included both direct spending for job creation, such as investments by the Department of Energy in renewable energy and energy efficiency retrofits, and grants by the Environmental Protection Agency, which covered the contracts, grants, and loans provided over the period 2009–12.

The evaluation considers three dimensions: differentiation between the short- and long-term impacts of the green ARRA, heterogenous effects according to the level of local green capabilities in the labor force, and how the green stimulus affected different sectors and groups of workers. County-level data are aggregated into commuting zones to examine local labor market effects. Popp et al. (2020) then consider the volume of green ARRA and nongreen ARRA per commuting zone.

An event study model that can jointly estimate green ARRA effects for the years before and after the crisis finds increased total employment due to this fiscal stimulus under a number of specifications: 15 jobs were created per $1 million of green ARRA in the long run. Job creation was also stronger in commuting zones with a prevalence of preexisting green skills: half of the jobs were created in construction and waste management, and almost all of them in manual labor positions. This is an important result, since it sheds light on how the green stimulus affects the economy’s structure. In the short term, there is little evidence of green ARRA’s employment effects and no evidence regarding changes in wages.

(continues)
Popp et al. (2020) find that the ARRA's green portion is more effective in reshaping rather than changing the economy, with little evidence of short-term impacts: regions with little preexisting “green-related” activity experienced little employment effect. However, increased demand for manual labor, especially in construction and waste management, shows that green subsidies can benefit unskilled workers, which can potentially bolster the political support for climate change policies.

**The transitional costs of sectoral reallocation: Evidence from the Clean Air Act and the workforce (Walker 2013)**

In a similar spirit, Walker (2013) also provides evidence of the effects of mitigation policies on wages by applying a difference-in-difference approach to assess the impact of the 1972 Clean Air Act amendments. The results indicate that workers in sectors affected by the policy suffered persistent losses of more than 5 percent of their preregulated earnings, with workers displaced from their previous jobs experiencing the majority of these losses.

While causal in their identification strategy, since the econometric approach of neither Walker (2013) nor Popp et al. (2020) considers the spillover effects on downstream industries indirectly affected by the green ARRA and the 1972 Clean Air Act amendments, they do not provide much insight into the labor market effects within the wider economy. In this regard, general equilibrium models can be better suited for examining the wider economic effects by accounting for impacts on directly regulated industries as well as on upstream and downstream sectors.

**4.1 Issues in Assessing the Economic Impacts of Clean Electrification**

Appropriate identification of the effects of electrification on job creation raises a number of methodological issues.

The first of these relates to the very measurement of electrification. The term *measurement of electrification* might refer to the degree of access to electricity (quantity) as well as the quality of the connection. Lee, Miguel, and Wolfram (2020) and Lee et al. (2016) highlight a factor complicating analyses, which is that a significant portion of rural households are “under-grid,” in that they lie below existing power lines but lack a connection. In this context,
the distance from an existing power line does not always provide an accurate measure of electrification status in rural communities. Further, the offer of electrification does not necessarily directly correlate with actual household electrification: the level of household take-up can often prove difficult to measure.

The second issue relates to data collection and quality in developing countries, since studies assessing household-level effects of electrification mostly rely on survey data and cannot rely on rich administrative databases as for developed countries. A few questions regarding such surveys are as follows: Was the survey designed to accurately capture electrification status of households (e.g., recording both access to and consumption of electricity)? Do multiple survey rounds allow the tracking of households over time? Does the survey also measure the electrification status of nonresidential buildings, such as workshops and factories, which carry out many of the productive use activities that could be generated thanks to electrification? Finally, what are the economic outcomes that can be measured accurately, and can the data provide additional insights into the economic mechanisms at play?

The third main issue is causal identification. Units receiving electricity access would ideally be selected at random—in which case, variation in electrification status is purely exogenous. We could then simply compare outcomes between units receiving access to electricity and those who do not. If treatment was indeed assigned by pure chance, then untreated units would represent a good counterfactual for what would have happened to the treated units in the absence of treatment.

However, the probability that some units will get access to electricity might depend on external factors that also determine the economic outcomes for these units; this introduces selection bias. In fact, due to the substantial investments required to expand electricity grids, governments might decide to target areas with the largest economic potential (that are expected to have a greater electricity demand), or areas with strong political support for ruling governments. This last point is less salient in the context of more limited investments, such as mini grids. Selection bias also occurs if the households that actually become electrified once offered a connection are wealthier, more educated, or have more credit access. These characteristics of the households have implications for their ability to reap the benefits of energy access and, in turn, for potential productive use jobs created.

Causal identification also hinges on the absence of other time-varying unobservable factors driving economic outcomes and occurring at the same time as electrification itself (confounding factors). Examples include major historical events or simultaneous macroeconomic fluctuations. Economic development benefits attributed to electrification might then instead capture the effects due to these other factors. In other words, causal estimation of the effect of electricity access on job creation requires a suitable quasi-experimental empirical setting. These are not necessarily common and tend to be tailored specifically to a given local context or project. In practice, the assessment of induced employment impacts might be limited to correlational evidence. We nevertheless provide a detailed description of each of these causal identification methodologies, as they offer a benchmark for best practices that can prove useful in the field.
Observational studies exploit a variety of designs in which geographical and/or time variation in electricity access can reasonably be considered exogenous. These studies have essentially relied on instrumental variables (IVs) and regression discontinuity (RD) designs to identify causal effects. More recent studies have begun to conduct field experiments in which households that receive electricity access are selected randomly. We will present both methodologies in turn.

4.2 Quasi-Experimental Observational Studies

Observational studies have used various case studies of electrification, clean or otherwise, in developing countries as quasi-natural experiments to analyze its economic effects. We will present the main studies, their methodologies, and the most relevant results.

Geography-Based Instrumental Variables

A common approach to address endogenous treatment status is to find an IV that strongly predicts treatment but remains unaffected by any other unobserved factors, for example, economic or political factors affecting a government's decision to electrify one community over another. The primary condition to identify a causal effect using an IV is that the instrument must affect the outcome of interest only through electrification and not any other channel (exclusion restriction).

This condition is not directly testable and is by no means guaranteed. Nonetheless, IV methods were among the first econometric approaches used in the literature to evaluate the socio-economic effects of electrification. When available, they offered a straightforward path to causal identification, justifying their relatively frequent use in existing assessments. In particular, local geography offers a good way to predict electrification status or the share of electrified households in a given village or region, as we can expect geography to be a major determinant of the cost of extending an electric grid.

Dinkelman (2011) authored the first paper to implement this method, in the context of South Africa's elaborate electrification program in the 1990s. The paper uses land gradient as an instrument for the electrification status of rural communities in the country's KwaZulu-Natal province. Land gradient is clearly exogenous and likely a strong factor determining governments' placement of electrification projects. There is also no obvious reason why land gradient should be directly correlated with income other than by affecting the construction cost of different types of infrastructure.

A similar study on Nicaragua is by Grogan and Sadanand (2013), who also use land gradient and past population density as IVs for households' electricity access within a municipality. In particular, greater population density is believed to reduce the marginal cost of constructing...
a new power line, since more households can benefit from it. For the case of Colombia, Grogan (2016) employs changes in distance to the nearest hydroelectric dam over time (as new dams are being built) to instrumentalize local electrification rates. Finally, in their study on the developmental effects of hydroelectric power in Brazil between 1970 and 2000, Lipscomb, Mobarak, and Barham (2013) simulate hypothetical electricity grids as a proxy for the actual electricity grid using a model in which the construction cost of hydroelectric dams is exogenously determined by geographical features. In practice, a model simulates the Brazilian electric grid’s evolution from 1970 to 2000 had investments been made solely on geography-based cost considerations. The results from this simulation are then used as an instrument to isolate exogenous variation in electricity supply from potential demand-side factors making the location of dams endogenous.

The aforementioned studies examine the effects of electrification on local employment rates and analyze how electricity access affects labor supply. A majority of these studies find significant and large positive effects of electricity expansion on labor supply, especially among women. Dinkelman (2011) finds a significant increase (of approximately 9 percentage points) in the female employment rate, which translates into 15,000 additional women joining the labor force and constitutes about 0.75 percent of all jobs created in the observation period. Women are also found to work significantly more hours per week (+3.5 percent). Male employment also increases but not significantly so. Likewise, Grogan and Sadanand (2013) find a 23 percentage point increase in the likelihood of women working, while Lipscomb, Mobarak, and Barham (2013) estimate an 18 percentage point increase in their employment probability. These findings are nuanced by Grogan (2016), who finds no significant effects on female self- or wage employment. Yet, most of this evidence largely supports the hypothesis that electricity access leads to significant reductions in time allocated toward household chores and home production, thereby freeing up labor for productive economic activities.

Even though geographical IV methods present challenges in recovering causal estimates due to potential violations of the exclusion restriction (discussed below), they have a few significant advantages that have helped researchers address the lack of impact evaluation studies on electrification in developing countries. First, geographical IV methods leverage exogenous variation in electrification between geographical units (e.g., at the municipal or regional level), which makes these methods particularly convenient when evaluating large-scale governmental efforts to expand electricity access to large parts of their populations, as was the case in South Africa and Brazil. In fact, geography-based IVs have the merit to plausibly control for governments’ preferences in allocating resources to one community versus another.

Second, studies employing geography-based IVs typically compare economic outcomes between areas with high and low electrification rates. While higher levels of aggregation leads to loss of information on individual households in such areas, it also takes care of spillover effects within a given area (such as interactions between households or crowding out effects), which would otherwise count as omitted variables threatening causal identification. Finally, as geographical data and household survey and census data become more extensive and widely available in developing countries, IV methods could still offer an important evaluation tool in
the years to come. This would especially be the case for analyzing the effects of electrification on job creation, which has so far been critically understudied due to data constraints.

Even though geography-based IVs are suitable for evaluating large-scale electrification projects, and their implementation using existing survey or census data is relatively straightforward, researchers have expressed concerns about their validity to proxy for electrification status (see, for example, Bensch et al. [2019]). The validity of the instrument hinges on the condition that land gradient (the IV) does not affect economic outcomes through other channels than electrification (the treatment)—in which case, the exclusion restriction would be violated. An important point is that these additional channels are typically unobserved: despite several robustness checks that researchers can perform, threats to the instrument’s validity can never be ruled out with certainty. Below we list three possible examples of confounding:

1. In rural areas, agriculture is often the main source of income. One could imagine that a steeper land gradient can have a detrimental effect on agricultural productivity, either through lowering soil quality due to, for example, more erosion, or through the larger amount of labor required to cultivate steeper land parcels. Agricultural productivity is then positively correlated with household income and wages, which are in turn correlated with job creation. If a study cannot rule out this channel in its setting, then its coefficient estimates for electrification will likely be upward biased, since flatter areas, which are more likely to be electrified, also have higher income levels to begin with.

2. Similarly, if land gradient is negatively correlated with income, flatter areas might experience in-migration from steeper areas, which in turn shapes local labor market developments (our outcome of interest).

3. Geographical features not only affect the construction of new power lines but of all forms of physical infrastructure, such as roads and railways. There is a general consensus in the literature that transportation infrastructure generates economic growth and jobs, perhaps more so than energy access. This causes confounding issues if electricity grid extensions occur simultaneously with road construction, or if areas with adequate access to a transportation network already lie on a faster growth trajectory before being connected to a grid. Since electric power lines are often built alongside roads, there might also be a selection bias in favor of areas with existing road access. If a study is unable to appropriately control for road and rail access in different areas, then the measured impact of electrification will be upward biased, since it partly reflects additional positive effects of other forms of infrastructure on economic growth and employment. Moreover, since road access and electrification are so closely correlated, perfectly controlling for road access might also eliminate any positive effect of electrification altogether. In fact, Bensch et al. (2019) replicate the results of Dinkelman (2011), showing that electrification has much smaller effects on labor supply in areas in proximity to national road networks.

A final issue with IVs are the so-called “weak” IVs, which do not have a strong enough correlation with electrification. This leads to larger confidence intervals in IV estimations, which translates to less precise estimates of hours worked and jobs created. Bensch et al. (2019) find that this is indeed an issue in the study by Dinkelman (2011).
Regression Discontinuity Designs

A range of more recent studies have adopted RD designs to estimate the causal effect of electrification. RD designs are especially useful when policies govern the eligibility for electricity access, and determine whether eligibility is granted above or below a certain cutoff. In this setting, the method amounts to comparing barely eligible and barely ineligible units (i.e., those being in close proximity to the eligibility cutoff) at a given time.

The reference study using the RD approach is by Burlig and Preonas (2016), who analyze India’s Rajiv Gandhi Grameen Vidyutikaran Yojana (RGGVY) program, which was implemented from 2005 onward. The objective of this program was to extend electricity access to 100,000 rural villages across 27 Indian states, and only villages with a population above 300 inhabitants were eligible to receive electricity access under it. RGGVY thus represents a suitable quasi-experimental setting to evaluate the impact of electrification on developmental outcomes, and on productive use jobs in particular.

In RD designs, identification relies on two conditions. First, one must ensure that the eligibility threshold cannot be manipulated—in which case, our causal estimates would suffer from selection bias. In our setting, threshold manipulation would imply that villages with a population just below 300 could increase their population to become eligible. This appears highly implausible, and evidence corroborates that village size is evenly distributed around the threshold of 300 inhabitants. Second, all covariates and unobservable variables potentially correlated with the outcome of interest must be continuous at the threshold. In other words, there should be no “jumps” in any variables of interest other than villages’ eligibility status. This condition would not be met if, for example, the eligibility threshold of 300 inhabitants also affected eligibility for other governmental social or infrastructure programs.

Ideally, in RD designs, all units that are eligible for treatment indeed receive it (sharp design). Using satellite data, Burlig and Preonas (2016) document a significant increase in nighttime brightness in eligible communities, concluding that they had indeed been provided with electricity access. In the so-called “fuzzy” designs, not all eligible units actually take up treatment and become connected to the grid. While causal estimates can still be recovered in such settings, their interpretation slightly changes. In what follows, we will discuss fuzzy designs further and provide examples of corresponding studies.

In the study by Burlig and Preonas (2016), electrification’s effects on a variety of economic and developmental outcomes is measured by comparing treated and untreated villages using 2011 census data, after implementation of the program. As regards employment outcomes, they find a significant decrease in the share of male agricultural workers (−0.7 percentage points, on a mean of 42 percent) and a small but significant increase in the share of men employed in the nonagricultural sector (+0.5 percentage points, on a mean of 10 percent). This is consistent with the hypothesis that electricity access favors structural transformation away from agriculture, but in economic terms, these effects are small. Finally, they find no significant effects of electrification on the intensive margin of labor (number of months worked per year), nor do they observe a significant increase in household ownership of electric appliances. These lackluster results are in sharp contrast with the large positive IV...
estimates presented above. We will later try to answer why results differ so sharply across different settings and methodologies.

Causal identification in RD designs relies on weaker assumptions than those used in settings with IVs. It is also easier to test these assumptions by plotting histograms of the running variable (village population in the study by Burlig and Preonas [2016]) and running placebo tests. In addition, RD designs explicitly define and compare treated and untreated units on both sides of the eligibility threshold, thereby focusing more directly on recovering causal treatment effect estimates than IV methods. Finally, a unique advantage of RD designs is that they can be performed using cross-sectional data, where units just below the threshold act as counterfactuals for units just above the threshold. This reduces the burden of data collection, since it is not necessary to follow treatment and control groups over time using multiple survey rounds.

The RD method has one major drawback: in practice, only a small number of projects feature exploitable discontinuities generated by clear eligibility criteria. Such projects are more likely to be one-time, large-scale government initiatives of sufficient magnitude to define an eligibility criterion in the first place. It is unlikely that suitable discontinuities could be found in the context of small-scale clean energy investments. One potential setting in which an RD design could be performed would be a government subsidy for solar home systems (or similar off-grid clean energy solutions) directed at households below a certain income threshold. Such a project would, however, face compliance issues (discussed below), since many households would likely not take up the subsidy.

It is also important to mention that RD designs are not immune to confounding issues. Estimates might be biased by unobserved contemporaneous economic developments affecting villages on either side of the threshold. Fetter and Usmani (2020) provide a striking example analyzing the effects of RGGVY in electrified areas simultaneously experiencing positive income shocks due to increase in commodity prices. In fact, in some Indian regions, electrification efforts coincided with a sudden demand surge for locally produced guar gum driven by the shale gas revolution in the United States. The study shows that in electrified areas exposed to this demand boom, the nonagricultural sector experienced much larger increases in employment than nonexposed areas that were also eligible for electrification. This suggests that the economic benefits of electricity access are context dependent. More specifically, electrification might facilitate job creation in favorable economic contexts but create few productive use jobs in the absence of economic growth opportunities—particularly when access to electrical appliances is restricted. This argument would also explain why IV methods have delivered such large positive effects, as these studies targeted emerging economies toward the beginning of their economic takeoff (post-Apartheid South Africa, late-twentieth-century Brazil).

“Fuzzy” Designs and LATE

Sharp designs, such as the RD design implemented by Burlig and Preonas (2016), assume that all households that are offered an electricity connection actually become electrified; they use village-level outcomes to evaluate the treatment effect of electrification. In general
terms, sharp designs require that units’ treatment assignment (the fact of being offered a connection) coincides with their final treatment status (the fact of being connected to the grid). This is unrealistic—which in turn may question the reliability of the impact assessment. Successfully evaluating the treatment effect of electrification requires additional survey data specifically measuring compliance with the treatment by the agents that drive the economic outcomes of interest (i.e., households, firms, individuals). Such detailed surveys to measure electricity take-up are not conducted in the study by Burlig and Preonas (2016), which instead relies on an alternative measure using satellite images that show an increase in nighttime brightness in the electrified villages. Such data, however, do not help researchers to conclude with certainty that all households contribute to the increase in brightness, that is, they all react to the assigned treatment.

Situations in which not all units assigned treatment actually respond to the treatment are referred to as “fuzzy” designs. These designs contain a fraction of individuals who are “never takers” (who never become treated, even if assigned to the treatment group) and/or a fraction of “always takers” (who always become treated, even if assigned to the control group). Two-sided noncompliance occurs when data contains both never takers and always takers. This is likely to happen in the case of electrification of rural villages: never takers are eligible households that never become connected, even though they could, while always takers are ineligible households that are “cheating” to become connected (a common issue documented by Burgess et al. [2020b]).

Econometricians have developed estimators to recover a “local average treatment effect” (LATE) in fuzzy designs that only considers the change in outcomes for compliant individuals. The LATE is measured by calculating the difference between the average change in outcomes for individuals assigned to the treatment group and the average change in outcomes for individuals assigned to the untreated group, divided by the share of compliers in the sample. This requires additional individual-level data on both final treatment status as well as treatment assignment. An important caveat of the LATE is that it can only be interpreted as a local estimate for those who comply and cannot be generalized to an entire population (decreasing its external validity). Admittedly, this caveat is shared across all quasi-experimental designs surveyed in this section.

The validity of the LATE hinges on two assumptions: an exclusion restriction (always) and a “no-defiers” condition (only with two-sided noncompliance). As for IV methods, the exclusion restriction states that outcomes respond to treatments, not to treatment assignment. The exclusion restriction rules out situations in which units’ decision to take up treatment is endogenous, which would generate selection bias. Endogeneity, however, may occur in the case of household electrification, where households’ decisions to connect to the grid are subject to income levels, financial constraints, or social aspirations, to name a few. To address this issue, the LATE’s estimation requires an IV for households’ treatment status: an assignment variable that strongly predicts which households become treated but is not correlate with any of the economic outcomes of interest, or with other unobserved variables affecting economic outcomes. This, of course, is not necessary if noncompliers are a random subset of the population—in which case, the original treatment assignment variable already satisfies the exclusion restriction.
The “no-defiers” condition, also known as the monotonicity assumption, requires that there are no individuals who would become treated if assigned to the control group, and remain untreated if assigned to the treatment group. Since we never observe counterfactuals, this condition cannot be verified, and its validity must be plausibly justified in each individual setting.

A recent study by Thomas et al. (2020) is the first observational study implementing a fuzzy design on the effects of electrification. The study uses eligibility criteria set by a law in the Indian state of Uttar Pradesh according to which only households within a 40 m radius of existing electric poles are eligible for government-provided electricity access. Treatment assignment is quasi-random in close proximity to the threshold, similarly to traditional RD designs. Because households may still decide not to take up a connection when eligible, or may connect illegally when ineligible, the study faces an issue of two-sided noncompliance. The distance from the nearest electric pole is an assignment variable, which clearly satisfies the exclusion restriction, since it is strongly correlated with households' final electrification status but should not directly affect economic outcomes. It can thus be used as an instrument for households' treatment status, which Thomas et al. (2020) observe after conducting surveys with 686 households.

Thomas et al. (2020) estimate significantly positive effects of electrification on household expenditures and appliance ownership over a period of four years. Electricity is also shown to increase the time spent by adults and children in different domestic and work-related activities (work, cooking, education, etc.) but not leisure. This evidence suggests that households reallocate their time toward income-generating activities, in turn suggesting that electricity generates time savings, which can be reallocated to productive uses. The results paint a more positive picture of the job creation potential of electrification than other rigorous quasi-experimental studies, such as that by Burlig and Preonas (2016), who evaluate the effect of rural electrification in India using an RD design and fail to find significant impacts on economic development.

The positive results observed by Thomas et al. (2020) could be due to several factors. First, outcomes are measured at least four years after households obtained their electricity connection; this is a longer time frame than that in other studies. Second, Thomas et al. (2020) argue that while Burlig and Preonas (2016) focus on the least developed villages, their study targets villages that are more representative of the Indian population at large, thus where the average economic growth potential is stronger.

The majority of studies using individual-level data are likely to face noncompliance issues, and very few observational studies have so far investigated outcomes at this finer level of disaggregation. Fuzzy designs will thus likely be central to any future research on the economic impacts of electrification. Recovering a LATE remains challenging due to the strong identification assumptions that must be met—which also hinge on extensive data collection efforts, most likely costly direct surveys. Furthermore, as for RD designs, the settings in which a valid instrument for households' treatment status can be found are limited and most often involve eligibility rules set by policy.
4.3 Randomized Controlled Trials

In impact evaluation, the surest way to obtain causal treatment effect estimates is for the treatment to be randomly allocated to individuals—in which case, the outcomes of the untreated group are a valid counterfactual for the treated group. By identifying situations in which treatment assignment is “quasi-random,” observational studies aim to construct a valid counterfactual outcome when treatment is not assigned randomly. Over the past decades, especially in development economics, economists have begun to perform field experiments where subjects are randomly selected to receive a treatment—so-called randomized controlled trials (RCTs). Only a few recent studies, which we review in the remainder of this section, have so far performed RCTs in which access to electricity is being randomized. This is due especially to the high costs of building new power lines as well as the strong cooperation required between researchers and national and local authorities to perform such experiments. Nevertheless, many questions remain unexplored, and RCTs constitute a promising avenue for future research complementing more traditional quasi-experimental approaches.

The main paper implementing an RCT is that by Lee et al. (2021). In their experiment, they randomly select households across 150 rural villages in Kenya (totaling 12,000 households) to receive a subsidy to connect to the electric grid. The amount of the subsidy is random as well and covers the connection cost partially or fully. By randomizing price offers, they are able to measure households’ willingness to pay, in turn consumers’ demand for electricity. All units take up a connection when it comes at no cost; however, take-up decreases sharply with connection cost.

The authors first estimate the treatment effects for the households in the full-subsidy group, which exhibits almost full compliance. Treatment effects can be estimated through a linear regression of the outcome of interest on an indicator for whether an individual was assigned to the full-subsidy group and a vector of the control variables. The results show a significant increase in households’ energy consumption and appliance ownership between 16 and 32 months after receiving a connection, albeit from a low baseline level, and no significant effects on asset ownership or student test scores. While the study does not explicitly focus on employment outcomes, it estimates, somewhat surprisingly, a significant negative effect on the hours worked in the previous week. Lee et al. (2021) do not elaborate further on this isolated result. Yet, it either disproves the hypothesis that electricity boosts labor supply, or simply indicates that electricity did not create any productive use jobs in that setting—at least under the limitations of the study, which does not capture, for example, informal employment.

RCTs have a few distinct advantages over observational studies discussed in previous sections. First, and most importantly, randomization of treatment removes potential selection biases, since individual characteristics (observable or unobservable) can be expected to have similar distribution (“balanced”) between the treatment and control groups. Since many RCTs
are implemented as “encouragement designs,” where incentives to receive a treatment are randomized rather than the treatment itself (as for the subsidy in Lee et al. [2021]), noncompliance might still occur (see the discussion of LATE in the previous section). However, because treatment assignment is random, it will be much less prone to violations of the exclusion restriction, in turn allowing local average treatment effects (see previous section) to be estimated.

Second, RCTs give researchers full control over the research design and, in particular, the data collection effort. Observational studies often face data quality issues as they rely on survey or census data collected by third parties, or data that have been aggregated at a larger scale. Also, observational studies conducting ex post analysis of certain policies’ effects only conduct one survey, asking households to compare their situation before and after the policy’s implementation (this is the case in Thomas et al. [2020]). This can lead to significant biases when households do not remember their situation correctly (i.e., measurement error), or when the policy has had a strong influence on their current situation. RCTs offer researchers an opportunity to conduct interviews before and after the intervention as part of the research design as well as to measure outcomes relevant to the specific research question at hand.

Finally, experimental approaches are better suited for eliciting information about how individuals respond to economic incentives, such as in the example of electrification. Variation in the level of the subsidy given to households yields experimental estimates of the demand for electricity connections; this in turn allows to calculate consumer surplus. Lee et al. (2021) combine the experimental demand curve with measures of the cost of delivering electricity and conclude that the social surplus of electrification is negative in the case of rural Kenya. In other words, their study suggests that the demand for electricity in rural Kenya is too low to cover its costs, at least in the medium term.

It is important to note that this is a purely economic and rather abstract calculation, which quantifies “welfare”—in this instance, the degree to which electricity answers people’s needs. It does not necessarily imply that electrification does not create jobs.

In Lee et al. (2021), the focus is on rural “under-grid” households (living below existing power lines but lacking a connection) in Kenya, which are among the poorest in the country. The authors highlight certain external factors that might explain why the demand for electricity is so low among this target group. First, these households are more likely to face binding credit constraints, hampering their ability to buy an electricity connection, even at a subsidized price. Further, given that the subsidy is only temporary, the connection’s monthly cost might be too much to afford. Second, bureaucracy and low reliability of power (e.g., due to frequent and long-lasting blackouts) reduces the attractiveness of electricity connections when they are already costly. Finally, the large cost estimates to connect a household (approximately five times consumers’ willingness to pay) might also result from poor institutional quality and leakage at various stages of the construction process. Lee et al. (2021) emphasize that the estimated social surplus would have been positive under more favorable assumptions related to the economic and institutional setting.

Importantly, RCTs also have significant drawbacks, most notably, their lack of external validity. Since RCTs have relatively limited sample size and their results are context
dependent, it is often difficult to extrapolate a result to a wider population. Experimental results should thus always be interpreted within the local context in which the experiments are conducted, and researchers should attempt to justify the external validity of their results. For example, they can do so by showing that the experimental sample is representative of the wider population across a wide range of characteristics. Observational studies are also concerned by this issue, however, especially in a setting where the effects of electrification are expected to be heterogeneous across people with different income and education levels, or across regions or economic contexts.

In their literature survey, Lee, Miguel, and Wolfram (2020) provide an overview of results of labor supply impacts from several studies focused on rural electrification (figure 4.1) and present additional results from their experiment performed on rural Kenyan households where they focus on how treatment effects are heterogeneous across different households. The randomized price offers make it possible to classify compliers into “adopters when price is high” and “adopters only when price is low.” By generating exogenous variation in households’ willingness to pay, the RCT thus allows to compare outcomes across a characteristic that is generally unobserved. Lee, Miguel, and Wolfram (2020) show that the effects of electrification are larger for households with a high willingness to pay. In particular, these households register a significant increase in the number of electric appliances, and their members are

![Figure 4.1: Labor Supply Impacts of Rural Electrification](source: Lee, Miguel, and Wolfram 2020)

**Source:** Lee, Miguel, and Wolfram 2020.

**Note:** IV = instrumental variable; pp = percentage point; RCT = randomized controlled trial; RD = regression discontinuity.
more likely to be employed or to own a business than members of low willingness to pay households. These results suggest that even among a relatively homogenous group of rural households, effects can vary for different groups of individuals. Households with high willingness to pay are shown to be wealthier and more educated, boosting their ability to benefit from an electricity connection for income-generating activities or in their daily lives.

Lee, Miguel, and Wolfram (2020) and Lee et al. (2021) barely focus their attention on labor market outcomes and the potential for electrification to create productive use jobs. Using a very similar experimental design, Barron and Torero (2014) examine the effect of electricity access on time allocation in El Salvador, where households are randomly offered vouchers partly covering connection costs. More specifically, they instrument the grid connection status of a household as a function of whether it received a discount voucher and the share of its neighbors within a 100 m radius that were eligible to connect. Their results indicate that electricity has a strong positive effect on female labor supply, increasing nonfarm employment and business ownership by 46 and 25 percentage points, respectively. They also find that electrification brings about a 78 percentage point increase in the probability of children engaging in educational activities, which likely generates long-term economic benefits on top of immediate productive use jobs. Annual income increases are estimated to be approximately $1,000, a substantial increase from baseline income. These results again underscore how electrification can have vastly different impacts across contexts, regardless of the evaluation method. A larger share of households with sufficient income, savings, or access to credit in El Salvador might explain the difference in the results from those in the Kenyan context. Barron and Torero (2014) also document the existence of large spillovers in areas with several connected households, which might increase the demand for electricity as well as people’s willingness to use electricity productively. These spillovers are largely absent in Lee et al. (2021).

A nascent literature has also used experimental approaches to study the demand for off-grid technology (such as mini grids or solar home kits) and its effects on various outcomes. Aklin et al. (2017) present evidence that solar minigrids in India (provided to rural communities) do increase electricity consumption by up to 1.4 hours a day but do not significantly increase the time spent working or business creation. Grimm et al. (2017) show that in Rwanda, solar home kits boost productivity for domestic activities, yet without evidence of productive use jobs being created—which is unsurprising given that home solar does not provide sufficient power for appliances other than light bulbs, charging ports, or TVs. Finally, in a similar design to that of Lee et al. (2021) implemented in Rwanda, Grimm et al. (2019) examine households’ willingness to pay for off-grid solar technology. The study reveals that while households are willing to devote some of their income to solar home kits, their willingness to pay is insufficient to cover market prices. The study, however, does not investigate any socioeconomic impact of solar devices. These three RCTs only involve a small sample of 300–1,300 households spread across treatment and control groups. It would thus be desirable to implement a larger-scale evaluation of the economic impacts of off-grid solar technology in developing countries.

RCTs have become a standard methodology in development economics due to their significant advantages in identifying causal effects in settings with limited data availability and where economic mechanisms are still poorly understood. Because data collection is at
TABLE 4.1
Detailed List of the Core References in Chapter 4

The following articles are the most highly cited studies examining productive use job creation resulting from electrification published in leading international academic journals over the past 10 years. They represent a select subset of some 100 peer-reviewed articles and reports that were reviewed in the preparation of the present literature review.

<table>
<thead>
<tr>
<th>YEAR</th>
<th>AUTHORS</th>
<th>CITATIONS</th>
<th>OUTLET</th>
<th>SETTING</th>
<th>METHODOLOGY</th>
<th>MAIN EMPLOYMENT FINDING</th>
</tr>
</thead>
<tbody>
<tr>
<td>2011</td>
<td>Dinkelman</td>
<td>920</td>
<td>American Economic Review</td>
<td>South Africa</td>
<td>IV</td>
<td>Significant increase (9.5 pp) in female employment</td>
</tr>
<tr>
<td>2013</td>
<td>Lipscomb, Mobarak, and Barham</td>
<td>357</td>
<td>American Economic Journal: Applied Economics</td>
<td>Brazil</td>
<td>IV</td>
<td>Significant increase (18 pp) in the probability of employment</td>
</tr>
<tr>
<td>2013</td>
<td>Grogan and Sadanand</td>
<td>172</td>
<td>World Development</td>
<td>Nicaragua</td>
<td>IV</td>
<td>Significant increase (23 pp) in female propensity to work outside home</td>
</tr>
<tr>
<td>2013</td>
<td>Barron and Torero</td>
<td>31</td>
<td>Unpublished</td>
<td>El Salvador</td>
<td>RCT</td>
<td>Increase in nonagricultural employment (46 pp) and female business ownership (25 pp)</td>
</tr>
<tr>
<td>2016</td>
<td>Grogan</td>
<td>19</td>
<td>Journal of Human Capital</td>
<td>Colombia</td>
<td>IV</td>
<td>No effects on female employment</td>
</tr>
<tr>
<td>2016</td>
<td>Burlig and Preonas</td>
<td>97</td>
<td>Working paper</td>
<td>India</td>
<td>RD</td>
<td>Small significant decrease in male agricultural employment (0.7 pp) and increase in male nonagricultural employment (0.5 pp). No effects on female employment</td>
</tr>
<tr>
<td>2017</td>
<td>Aklin et al.</td>
<td>91</td>
<td>Science Advances</td>
<td>India</td>
<td>RCT</td>
<td>No significant effect of solar microgrids on time spent working</td>
</tr>
<tr>
<td>2020</td>
<td>Fetter and Usmani</td>
<td>6</td>
<td>Working paper</td>
<td>India</td>
<td>RD</td>
<td>Significant increase in nonagricultural employment in electrified areas simultaneously experiencing economic boom</td>
</tr>
<tr>
<td>2020</td>
<td>Thomas et al.</td>
<td>5</td>
<td>Journal of Development Economics</td>
<td>India</td>
<td>LATE</td>
<td>Significant increase in time spent at home for both children’s education and adults’ work activities</td>
</tr>
<tr>
<td>2020</td>
<td>Lee, Miguel, and Wolfram</td>
<td>29</td>
<td>Journal of Economic Perspectives</td>
<td>Kenya</td>
<td>RCT</td>
<td>Increase in the probability of employment only for households with high-willingness to pay (10 pp).</td>
</tr>
<tr>
<td>2021</td>
<td>Lee, Miguel, and Wolfram</td>
<td>70</td>
<td>Journal of Political Economy</td>
<td>Kenya</td>
<td>RCT</td>
<td>Decrease in weekly hours worked (~2.6 hours)</td>
</tr>
</tbody>
</table>

Note: IV = instrumental variable; LATE = local average treatment effect; pp = percentage point; RCT = randomized controlled trial; RD = regression discontinuity.
the heart of experimental economic research, RCTs are better suited for individual-level analysis than many observational studies. However, RCTs also present significant challenges, which make their widespread implementation costlier. First, they often require close cooperation between researchers and local governments, especially when it comes to studying the impact of government-financed infrastructure projects. As a major financial contributor and institutional actor in improving energy access in the developing world, the World Bank would be in a unique position to promote and conduct similar research initiatives. Second, since data are being collected in real time, it becomes more difficult to measure outcomes over a longer term than in observational studies. Third, and perhaps most important, RCTs have limited external validity, as do the instrumental variable and regression discontinuity designs, discussed above. Therefore, especially for questions with a strong context dependence, for example, economic impacts of electrification (as shown by previous observational and experimental research), a large number of RCTs need to be conducted to draw robust conclusions.

Endnotes

1. County-level data are aggregated into 709 commuting zones. The mean values per commuting zone for the green ARRA and the nongreen ARRA are $103 million and $442 million, respectively.

2. A common example would include individuals receiving a treatment based on their date of birth, resulting in an almost random (quasi-random) assignment of treatment with a given group.
FIVE CONCLUSION
Over the past decade, the economics literature has used both observational and experimental methods to study the economic impacts of electrification, specifically, the creation of jobs associated with the productive use of electricity in South Asia, Latin America, and Sub-Saharan Africa. The literature surveyed in the previous section primarily focuses on labor supply and business creation as potential job creation mechanisms. Electricity access is believed to boost productivity in performing domestic tasks, freeing up time for income-generating activities, especially for women. Household electrification can also spur microentrepreneurial activity, especially for certain services, which can be performed from home but require electricity supply (e.g., cooking, sewing, ironing, phone charging, etc.).

Across studies, results have spanned the entire range of potential effects—from large impacts of electrification on labor supply, business creation, and overall employment to no measurable effects, as summarized in table 5.1. This suggests that effects are likely context dependent and that electrification alone is not sufficient to drive economic development in the absence of other favorable factors (Lee, Miguel, and Wolfram 2020). The largest effects appear to occur in settings with larger GDP per capita. Even within the world’s poorest communities, differences in income, education, and access to credit generate differences in electricity take-up, appliance ownership, energy expenditures, and employment gains. For example, Peters and Sievert (2016) review potential explanations for why estimated effects are often smaller for Sub-Saharan Africa than for Asia or Latin America. Further research into the heterogeneity of treatment effects is necessary and will help determine where and when investments in electrification reap larger and more widely shared benefits.

From a policy maker’s point of view, recent research has shown that households’ willingness to pay is often far below the cost of extending the traditional grid. This is primarily due to income, but also to households’ perceptions of the quality and reliability of different types of electricity connections (traditional grid or solar home systems) and their social aspirations (for example, see Fowlie et al. [2019] and Lee et al. [2016]). Some studies have highlighted the large potential of off-grid solutions to provide basic levels of energy supply to households in remote areas at a lower cost than physical grids (Alstone, Gershenson, and Kammen 2015; Grimm et al. 2019). Additional research will thus be needed to determine the optimal incentive and financing structure of electrification projects, with a particular focus on off-grid systems such as solar home systems and solar microgrids. This will affect take-up, and, in turn, also the number of productive use jobs that electrification is able to provide.

A more detailed understanding of the labor market consequences of electrification also constitutes a promising avenue for future research. The majority of papers so far to our knowledge focus on a limited number of measures of labor supply, for example, employment rates (extensive margin), hours worked (intensive margin), and business ownership. Yet, previous studies rarely address the interplay between electrification and the local employment structure. Does electrification create jobs equally in areas with a large proportion of (non-)agricultural jobs? How are the jobs being created distributed across the formal and informal sectors? Furthermore, little to no attention has been directed toward labor demand. How do local agricultural and nonagricultural firms respond to electrification? Does electrification boost labor productivity (and thus create jobs) through investments in machinery? Finally, the medium- to long-term consequences of electrification still remain unexplored. In particular, improvements in educational outcomes attributable to residential and nonresidential electrification could translate into long-term employment and income gains.
<table>
<thead>
<tr>
<th>AUTHORS</th>
<th>REGION</th>
<th>POLICIES ASSESSED</th>
<th>METHOD</th>
<th>MAIN RESULT</th>
<th>EMPLOYMENT IMPACTS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pai et al. 2021</td>
<td>Global</td>
<td>Paris-compatible “well below 2°C” scenarios</td>
<td>IAM and employment factors</td>
<td>Five million more jobs in the global energy sector.</td>
<td>Net positive for the energy sector</td>
</tr>
<tr>
<td>Popp et al. 2020</td>
<td>United States</td>
<td>2009 American Recovery and Reinvestment Act</td>
<td>Ex post econometric analysis</td>
<td>Fifteen jobs created per $1 million of green ARRA in the long run.</td>
<td>Positive</td>
</tr>
<tr>
<td>Walker 2013</td>
<td>United States</td>
<td>1972 Clean Air Act Amendments</td>
<td>Difference-in-difference</td>
<td>Workers affected by policy suffered 5 percent loss of preregulated earnings.</td>
<td>Negative impact in regulated industries</td>
</tr>
<tr>
<td>Hafstead et al. 2018</td>
<td>Developing economies</td>
<td>Global carbon tax increasing to $160 by 2050</td>
<td>CGE</td>
<td>Job gains in less polluting industries outweigh job losses, but labor market rigidity may impede labor shifts. The aggregate impacts of energy transition on employment are relatively small.</td>
<td>Employment gain offset losses in fossil-fuel-intensive industries</td>
</tr>
<tr>
<td>Muro et al. 2019</td>
<td>United States</td>
<td>Analysis of occupations related to clean energy</td>
<td>Ex post-Difference-in-difference</td>
<td>The average wage in clean energy jobs exceeds the national average by about 10 percent, with a peak of 20 percent in clean energy production.</td>
<td>Positive</td>
</tr>
<tr>
<td>Grafakos et al. 2020</td>
<td>Mexico, Indonesia, and Rwanda</td>
<td>NDCs of each country considered</td>
<td>Input–output</td>
<td>Mexico: Total employment increases by 600,000 jobs compared with BAU. Indonesia: NDC targets result in the creation of 7.2 million job-years. Rwanda: The high-ambition scenario results in the creation of 31,000 direct job-years.</td>
<td>Positive employment impacts proportional to climate policies' ambition</td>
</tr>
<tr>
<td>Sastresa et al. 2010</td>
<td>Spain (Aragon)</td>
<td>Expansion of renewable energy in Aragon</td>
<td>Employment factors</td>
<td>Jobs/MW ratio over the period 1998–2007 is in the range of 1.3 to 5.5—the most recent estimate is on the lower end, at 1.4.</td>
<td>Renewable energy generates between 1.8 and 4 times as many jobs/MW installed as conventional energy sectors</td>
</tr>
<tr>
<td>Van der Zwaan, Cameron, and Kober 2013</td>
<td>Middle East</td>
<td>Paris-compatible 2°C scenario</td>
<td>Bottom-up analysis</td>
<td>Depending on the share of imports for renewable energy equipment, between 155,000 and 400,000 jobs can be created in the Middle East by 2050.</td>
<td>Positive</td>
</tr>
<tr>
<td>World Bank 2022</td>
<td>Pakistan</td>
<td>Government-adopted targets to 2030</td>
<td>Employment factors</td>
<td>Under the more ambitious renewable energy policy scenario, more than 190,000 direct jobs would be created in the renewable energy industry and an additional 137,000 indirect jobs in related sectors.</td>
<td>Positive</td>
</tr>
<tr>
<td>Simas and Pacca 2014</td>
<td>Brazil</td>
<td>Wind power projects from 2010 to 2017</td>
<td>Input–output</td>
<td>Confirmation that direct jobs estimated in terms of job-years/installed capacity tend to overestimate job creation.</td>
<td>N/A</td>
</tr>
</tbody>
</table>
### TABLE 5.1
Synthesis of All Results Reported in the Present Review (Continued)

<table>
<thead>
<tr>
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</thead>
<tbody>
<tr>
<td>Garrett-Peltier 2017</td>
<td>United States</td>
<td>Comparison of $1 million investment in fossil and renewable energy sectors</td>
<td>Input-output</td>
<td>$1 million of demand for renewable energy generates 7.5 FTE jobs (4.5 direct + 3 indirect), with the same amount generating 7.7 FTE jobs in energy efficiency (4.6 direct + 3.1 indirect).</td>
<td>Shifting a $1 billion investment from fossil fuels to renewable energy or energy efficiency would generate a net balance of 5,000 FTEs</td>
</tr>
<tr>
<td>Dai et al. 2016</td>
<td>China</td>
<td>ReMax scenario (renewable energy accounts for 60 percent of the primary energy in 2050)</td>
<td>CGE</td>
<td>Renewable-energy-related activities would represent 3.4 percent of GDP as against 2 percent in the baseline and create 4.12 million jobs in 2050.</td>
<td>Net negative: Very large employment losses in the coal sector not fully compensated by gains in renewable energy sector</td>
</tr>
<tr>
<td>Fragkos and Paroussos 2018</td>
<td>European Union</td>
<td>Target for renewable energy to account for 53 percent of gross final energy demand by 2050</td>
<td>CGE (with bottom-up employment factors)</td>
<td>200,000 additional jobs by 2050 compared with baseline.</td>
<td>Positive</td>
</tr>
<tr>
<td>Yahoo and Othman 2017</td>
<td>Malaysia</td>
<td>CO₂ intensity reduction of 40 percent from 2005 by utilizing (1) a compensated carbon tax and (2) sectoral command and control</td>
<td>CGE</td>
<td>Carbon tax results in 0.60 percent increase in real GDP and 1.55 percent increase in employment across the entire economy, while command and control reduces real GDP by 0.35 percent and decreases employment by 0.75 percent.</td>
<td>Positive for carbon tax Negative for command-and-control policy</td>
</tr>
<tr>
<td>Dinkelman 2011</td>
<td>South Africa</td>
<td>Electrification program (1990s)</td>
<td>Ex post-Instrumental variable</td>
<td>Female employment rate increases significantly, by 9 percentage points (15,000 additional women joining the labor force).</td>
<td>Positive for female employment</td>
</tr>
<tr>
<td>Grogan and Sadanand 2013</td>
<td>Nicaragua</td>
<td>Rural electrification (1971–2005)</td>
<td>Ex post-Instrumental variable</td>
<td>Twenty-three percentage point increase in female propensity to work outside the home.</td>
<td>Positive for female employment</td>
</tr>
<tr>
<td>Grogan 2016</td>
<td>Columbia</td>
<td>Rural electrification (1973–2005)</td>
<td>Ex post-Instrumental variable</td>
<td>No significant effects on female self- or wage employment.</td>
<td>Neutral</td>
</tr>
<tr>
<td>Lipscomb, Mobarak, and Barham 2013</td>
<td>Brazil</td>
<td>Electrification (1960–2000)</td>
<td>Ex post-Instrumental variable</td>
<td>Eighteen percentage point increase in the probability of employment.</td>
<td>Positive</td>
</tr>
<tr>
<td>Burlig and Preonas 2016</td>
<td>India</td>
<td>India's RGGVY program</td>
<td>Ex post-Regression discontinuity</td>
<td>0.7 percent decrease in the share of male agricultural workers and 0.5 percent increase in the share of men employed in the nonagricultural sector.</td>
<td>Neutral</td>
</tr>
</tbody>
</table>

(continues)
### TABLE 5.1
Synthesis of All Results Reported in the Present Review (Continued)

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</tr>
</thead>
<tbody>
<tr>
<td>Fetter and Usmani 2020</td>
<td>India</td>
<td>India's RGGVY program</td>
<td>Ex post-Regression discontinuity</td>
<td>Significant increase in nonagricultural employment in electrified areas simultaneously experiencing a (fracking-related) economic boom.</td>
<td>Positive</td>
</tr>
<tr>
<td>Thomas et al. 2020</td>
<td>India</td>
<td>Rural electrification (2018)</td>
<td>Ex post-Difference-in-indifference</td>
<td>Significant increase in time spent at home for both children's education and adults' work activities.</td>
<td>Neutral</td>
</tr>
<tr>
<td>Lee et al. 2021</td>
<td>Kenya</td>
<td>Rural electrification (2013–17)</td>
<td>Randomized controlled trial</td>
<td>Increased access to electricity did not create any productive use jobs in this particular setting.</td>
<td>Negative</td>
</tr>
<tr>
<td>Barron and Torero 2014</td>
<td>El Salvador</td>
<td>Rural electrification (2009–15)</td>
<td>Randomized controlled trial</td>
<td>Increase in female nonfarm employment and business ownership by 46 and 25 percentage points, respectively.</td>
<td>Positive</td>
</tr>
<tr>
<td>Aklin et al. 2017</td>
<td>India</td>
<td>Rural electrification (2014–15)</td>
<td>Randomized controlled trial</td>
<td>Solar mini grids in India increase electricity consumption by up to 1.4 hours a day but do not significantly increase the time spent working or business creation.</td>
<td>Neutral</td>
</tr>
<tr>
<td>Grimm et al. 2017</td>
<td>Rwanda</td>
<td>Rural electrification (2011–12)</td>
<td>Randomized controlled trial</td>
<td>Solar home kits boost productivity for domestic activities, yet without evidence of productive use jobs being created.</td>
<td>Neutral</td>
</tr>
</tbody>
</table>

**Note:** BAU = business as usual; CGE = computable general equilibrium; CO₂ = carbon dioxide; FTE = full-time equivalent; GDP = gross domestic product; IAM = integrated assessment model; NDC = Nationally Determined Contribution; RGGVY = Rajiv Gandhi Grameen Vidyutikaran Yojana.

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### 5.1 Recommendations for Future Work

In what follows, we provide concrete guidance for future World Bank projects wishing to evaluate the effects of clean energy investments on employment in developing countries.

First and foremost, future projects should embed provisions for data collection as early as possible. Lack of data is the reason behind the paucity of employment impact assessments in the existing literature. This issue is particularly acute in developing economies, where official statistics may not be collected at the level of detail and/or spatial granularity necessary to implement the methodologies outlined in this report.

Specific data collection initiatives could therefore be embedded in future World Bank clean energy projects to facilitate ex post employment impact evaluations. Such initiatives could
span the complexity gamut. They could range from simple surveys conducted in the region of interest before and after an intervention to gauge employment-related metrics at different levels of representativeness, or could have more complex designs allowing for causal identification. The latter could involve surveying the same population in successive rounds in a panel design, all the way to a full-fledged randomized controlled trial. Most importantly, assessing the impact of a clean energy investment program requires at a minimum to establish some ex ante estimate of the status quo at project inception, to provide a reference point.

The present literature review has also revealed a focus on the household-related consequences of electrification in existing contributions and an associated lack of evidence of its impacts on small and medium business creation and development. The Bank could therefore inform both its future assessments of renewable electricity investments and the corresponding research literature at large by funding data collection targeted specifically at the private sector. In particular, joint collection of data with other Global Practices across the Bank should be included at the design stage of investment projects.

Future projects should aim at filling this knowledge gap by looking at how electrification can increase firms’ investments in machinery, augment labor productivity, boost labor demand, and thus create more jobs. This could also shed light on the extent to which business creation (especially microenterprises, which could constitute an important job creation channel from clean energy investments) is encouraged by facilitating electricity access.

The electrification impact assessments presented in the existing literature have mostly been conducted within a year of the interventions when using primary data. This raises an issue, particularly for the evaluation of more structural impacts on the local economy, such as increases in the number of working hours available for nondomestic work, the creation and development of new businesses, or even educational attainment over an even longer time frame. Data collection repeated over a longer time horizon (two, three, or even four years after the initial investment) would constitute an invaluable source of information to understand clean electrification’s medium- and long-term structural effects on employment, even though it would undoubtedly be costly.

Finally, financing a full randomized controlled trial could be considered for one or two specifically chosen projects. Given the cost and complexity involved in an RCT’s design, funding, and execution in a developing country setting, this final recommendation could not be applied to more than a handful few projects. Yet, recent examples in the literature (especially Lee et al. 2021) demonstrate the plausible feasibility of such an assessment. A labor-market-focused RCT would provide the best possible empirical setting to ascertain the causal impacts of clean electricity investments over the widest range of local employment impacts, thus estimating direct, indirect, induced, and productive use jobs simultaneously.

Should this initial trial be successful, a large-scale, coordinated, multicountry evaluation could be envisioned to help provide a comprehensive understanding of electrification’s
impacts, especially regarding the opportunity to create productive use jobs. This project could follow an approach comparable to that of the Graduation Programme evaluated in the seminal multicountry randomized trials of Banerjee et al. (2015). Adopting such a design would greatly improve policy impact, as it would help address both internal and external validity concerns, thus provide a comprehensive evidence foundation for designing future investments. The World Bank is uniquely placed to leverage its convening power to design and implement such an ambitious and cutting-edge project.
References


REFERENCES


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