ABSTRACT

Title of dissertation:	ANALYSIS OF THE LABOR IMPACTS OF CLEAN ENERGY TRANSITIONS IN THE POWER SECTOR IN INDIA Anjali Sharma, Doctor of Philosophy, 2020
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The inevitability of climate action means that India needs to rapidly transition to a low-carbon economy while working towards its development goals. Though considered an emerging economy, India still lags behind on development indicators such as employment generation, and poverty eradication. As creation of 'green jobs' is recognized as an important co-benefit of climate mitigation, clean energy transitions can help India meet both its climate and employment goals. However, assessments of the labor impacts of clean energy transitions for India remain limited. In this dissertation, I explore the case of the power sector in India in detail.

I first assess the economy-wide labor impacts of power generation in India in 2030 under different decarbonization scenarios. I use input-output modeling for this analysis. Second,

I assess the regional distribution of the labor impacts associated with clean energy transitions using a spread-sheet based model. Finally, I assess the distribution of jobs in renewable and fossil-fuel based industries by skills.

My results show that the total job creation in scenarios with accelerated deployment of renewable energy (RE) is relatively lower than business-as-usual scenarios on account of lower total power generation in the former scenarios, and greater economy-wide labor impacts of coal. I also find that the new jobs that are generated in solar and wind sectors will be concentrated in the western and southern parts of India, with 60% of the total jobs being generated in the states of Rajasthan, Gujarat, Andhra Pradesh, Karnataka, and Tamil Nadu. Clean energy transitions would increase the requirement of semi-skilled, and skilled RE workforce, particularly for solar, in these states.

In order to maximize the employment benefits associated with clean energy transitions, the Indian government should design industrial policies to steer domestic manufacturing of clean energy technologies. Coal-rich eastern states should be prioritized as locations for development of new industries to compensate for the clean energy transitions related job, and economic revenue losses. Finally, employment data for energy sector, including renewable technologies, should be collected regularly for a better assessment of the social and economic impacts of clean energy transitions.

ANALYSIS OF THE LABOR IMPACTS OF CLEAN ENERGY TRANSITIONS IN THE POWER SECTOR IN INDIA

by

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List of Abbreviations

CEA	Central Electricity Authority
CEEW	Council on Energy, Environment, and Water
CGE	Computable General Equilibrium
CII	Confederation of Indian Industries
CIL	Coal India Limited
CPI	Climate Policy Initiative
DEI	Distributional Employment Impacts
EPC	Engineer-Procure-Construct
FTE	Full Time Equivalent
GoI	Government of India
I/O	Input-Output
ILO	International Labor Organization
INDC	Intended Nationally Determined Contribution
IPCC	Intergovernmental Panel on Climate Change
IRENA	International Renewable Energy Agency
LCOE	Levelized Cost of Energy
MNRE	Ministry of New and Renewable Energy
NEP	National Electricity Plan
NRDC	National Resources Defense Council
NSQF	National Skills Qualification Framework
O&M	Operations & Maintenance
OECD	Organization for Economic Co-operation and Development
PIB	Press Information Bureau
RE	Renewable Energy
T&D	Transmission and Distribution
TERI	The Energy and Resources Institute
TPP	Thermal Power Plant

1 Introduction

The purpose of this quantitative study is to assess the labor impacts associated with clean energy transitions in the power sector in India. While creation of 'green jobs' is recognized as an important co-benefit of climate action, few studies have looked into the employment impacts of clean energy transitions in India. In this study, I assess the economy-wide labor impacts of power generation in India in 2030 under different decarbonization scenarios. I also examine the regional distribution of these labor impacts, and assess the skill requirements for clean energy transitions in the power sector.

1.1 Background

Though considered a fast-growing economy, India lags behind on development indicators such as poverty eradication, and employment generation. As per the World Bank, 176 million Indians still live under extreme poverty. When measured against a higher poverty line of $3.20 per day per capita, almost 700 million Indians fall below the poverty line (World Bank, 2020). As per another World Bank report, titled 'Jobless Growth', India needs to create more than 8 million jobs every year in order to keep the employment rate[1] constant (World Bank, 2018). In a paper about employment trends in India, the author found that job growth in India has been sluggish, and most of the jobs are available in unorganized sector and offer low wages (Kapoor, 2017). Hence, job growth remains another major challenge in India and there is a need to create decent, well-paying jobs.

[1] Employment rate is the percentage of labor force that is employed.

These challenges are highlighted in the Nationally Determined Contributions (NDC) that India submitted for the Paris Agreement. While India committed to increase the share of non-fossil-fuel based power capacity to 40%, it also argued that climate change makes its development process ‘doubly challenging’ (GoI, 2015). As a significant proportion of its population is highly vulnerable to the impacts of climate change, India needs to achieve its development targets while undertaking climate action in order to safeguard the wellbeing of its citizens. The crucial question is: can India fulfil its development goal of employment generation while transitioning away from fossil fuels?

As per the latest estimates by International Renewable Energy Agency (IRENA), there are more than 11 million renewable energy (RE) jobs worldwide as of 2018 (IRENA, 2019). A recent International Labor Organization (ILO) report estimated that mitigation activities consistent with the 2 deg. target can generate 24 million green jobs across the world by 2030 (ILO, 2018). Across labor impact studies, the general consensus is that clean energy transitions will have a positive impact on employment generation (Garrett-Peltier, 2017; Markandya et al., 2016; Pollin & Chakraborty, 2015; Oliveira et al., 2014; Cai et al., 2011; Wei et al., 2010; Sastresa et al., 2010).

However, most of the studies only focus on estimating the employment impacts of RE technologies. A simultaneous assessment of potential job losses because of the decline in fossil-fuel sectors remains largely missing. Moreover, majority of the academic literature comes from developed countries, and limited work has been done for emerging and developing economies (Cameron & van der Zwaan, 2015). Assessments of ‘distributional labor impacts' i.e. distribution of jobs on the basis of location, gender, education, and skill requirements also remain limited. It is important to study these distributional impacts in order to evaluate whether the current labor force possesses the skills and educational levels that are required for RE sectors (Cai et al., 2014).

The distributional aspects of labor impacts, and concerns of fossil-fuel workers who are likely to lose their jobs in clean energy transitions have received greater attention in academic literature exploring the politics, and justice of energy transitions (Healy & Barry, 2017; Jenkins et al., 2016; Stevis & Felli, 2015; Newell & Mulvaney, 2013). Studies on 'just transitions' form an important body of work on this topic. Just transition is a concept that puts defending and promoting workers' livelihoods at the heart of clean energy transitions. It found mention as one of the guiding principles in the preamble of Paris Agreement where the parties were asked to account for 'just transition of the workforce and the creation of decent work and quality jobs' while working towards climate action. Since 2015, the concept of just transition has gained further traction, and, in fact, was a key theme at the 2018 COP (Conference of Parties) at Katowice, Poland. At this COP, more than 50 leaders and parties across the world signed the Silesia Declaration for Solidarity and Just Transition to highlight political support for the fair transition of workers who are likely to lose their jobs due to climate action.

There is limited data available regarding current and future jobs in RE sectors in India. RE sectors such as solar and wind are not included as separate sectors in employment surveys which makes it difficult to estimate the current level of employment in these industries.

Based on secondary sources such as government, and industry reports, the latest estimates for solar and wind jobs vary between 39,000-115,000 jobs, and 23,000-70,000 jobs respectively (IRENA, 2019; Kuldeep et al., 2019; SCGJ, 2016; MNRE & CII, 2010). The most commonly available employment projections for solar and wind sectors in India are for the year 2022 as India plans to add 175 GW RE capacity by 2022. This target includes 100 GW of solar, and 60 GW of wind capacity. Studies project that between 200,000-800,000 solar and wind jobs will be generated in India by 2022. The estimates across different studies vary widely because of differences in types of jobs accounted for in the analysis, and methodology followed.

Moreover, most of the jobs in RE sectors in India are in construction and installation sectors where the nature of work is transient, and project-based. Although this trend is not particular to India, and has been reported in other countries as well (Cameron & van der Zwaan, 2015), it highlights that a transition away from fossil fuels is likely to generate more temporary than full-time employment.

None of the above-mentioned studies compare their RE job estimates with coal sector jobs in India. While estimates for the total employment in coal sector in India are not available, Coal India Limited (CIL), the agency that produces more than 80% of the coal in India, has around 300,000 workers on its payroll (CIL, 2019). These job numbers do not cover all those who are directly employed in the coal sector in India, particularly those who work on contract-basis. Thus, this statistic is likely to be an under-estimate of the total number of direct jobs in the coal sector in India. Nonetheless, these coal job numbers are comparable to the ~330,000 direct jobs that are projected to be generated due to the addition of 160 GW of solar and wind capacity in India by 2022 (Kuldeep et al., 2019). Although India does not plan to shut down its coal mines by 2022, it is important to assess the total employment in coal sector in India. Coal mining workers are likely to lose their jobs in the medium- and long-term i.e. 2030 and beyond, if not immediately, as India transitions to a low-carbon economy. Transitioning away from coal is also likely to have a pronounced impact on other sectors and workers of the economy that are indirectly associated with coal sectors, for eg. railways, as it depends on coal for a significant proportion of its freight.

1.2 Statement of the problem

The labor impacts of clean energy transitions remain poorly understood in the Indian context. Particularly, questions such as impacts of clean energy transitions on the coal sector remain unanswered. Given that almost 3/4th of the total power generated in India still comes from coal, clean energy transition can result in substantial job losses in India because of the decline in coal sector. Moreover, transition to low-carbon energy systems can result in regional inequalities in India. Majority of the coal mines are located in the eastern part of the country, whereas, most of the high quality solar and wind potential has been identified in western and southern India (Deshmukh et al., 2017). This indicates a mismatch in the locations of potential job gains and losses due to clean energy transitions in India. However, studies on the distributional labor impacts of clean energy transitions also remain limited for India.

Assessment of the labor impacts of clean energy transitions is important in order to evaluate the employment generation potential of RE industries. This is crucial for India as employment generation remains an important development challenge in the country. It is also important to evaluate whether green industries will be able to compensate for the job losses in coal sector due to clean energy transitions. Moreover, assessment of the distribution of these labor impacts on the basis of location, and skill requirements is a necessary first step towards designing just transition policies and fulfilling one of the primary objectives of these policies i.e. providing compensation and economic opportunities to those who will be losing out in clean energy transitions.

In this study, I assess the labor impacts associated with clean energy transitions in the power sector in India. I focus on the power sector, which is the biggest source of GHG emissions in India. Decarbonizing the power sector is central to India's current climate mitigation strategy. As per India's Nationally Determined Contribution (NDC) to the Paris Agreement, India plans to increase the share of renewable energy (including nuclear) in its total installed power capacity to 40% by the year 2030.

1.3 Conceptual framework

Figure 1 presents a conceptual framework that can be used to understand the labor impacts associated with clean energy transitions. This framework accounts for two types of labor impacts: a) jobs that are created because of new RE technology, b) jobs that are lost in the process of setting up new RE-based plants, and due to the closure of fossil-fuel based plants.

Addition of new RE technologies leads to job gains. These job gains can be categorized as direct, and indirect jobs. The job impacts can also include induced jobs but I have only represented direct and indirect jobs here for the sake of simplicity (the definitions of these job types are presented in section 1.7). Direct jobs are those jobs that constitute the "core activities" of RE technologies. These jobs tend be local jobs. For example, when a new RE power plant is built, the direct jobs that are generated as a result of it, such as jobs in construction, installation, and maintenance of the power plant, are located at the plant site. Indirect jobs i.e. jobs that are generated in other sectors of the economy because of the construction of that RE power plant can be both local and non-local. Construction of RE power plant is likely to increase demand for raw materials such as glass and steel. If there are industries near the RE plant site that can provide these raw materials, the new indirect jobs generated in these sectors can be categorized as local. Otherwise, the indirect jobs will be non-local.

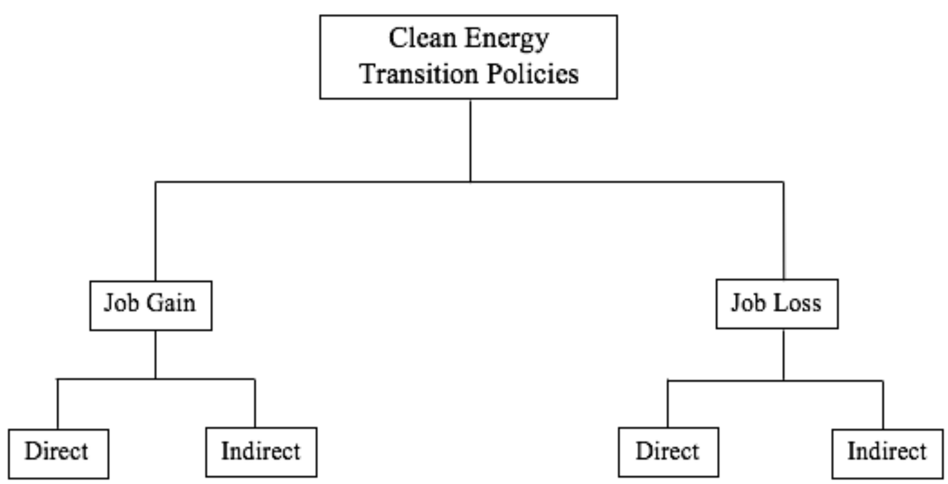

Figure 1.1**:** Analytical framework for labor impacts of clean energy transitions

Addition of new RE technologies can also lead to job losses. Setting up new power plants requires land. This can lead to closure of common lands or acquisition of farm lands, and as a result impact the livelihoods of those dependent on them (Yenneti et al., 2016). Since these job losses are in sectors other than the core RE sectors, I categorize them as indirect job losses due to clean energy transitions. Moreover, land-related job losses are local as they happen at the site of the new RE plants.

Jobs are also lost when fossil-fuel based operations get shutdown because of clean technologies. The labor impact in this case can also be categorized as direct, and indirect jobs. For example, shutting down of a thermal power plants will lead to a loss of local jobs in areas where people are directly employed in the sector such as coal mining, and operating the thermal power plants. But the shutdown of the thermal power plants will negatively impact other sectors of the economy as well. This includes sectors that provide raw materials or services for the operation of the thermal power plant. I categorize these losses as indirect job losses.

While new RE technology does not always replace fossil-fuel based technology, as is the case of power sector in India, I have included the possibility of closure of fossil-fuel based plants in this framework to account for all the probable labor impacts associated with clean energy transitions. The framework in figure 1.1 does not account for job gains due to addition of new thermal capacity as the primary focus of the framework is to highlight the labor impacts associated with clean energy transition policies i.e. policies aimed at reducing carbon emissions. However, it could be the case that while new RE capacity is being installed, it does not replace fossil-fuel based capacity, and new thermal capacity continues to get installed as well because of financial and technical reasons. This is the case for India as per the National Electricity Plan 2018. I take these fossil-fuel based capacity additions into account for the analysis in this study.

1.4 Research questions

In this study, I followed three-paper format to address the over-arching research question: What are the labor impacts of clean energy transitions in the power sector in India?

The three research questions explored are as follows:

1. Will clean energy transitions in the power sector lead to net employment generation in India under different decarbonization scenarios?
2. What is the spatial distribution of the labor impacts associated with clean energy transitions in the power sector in India?
3. What are the skill requirements for the labor impacts associated with clean energy transitions in the power sector in India?

1.5 Overview of methods and results

The following table presents an overview of the methodology followed for the three papers, and their results.

Table 1.1: Overview of methods and results for chapters 2,3 and 4

	Chapter 2	**Chapter 3**	**Chapter 4**
Research Question	Will clean energy transitions in the power sector lead to	What will be the spatial distribution of the labor impacts	What will be the skill requirements for the labor

	net employment generation in India?	associated with clean energy transitions in the power sector in India?	impacts associated with clean energy transitions in the power sector in India?
Labor impacts studied	Total direct and indirect labor impacts associated with power generation in India in 2030 under different decarbonization scenarios.	Changes in state-level direct jobs associated with coal, solar, and wind sectors in India on account of changes in installed capacity between 2017 and 2027.	Skill requirements for direct jobs under two scenarios: business-as-usual ('ref'), accelerated deployment of RE ('pol') – for the year 2027. State-wise share of skill requirements for direct jobs in solar and wind sectors.
Method	Input-output analysis	Spreadsheet based model	Spreadsheet based model
Results	Job creation in scenarios with accelerated RE deployment is relatively lower than business-as-usual scenarios on account of lower total power generation in the former scenarios, and greater economy-wide labor impacts associated with the coal sector. Even with accelerated RE	2027 target of installing 250 GW of solar and wind capacity will generate jobs primarily in western and southern parts of India as 60% of the total jobs will be located in the states of Maharashtra, Rajasthan, Gujarat, Tamil Nadu, Andhra Pradesh, and Karnataka.	Under both ref and pol scenarios, majority of the jobs in the power sector are created in the 'skilled' category i.e. jobs that require short- or long-term diplomas or graduate degrees. Clean energy transitions will increase the requirement of semi-skilled, and skilled jobs in the solar sector (i.e.

	deployment, coal jobs constitute 65-75% of the total jobs from power generation in 2030. Estimates for total number of jobs from solar PV under different scenarios with accelerated RE deployment vary between 1.2-3.3 million, whereas wind jobs vary between 0.3-0.4 million.	If plans for net coal capacity addition are also taken into account, overall job gains are relatively higher for coal-rich states - such as Chhattisgarh, Odisha, Jharkhand, and Madhya Pradesh - highlighting that coal sector is a major source of employment in power sector in India.	jobs at NSQF levels 1-5). States of Maharashtra, Rajasthan, Gujarat, Tamil Nadu, Andhra Pradesh, and Karnataka should be considered the priority locations for setting up RE training institutes.
Research Contribution	First time assessment of direct and indirect jobs associated with electricity generation in India under different decarbonization scenarios.	Constructed a generalizable analytical framework to assess the spatial distribution of the labor impacts of clean energy transitions.	First step towards building a standardized framework for the skills requirement for power sector jobs in India.

1.6 Research and policy contributions of the study

This study is aimed at understanding the labor impacts associated with clean energy transitions in India, and addressing a couple of crucial gaps in the academic literature on this topic for India – i) impact of clean energy transitions on the employment associated with electricity generation under different decarbonization scenarios, and ii) distribution of the clean energy labor impacts in India on the basis of location, and skills.

In chapter 2, I conducted scenario analysis to explore the labor impacts from power generation in India in 2030 under different decarbonization scenarios. Projections for the labor impact of clean energy transitions in India remain largely limited to estimates of direct jobs in solar and wind sectors. As coal constitutes majority of the power generation mix in India, it is important to include coal sector in the labor analysis as well. Moreover, it is important to assess both direct as well as indirect labor impacts, as done in this chapter.

Chapter 3 and 4 add to the limited academic literature on the distributional labor impacts of clean energy transitions for India. In chapter 3, I constructed an analytical framework to assess the spatial distribution of the labor impacts of clean energy transitions in the power sector. This framework can be used in the context of other industries or countries as well. For example, labor impacts of shifting manufacturing from petrol/diesel based vehicles to electric vehicles for any specific region can be explored using the analytical framework. This can be helpful assessing the spatial inequalities that are likely to accompany clean energy transitions, and plan appropriate just transition plans especially for the negatively affected communities. In chapter 4, using secondary data sources, I first constructed a database of power sector jobs in coal, solar, and wind sectors. I then arrived at the distribution of these jobs across three skill categories – semi-skilled, skilled, and high-skilled – using the National Skill Qualification Framework (NSQF) for India.

An important point to note is that the target year for the input-output analysis done in chapter 2 is 2030, whereas the target year for the distributional labor impact analyses done in chapters 3 and 4 is 2027. For the input-output modeling based study in chapter 2, I required projections for source-wise electricity generation in India for the scenario analysis. I relied on secondary literature on electricity supply projections for the year 2030 for this analysis. For the distributional labor impact analyses in chapters 3 and 4, I required projections or plans for power capacity installation by energy source and state. I relied on Government of India's National Electricity Plan (NEP) for this analysis. As the NEP outlines the trajectory for India's power sector till the year 2027, the target year of analysis for chapters 3, and 4 is 2027.

Results of the input-output analysis done in chapter 2 suggest that the employment gains associated with RE-heavy scenarios is likely to be lower in comparison to coal-heavy business as usual scenarios in India. These results highlight that the direct and indirect jobs associated with electricity generation from cleaner sources of such as solar, and wind are unlikely to compensate for the jobs associated with electricity generation from coal in India. Hence, it is important to broaden the scope of sectors and strategies than can help India meet its twin targets of clean energy transitions, and employment generation. Some sectors that are not included in the analysis in this study are energy efficiency, and manufacturing of clean energy equipment which implies that the estimates for total number of job gains associated with clean energy transitions are likely to be an underestimate in this study. Inclusion of these sectors can provide a more comprehensive analysis.

However, while employment analysis of scenarios involving increased domestic manufacturing of RE technology is important, it should be noted that some of the major policies followed by the Indian government to boost RE manufacturing, such as Domestic

Content Requirement (DCR), have not been able to deliver expected outcomes. In the case of solar energy, DCR has not resulted in globally competitive solar PV manufacturing in India. In fact, DCR-focused policies resulted in leakage to thin-film cells, and trade disputes at WTO that have forced India to reassess its DCR strategy. Researchers have argued that instead of solely focusing on price distortion mechanisms to stimulate solar manufacturing, the focus should be on broader industrial policies such as improving India's innovation and R&D capacities.

As per World Bank, India's total workforce stands at ~500 million in 2019, and India needs to generate ~10 million jobs annually till 2030 to provide employment to its growing working age population (FICCI, 2018). Assessing the projections of 13-16 million total jobs in the power sector in year 2030 (under RE heavy scenarios) in the light of the overall employment target for the Indian economy suggests that electricity generation constitutes a small proportion of the total number of jobs in India. Hence, meeting the overall employment target for the Indian economy requires policies that can help develop labor-intensive sectors such as the manufacturing sector.

Results of the distributional labor impact analysis from chapters 3, and 4 suggest that as India retires its thermal capacity, it will result in direct as well as indirect job losses in the coal-rich eastern states, particularly in the coal mining sector. In addition to job loss, the decline of coal sector will also reduce the royalties that are obtained from coal mining, negatively impacting the GDP of coal-rich states. Coal-rich eastern states would require government support in order to provide compensation and economic opportunities to the workers who will be losing out in the clean energy transitions

Moreover, accelerated deployment of RE will increase the skill requirements, particularly for solar jobs at NSQF levels 1-5, in India. However, at the same time, clean energy transitions will decrease the requirement of semi-skilled, and skilled jobs associated with coal mining, and operating TPPs. In the semi-skilled category, it might be possible for the workers in non-green jobs to transition to green jobs as these jobs do not require vocational education, and can be performed by anyone with education level below Xth standard. However, an important challenge for this transition would be 'location'. The semi-skilled workers, especially in the coal mining sector, who will be losing jobs because of clean energy transitions are unlikely to be located in the same states which hold the highest potential from solar and wind jobs as highlighted in chapter 3. Because of these spatial differences, it is unlikely that these semi-skilled workers working in non-green jobs can be seamlessly absorbed in the green industries, and thus would require retraining or skill upgradation in order to find work in other industries. An important strategy could be to prioritize development of new industries in the regions that are expected to lose out jobs, and revenue due to the transition away from coal.

1.7 Limitations

For the analysis in chapter 2, an important drawback of using the input-output (I/O) methodology is that input-output tables are 'static'. An I/O table is prepared based on the data for a particular year. The structure of industries in I/O tables does not change as coefficients in matrix remain fixed. Moreover, it is also assumed that relative prices remain fixed. This means the static I/O models do not allow for input substitution even if a different and cheaper mixture of inputs becomes available. For the scenario analysis done in chapter 2, in order to make projections for 2030, I updated the electricity sector of the available 2015 input-output table for the target year of analysis i.e. 2030. However, by only updating the electricity sector coefficients, I assumed the coefficients for other sectors of the economy to remain static between 2015 and 2030. As calculations that are done based on current coefficients fail to take into account emergence of new production methods, or the technological advancements that might happen in the future, this is an important drawback of this analysis.

For the spatial analysis in chapter 3, an important limitation is that it does not account for the indirect labor impacts associated with clean energy transitions. I only estimated 'direct' labor impacts using technology-specific employment factors in this chapter. The trends of labor impacts might change if the indirect impacts are also taken into account.

I constructed a spreadsheet based model for the analysis and relied on secondary data sources for employment factors to estimate the labor impacts. However, for each technology, only single point estimates were available for employment factors. The results would have been more robust if a range employment factors, based on assessment of employment requirements in different sub-national regions or projects, was available, and used for the analysis.

Finally, for the analysis in chapter 4, an important limitation of this study is that I could not construct NSQF-based job database for the direct jobs at thermal power plants due to the unavailability of data. Building a database for thermal power plant jobs, on lines with the one constructed for mining, solar, and wind jobs would have been useful in understanding the differences in the skill requirements for non-green, and green jobs in the power sector in India. It can, in turn, help assess the potential of transition from coal to solar/wind jobs, and evaluate the retraining requirements as well.

1.8 Future work

An important direction of future work on the topic of labor impact of clean energy transitions is primary data collection, and assessment of direct, and indirect jobs in both renewable energy, as well as the coal sector in India. It is important to collect data on the magnitude, and nature of employment in the energy sector in order to better assess the economic, and social impacts of clean energy transitions.

In the light of covid19, as governments across the world design policies for economic recovery, especially to increase domestic employment opportunities, this study has some useful insights to offer. An important point to note is that the employment benefits associated with installation of RE technologies such as solar and wind in the power sector are largely limited to short-term jobs in sectors such as installation and construction in the absence of strong domestic manufacturing base. Policy packages that are aimed at improving employment prospects using green industries should be informed by studies that look into the economy-wide job gains, as well as losses, expected due to the growth in renewable sectors, and a simultaneous decline in fossil-fuel industries.

Moreover, the analytical framework presented in this study to assess the spatial distribution of the labor impacts associated with clean energy transitions can be used for assessment of other renewable technologies such as electric vehicles as well.

1.9 Definition of terms

Direct Jobs – These jobs constitute the 'core activities' of the RE sectors such as construction and maintenance of new RE power plants.

Indirect Jobs – Indirect jobs are the jobs in upstream sectors that support the 'core activities' of RE sectors. For example, construction of a new solar power plant would require intermediate inputs such as steel and glass. Although those working in steel or glass industries would not identify as being employed in the RE industry, they do produce the inputs necessary for the industry. Such jobs get classified as 'indirect jobs'.

Induced Jobs – Induced jobs are those jobs that are generated in the economy due to the income spending of those that are directly or indirectly involved in RE sectors.

Person-years per MW - One person-year implies full-time employment of one person for one year. The 'person-year per MW' metric is used to account for short-term or one-time jobs such as jobs in manufacturing, construction, and installation phases of RE development. Jobs in these sectors are only required in initial phases, until a power plant is ready for operation

Jobs per MW – Jobs in activities such as O&M of the RE power plant require the workers to be employed throughout the year, and usually last for the lifetime of a power plant. Such jobs are considered long-term or full-time jobs, and are estimated using the jobs per MW metric.

1.10 Organization of study

In chapter 2, I present the analysis of the direct and indirect jobs from power generation in India in 2030 under different decarbonization scenarios.

In chapter 3, I present the analysis of the spatial distribution of the labor impacts associated with clean energy transitions in India.

In chapter 4, I present the analysis of the skill requirements for the labor impacts associated with clean energy transitions in India.

Finally, the conclusions are summarized in chapter 5.

2 Input-Output Analysis of the Labor Impacts of Clean Energy Transitions

2.1 Abstract

This paper presents an analysis of the impact of clean energy transitions on employment generation in India. The inevitability of climate action means that India needs to rapidly transition to a low-carbon economy while working towards its development goals. In this paper, I specifically look at the development target of employment generation, and explore the labor impacts of clean energy transitions in the power sector. The Indian government has announced ambitious plans for renewable energy deployment in the country. However, data on current levels of employment in renewable energy (RE) sectors remains scarce and scattered. Moreover, employment projection studies for the power sector mainly focus on estimating direct employment in solar and wind sectors, and do not provide economy-wide projections for the whole power sector.

In this paper, I first present a review of the labor estimates RE sectors in India, based on primary and secondary data sources such as industry surveys, and government reports. Then, I present estimates for economy-wide employment from power generation in India for the year 2030 under different decarbonization scenarios. The results show that that the total job creation in scenarios with accelerated RE deployment is relatively lower than business-as-usual scenarios on account of lower total power generation in the former scenarios, and greater economy-wide labor impacts associated with the coal sector. Moreover, even with accelerated RE deployment, coal jobs constitute 65-75% of the total jobs from power generation as coal remains the major fuel for power generation in India for the next decade. Majority of the jobs in RE sectors are created from solar generation.

Estimates for total number of jobs from solar PV under different scenarios with accelerated RE deployment vary between 1.2-3.3 million, whereas wind jobs vary between 0.3-0.4 million.

Key words: green jobs, input-output, power sector, energy transitions, India

2.2 Introduction

In the past few years, India's renewable energy policies have drawn enormous attention and optimism across the world. In 2015, the Indian government stepped up its solar capacity addition targets by five times, committing to install a total of 100 GW of solar energy by 2022. The overall target is to add 175 GW of renewable energy by 2022 & 275 GW by 2027, and become one of the largest producers of green energy in the world (PIB, 2015).

However, this massive addition of clean energy will take place as India works towards its development goals. Though considered a fast-growing economy, India lags behind on development indicators such as poverty eradication, and employment generation. These challenges are repeatedly highlighted in the INDC (Intended Nationally Determined Contributions) that India submitted to the UNFCCC in 2015. In its INDC, India argued that climate change makes India's development process 'doubly challenging'. However, the Indian government also recognizes that a significant proportion of its population is highly vulnerable to the impacts of climate change (GoI, 2015). India needs to achieve its development targets while undertaking climate action in order to safeguard the wellbeing of its citizens.

In this paper, I focus on the goal of employment generation. Creation of 'green jobs' is now recognized as an important co-benefit of climate mitigation. As per the latest estimates by IRENA, an agency that provides annual reviews of jobs in RE sectors, there are more than 11 million RE jobs worldwide as of 2018 (IRENA, 2019). A recent ILO report estimated that mitigation activities consistent with the 2 deg. target can generate 24 million green jobs across the world by 2030 (ILO, 2018). These positive outlooks regarding green jobs suggest that climate action can help India meet both its climate mitigation as well as employment goals. However, assessments of the labor impacts associated with clean energy transitions remain limited for India. Hence, in this paper, I explore the question: will clean energy transitions in the power sector in India lead to net employment generation?

I first present a review of the labor estimates RE sectors in India, based on primary and secondary data sources such as industry surveys, and government reports. Then, I present estimates for economy-wide employment from power generation in India for the year 2030 under different decarbonization scenarios. I use input-output modeling for the scenario analysis. The results show that that the total job creation in scenarios with accelerated deployment of RE is relatively lower than business-as-usual scenarios on account of lower total power generation in the former scenarios, and greater economy-wide labor impacts associated with coal sector. Moreover, even with accelerated RE deployment, coal jobs constitute 65-75% of the total jobs from power generation as coal remains the major fuel for power generation in India for the next decade. Majority of the jobs in RE sectors are created from solar generation. Estimates for total number of jobs from solar PV under different scenarios with accelerated RE deployment vary between 1.2-3.3 million, whereas wind jobs vary between 0.3-0.4 million. These results suggest that clean energy transitions in the power sector in India are unlikely to result in net employment generation by 2030. While the magnitude and share of jobs in the RE sectors such as solar and wind will increase substantially by 2030, coal will account for 65-75% of the total jobs in the power generation sector in 2030.

In the next section, I present a review of the literature on the labor impacts of clean energy transitions. In section 2.4, I present the analytic framework for the input-output modeling used for the analysis. I present the methodology in section 2.5, and present the results in section 2.6. In section 2.7, I discuss the findings, and finally present the conclusions and policy implications in section 2.8.

2.3 Literature Review

2.3.1 Overview of labor impact studies

Academic literature generally provides an optimistic assessment of the labor impacts of clean energy transitions. There are three commonly used methodologies for the estimation of job creation associated with RE technologies – Analytic, Input-Output (I/O) Modeling, and Computational General Equilibrium (CGE) Modeling. Majority of the studies focus only on power sector as this sector holds potential for rapid decarbonization.

Most of the labor impact studies only estimate job creation in RE sectors, and do not provide estimates for labor impacts in the fossil-fuel sectors. Moreover, due to differences in assumptions and methodologies, job estimates associated with different RE technologies vary widely across studies (Cameron & van der Zwaan, 2015). These differences make it difficult to compare job estimates across studies. Using an Excel-based analytical model, Wei et al. (2010) found that aggressive energy efficiency policies and 30% renewable energy portfolio standards (RPS) could generate 4 million job-years[2] in the US by 2030. Another US focused study based on I/O modeling found that an additional investment of 1 million dollars in renewable or energy efficiency sectors creates around 8 full-time equivalent (FTE) jobs. This was found to be higher than fossil-fuel sectors as they created only 3 FTE jobs for every additional 1 million dollars (Garrett-Peltier, 2017). Lehr et al. (2012) predicted that high exports in combination with high PV expansion can add more than 200,000 jobs to the German economy by 2030. In an I/O modeling based analysis of the employment impacts of RETs in the EU between 1995 and 2009, Markandya et al. (2016) found that RE expansion led to a net employment generation of 530,000 across the EU. Oliveira et al. (2014) analyzed the employment impacts of building retrofitting measures using I/O analysis for Portugal, and concluded that it would lead to net employment generation. Using primary data from a single community in Spain, Sastresa et al. (2010) found that each MW of solar PV generated about 40 jobs in the region in 2007. Cai et al. (2011) investigated the employment impacts of mitigation policies in China using

[2] One job-year (or person-year or Full Time Equivalent (FTE)) means full-time employment of one person for one year.

I/O analysis and concluded that these policies lead to a net gain of 472,000 jobs between 2006 and 2010. Pollin & Chakraborty (2015) analyzed the employment potential of RETs using I/O modeling for India and concluded that India can generate 12 million jobs in the next 20 years by investing 1.5% of its GDP in renewable energy and energy efficiency programs.

While there exists substantial empirical evidence for the job creation potential of RE technologies, researchers have argued that the high job growth estimates could be a result of overly optimistic assumptions and selective reporting in some cases (Lambert & Silva, 2012).

It is important to highlight the methodological differences in labor impact studies in order to communicate the job estimates in a transparent manner. Hence, in the next sub-section, I list some important reasons for variations in estimates of labor impacts of clean energy transitions or 'green jobs' across studies.

2.3.2 Reasons for variations in green jobs estimates

Variations due to types of jobs accounted for

Jobs generated through RE technologies can be classified into three categories – direct, indirect, and induced jobs. As per IRENA, these jobs can be broadly defined as follows (IRENA, 2012):

- *Direct Jobs* – These jobs are directly related to RE sectors such as construction of RE power plants, and their operation and maintenance. It does not include jobs that are generated in producing the intermediate inputs that are necessary for RE sectors.

- *Indirect Jobs* – Indirect jobs are associated with upstream industries that supply and support deployment of RE technologies. For example, these jobs can include production of steel, plastic or provision of financial services.
- *Induced Jobs* – Induced jobs are the jobs that are created because of the income spending by people who have direct or indirect employment with RE sectors.

The types of jobs that are accounted for in a study depend on the methodology used for analysis. The choice of method, in turn, is informed by availability of data for the region of analysis.

Variations due to methodology

Studies on the labor estimates associated with clean energy transitions rely on the following three methodologies – Analytic method, Input-Output modeling, and Computational General Equilibrium (CGE) modeling.

Analytical studies are spreadsheet based models. Using surveys or secondary data sources, information on employment factors (EF) i.e. jobs per MW is collected. These studies are primarily focused on calculating direct jobs.

Input-Output Modeling based studies use input-output tables to estimate all three kinds of employment – direct, indirect, and induced. An input-output table represents the production process of each sector of the economy through a vector of coefficients. It provides information on intermediate inputs used by different sectors of the economy, as well as their total outputs. ‘Employment Multipliers’, i.e. employment/output ratio for each sector of the economy, are used to calculate the employment that is generated as a result of a change in the output of a particular industry.

In CGE-based studies, general equilibrium models are used for analysis. Like I/O studies, these models can also estimate all three kinds of employment. While I/O tables form the foundation of CGE models, these models also incorporate price changes and utility maximization of households (Perrier & Quirion, 2018).

One major reason for variation in green job estimates is because of the methodology used for analysis. Studies that rely on analytical method tend to focus on direct jobs only and thus, are more likely to arrive at lower employment estimates in comparison to input-output models (Cameron & van der Zwaan, 2015). Moreover, variations in estimates can also arise due to differences in scope, assumptions, and data sources used for the studies (Simas & Pacca, 2014). While input-output models can be used to calculate all three kinds of employment, some studies only focus on direct and indirect employment impacts (Cai et al., 2014), while others calculate all three kinds of employment (Tourkolias & Mirasgedis, 2011) . I/O and CGE based studies generally carry out analysis at national level, making use of national level investment and employment statistics from secondary sources. Analytic methods tend to rely on primary data collected from a particular region, and provide estimates for that region only. Differences in estimates can also arise based on location of data collection, as well as the year in which data was collected. Moreover, it is highly unlikely for OECD and non-OECD countries to have similar levels of technological and labor conditions for production. Employment estimates can vary widely across countries, and national circumstances should be taken into account while making country-level comparisons.

Variations due to metrics used

Two kinds of metrics are used to report the results of labor impact studies:

Person-years or Job-years per MW - Person-year or job-year metric is used to indicate full-time employment of one person for one year. This metric is generally used to normalize employment numbers for jobs that are temporary or short-term in nature such as jobs in manufacturing, construction, and installation phases of RE power plants.[3]

Jobs per MW – This metric is used to account for jobs that employ people throughout the year, and last for the entire lifetime of a power plant such as jobs in operation and maintenance of power plants.

Variations arise in job estimates associated with RETs across different studies as studies do not distinguish jobs based duration i.e. whether they are short-term or long-term, and use 'person-years per MW' & 'jobs/MW' interchangeably (Cameron & van der Zwaan, 2015).

2.3.3 Green jobs in India

There is limited data available regarding current and future jobs in RE sectors in India. RE sectors such as solar and wind are not included as separate sectors in employment surveys in India which makes it difficult to estimate the current level of employment in these industries. In figure 2.1, I present the latest estimates for employment in solar and wind

[3] For example, it could be the case that 6 people were employed during the construction phase of a solar power plant of 1 MW capacity but all those jobs only lasted 2 months. While the construction phase employed 6 people, only 1 person-year/MW was required for the construction of that power plant. All those 6 workers only got employed for 2 months in that power plant.

sectors in India, based on selected secondary data sources. In appendix A1, I present a list of academic, and grey literature on green jobs available for India.

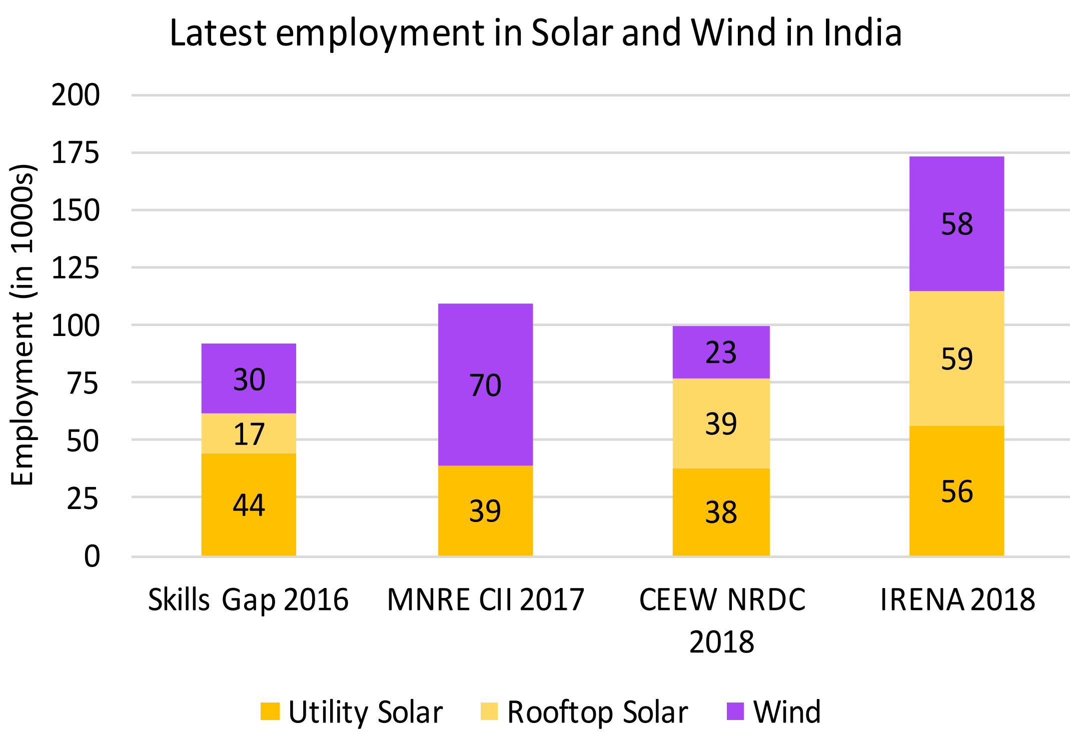

Figure 2.1: Latest job estimates for solar and wind in India

These estimates are as per three reports – Skills Gap report (SCGJ, 2016); (MNRE & CII, 2010); (Kuldeep et al., 2019); and (IRENA, 2019). The year in the x-axis along with the name of the report refers to the year for which employment estimate is provided. The Skills Gap provides estimates for 2016; MNRE & CII (2010) has projections for 2017; and the estimates provided in Kuldeep et al. (2019), and IRENA (2019) are for the year 2018.

It can be observed from figure 1 that the latest estimates for solar and wind jobs vary between 39,000-115,000 jobs, and 23,000-70,000 jobs respectively. While all these studies focus on estimating direct jobs in the RE sectors, their estimates vary because of differences in methodology, and the year for which the estimates are provided. The Skills Gap report provides employment estimates for the year 2016, MNRE & CII report provides estimates for 2017, and CEEW & NRDC, and IRENA reports provide estimates for 2018. However, even for the same year 2018, it can be observed that the job estimates from CEEW & NRDC, and IRENA reports for solar and wind sectors vary by 38,000 jobs and 35,000 jobs respectively. The variations in estimates across different studies arise from the factors discussed in section 2.3.2.

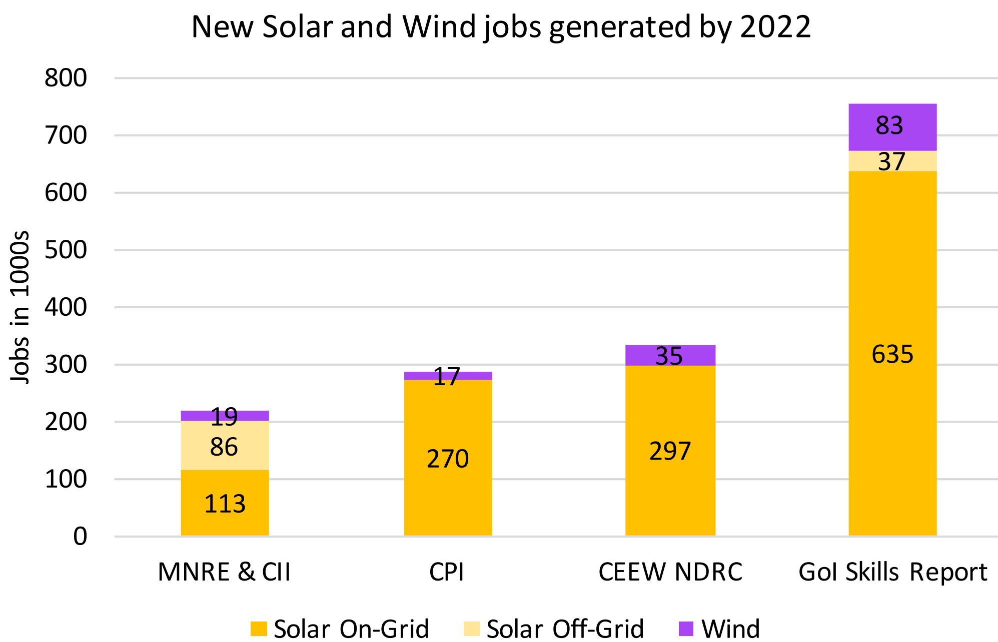

Figure 2.2: New jobs generated in solar and wind sectors by 2022

Figure 2.2 shows the employment estimates for the 175 GW RE capacity addition target set by government of India for the year 2022. This target includes 100 GW of solar, and 60 GW of wind capacity. The most commonly available employment projections for solar and wind sectors in India are for the year 2022 for the 160 GW capacity addition target.

From figure 2.2, it can be observed that not all studies account for the solar sector in the same manner. While the think-tanks CEEW & NRDC (Kuldeep et al., 2019), and CPI

(Mehra et al., 2018) provide estimates only for grid-connected solar, the MNRE & CII (2010), and Skills Gap (SCGJ, 2016) reports provide estimates for both on-grid and off-grid solar.

It can also be observed that estimates for employment generation by 2022 vary widely. Job projections from Skills Gap report are almost double of what has been projected by CEEW & NRDC, resulting in a difference of almost 300,000 jobs between their estimates.

Figures 2.1 and 2.2 highlight that studies on current levels of green jobs, and projections for future based remain limited. Also, majority of the employment estimates only account for direct jobs in the RE sectors. Estimates of indirect jobs, in addition to direct job estimates, can provide a better assessment of the employment potential of RE technologies. Moreover, in order to understand the economy-wide labor impacts of clean energy transitions in the power sector, it is important to study the labor impacts associated with all the fuels used for power generation, and not just solar and wind. I address both these gaps in this paper, and conduct an input-output modeling based scenario analysis to study the labor impacts associated with clean energy transitions in the power sector in India.

2.4 Methodology

I used input-output modeling to assess the labor impacts of clean energy transitions under different power sector decarbonization scenarios. I focused on employment impacts due to electricity generation in this paper. Input-Output (I/O) modeling allows for the assessment of both direct and indirect labor impacts. I used EXIOBASE input-output tables for the year 2015 for the analysis (Wood et al., 2015). While the Statistics ministry of the Government of India (GoI) also prepares detailed national-level input-output tables, the most recent table available is for the year 2008. Hence, I used EXIOBASE input-output table which is available for a more recent year i.e. 2015, and provides disaggregated data for 163 industries for India. As the EXIOBASE table captures different sources of electricity generation separately, labor impact analysis for different generation technologies can be carried out without modifying the input-output table. This is not always the case – for example, in the case of input-output tables prepared by GoI, electricity generation, transmission, and distribution are all combined together under an aggregate 'electricity' sector. To estimate technology-wise labor impact in this case, the first step would be to split aggregate electricity sector into separate sectors for different technologies such as coal, solar, wind and others.

2.4.1 Details of input-output modeling

The basic structure of an Input-Output table represents the production process of each sector of the economy. It is a matrix where columns represent all the inputs that are used to produce the output of particular industries. Each row shows the flow of output for intermediate consumption and final use. There is one fundamental equation for I/O models:

$$x - Ax = y \tag{1}$$

Equation (1) can also be written as:

$$(I-A)\, x = y \tag{2}$$

$$x = (I-A)^{-1} y \tag{3}$$

Equation 1 implies that the proportion of gross output 'x' that is not used in the course of production (i.e. for intermediate consumption) is left for final deliveries 'y'. 'A' is a square matrix, and each coefficient 'a_{ij}' represents the amount of input 'i' required to produce one unit of output 'j'.

Matrix $(I-A)^{-1} = L = [l_{ij}]$ in equation 3 is called Leontief Inverse (Miller & Blair, 2009). Each element of Leontief Inverse matrix represents the total amount of goods and services 'i' that are required to deliver one unit good or service 'j'.

One big drawback of using this methodology is that input-output tables are 'static'. An input-output table is prepared based on the data for a particular year. The structure of industries in I/O tables does not change as coefficients in matrix A remain fixed. Moreover, it is also assumed that relative prices remain fixed. This means the static I/O models do not allow for input substitution even if a different and cheaper mixture of inputs becomes available. Calculations that are done based on current coefficients could fail to take into account emergence of new production methods, or the technological advancements that might happen in the future (Lambert & Silva, 2012). Given these assumptions, it is challenging to make long-term projections using I/O models. They are most suitable for analyzing current and short-term scenarios.

I take this drawback into account for the analysis. To work around the challenge of 'static' nature of input-output tables, I updated the coefficients for the sector most relevant for the analysis, i.e. the electricity sector, for the target year of analysis. Updating coefficients only for one sector i.e. electricity sector implies that the assumption of static structure still holds for other sectors of the economy, and this remains a drawback of this analysis. The target year for the analysis was chosen to be 2030. As assumptions of I/O modeling make it difficult to carry out long-term projections, such as mid-century projections, 2030 was chosen as the target year for analysis. An important data requirement for this input-output analysis is energy source-wise electricity generation projections for the target year. Such projections are available for the year 2030 from different studies. I discuss these studies in section 2.4.3.

2.4.2 Analytic framework

The following analytic framework was used for the analysis:

- *Step 1: Design Scenarios*

  I obtained scenarios for India's electricity generation for the target year i.e. 2030 from secondary literature. Electricity generation values allowed the estimation of the total output from different electricity generation technologies based on which I estimated the associated labor impacts using input-output modeling. Further details of these scenarios are presented in section 2.4.3.

- *Step 2: Update Input-Output Table*

  The EXIOBASE input-output table available for analysis is based on the data for 2015. In order to make projections for the target year of 2030, I updated the electricity generation related coefficients in the input-output table for 2030. In addition, I also updated the coefficients for 2018 so as to obtain an estimate for the current levels of direct and indirect employment in electricity generation sector in India. I updated coefficients for the following electricity generation technologies in the input-output table: coal, gas, nuclear, hydro, wind, petroleum, biomass, and solar PV.

The following two steps were followed to update the input-output table:

a) *Updating rows*: As the first step, I updated the rows corresponding to the above-mentioned electricity generation technologies. For that, I first calculated the total input from electricity generation into each industry for the base year (i.e. 2015). I arrived at the input values by adding values corresponding to all the energy generation technologies for each column (equation 4). I then arrived at electricity rows for the target year by distributing total input for each column among different electricity technologies based on their share in the total output for the target year (equation 5). Rows for all the other industries were not updated, and kept as is.

$$\text{Total Input} = \sum [t_{ij}] \qquad (4)$$

where t_{ij} refers to the elements in electricity rows of base Input-Output table; 'i' refers to rows, corresponding to coal, gas, nuclear, hydro, wind, petroleum, biomass, and solar PV.

'j' refers to all columns, for all industries

Updated electricity row = $[t'_{ij}]$ = Output $Share_i$ * Total $Input_j$ (5)

'i' refers to rows, corresponding to coal, gas, nuclear, hydro, wind, petroleum, biomass, and solar PV.

'j' refers to all columns, for all industries

b) *Updating columns:*

As the second step, I updated the columns corresponding to the electricity-generation technologies. For this, elements in columns corresponding to each generation technology were multiplied by a corresponding multiplier (equation 6). For each technology, I arrived at the multiplier by dividing the total output for that technology in the target year by the total output for base year. Columns for all the remaining industries were kept as is.

Updated electricity column = $[t\hat{}_{ij}]$ = $[t'_{ij}]$ * $Multiplier_j$ (6)

t^*_{ij} refers to elements in Input-Output table obtained as per part (a)

'i' refers to all rows, for all industries

'j' refers to columns, corresponding to coal, gas, nuclear, hydro, wind, petroleum, biomass, and solar PV.

For updating both rows and columns, I used total output values for the electricity-generation sectors. I estimated total output for a technology by multiplying the total electricity generated from that technology in the target year with the levelised cost of energy (LCOE) for that technology for that year (equation 7).

$$\text{Total Output}_i = \text{Total Generation}_i * \text{LCOE}_i \qquad (7)$$

'i' refers to an electricity generation technology - coal, gas, nuclear, hydro, wind, petroleum, biomass, and solar PV

For LCOE, I relied on secondary literature. The following table 1 provides the LCOE values used for analysis. The details of electricity generation are given in section 2.4.3 where I explain the scenarios in detail.

Table 2.1: LCOE values in Euros/kWh for different electricity generation technologies

Sources	**2018**	**2030_a**	**2030_b**	**2030_c**
Coal	0.046	0.060	0.048	0.045
Gas	0.064	0.091	0.091	0.091
Nuclear	0.049	0.050	0.050	0.050
Hydro	0.041	0.060	0.060	0.060
Wind	0.052	0.032	0.032	0.032
Petroleum	0.192	0.192	0.192	0.192
Biomass	0.047	0.113	0.113	0.113
Solar PV	0.053	0.048	0.038	0.053

These values are based on secondary literature – 2018 is based on (IRENA, 2018), 2030_a based on (Pachouri et al., 2017); 2030_b and 2030_c based on values reported by TERI and (Pachouri et al., 2017), IEA (IEA, 2017). The only different between 2030_b and 2030_c is the difference in the values for coal and solar technologies based on the two different methodologies followed by IEA (IEA, 2017) for calculating the LCOE.

- *Step 3: Employment Calculation*

After updating the input-output table, I calculated the ‘Leontief inverse’ matrix L. Then, to estimate the employment in electricity sectors for the target year, I first pre-multiplied the Leontief Inverse matrix by the employment coefficients ‘e’ i.e. employment/output ratios for each industry in the input-output table (equation 8). These ratios were calculated based on the employment and output data available for all industries in the EXIOBASE database. However, I improved the employment, and output data for RE sectors. For employment, I used estimates for solar and wind jobs from IRENA (IRENA, 2019) for the year 2018 as presented in figure 2.1. I estimated the total output for these sectors for the year 2018 using equation 7. I then post-multiplied the matrix obtained based on equation 8 with a diagonal matrix containing total output values for only for electricity generation sectors for the target year (equation 9).

$$Q = (e) * L \tag{8}$$

‘e’ refers to the vector of employment/output ratio for each industry in the input-output table

$$E = Q * X \tag{9}$$

‘X’ is a diagonal matrix of total output only for electricity generation sectors for the target year

Matrix ‘E’ i.e. the ‘employment coefficient’ matrix provides estimates for employment. The sum of row provides total labor from each industry driven by total output in the electricity generation sectors. The sum of columns corresponding to electricity generation sectors provides estimates for total employment in each generation technology.

- *Step 4: Parameter Sensitivity Analysis*

  As the final step, I performed parameter sensitivity analysis by varying the parameters for LCOE used in the calculation of total output in order to understand how sensitive the results were to the values of LCOE. The results of the sensitivity analysis are presented in appendix A5.

  The analytic framework followed for the analysis can be summarized as follows:

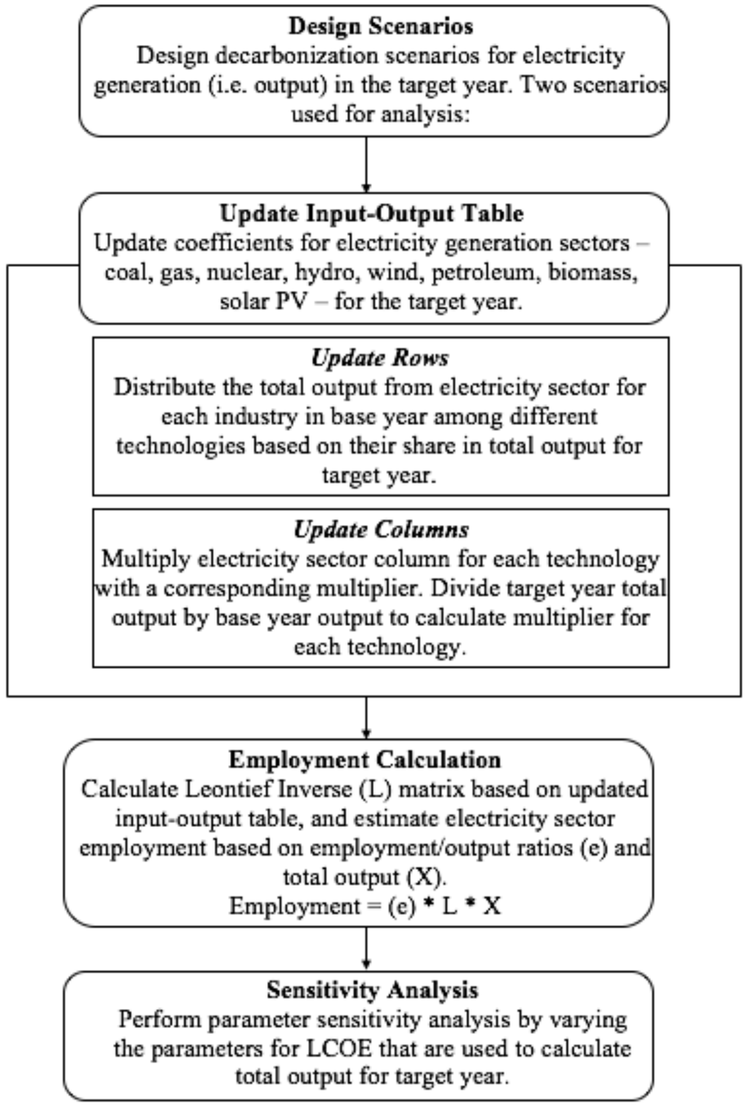

Figure 2.3: Analytical framework for Input-Output modeling

2.4.3 Scenario details

I relied on secondary literature to obtain scenarios for electricity generation in India for 2030. I used different electricity generation scenarios for the analysis in order to explore the employment impacts for a range of electricity generation projections, instead of only relying on estimates from a single study. The details of the scenarios used for analysis are given in table 2.2. I classified scenarios as ‘reference’ (ref), and ‘policy’ (pol) for each study. While the assumptions that have been used to construct the scenarios vary widely across studies, 'reference' scenarios reflect business-as-usual pathways, and 'policy' scenarios represent pathways based on policies for increased deployment of RE or increased climate mitigation.

Table 2.2: Details of the electricity generation scenarios for India for 2030

Study	Scenario Name	Details
Planning Commission LCSIG Report, 2014	Baseline, Inclusive Growth (Ref)	Model is designed to take into account development targets such as poverty reduction, better health and education etc.
	Low Carbon, Inclusive Growth (Pol)	Aims to achieve growth targets laid out in the baseline scenario but with greater emphasis on carbon emission reduction.
IEA India Energy Outlook, 2015	New Policies Scenario (Pol)	Takes into account policies for electricity sector in India such as RE capacity addition targets, universal electricity access. However, conservative assumptions made regarding achievement of policy targets.
	Indian Vision Case (Pol+)	Scenario based on assumptions of increased manufacturing (under 'Make in India' plans), universal electricity access, accelerated deployment of RE, increased energy efficiency
NITI Aayog Draft National Energy Policy, 2017	Business as Usual (Ref)	BAU pathway has greater emphasis on coal, and lesser emphasis on RE relative to Ambitious scenario
	Ambitious (Ref)	Assumptions include increased domestic fuel production, increased use of 'cleaner' fossil-fuels such as gas, accelerated RE via market mechanisms, reduced T&D losses
	Business as Usual (Ref)	Electricity generation for target year 2030 estimated based on

Central Electricity Authority (CEA), 2019		trends for electricity installation and generation between 2009 and 2019
	Ambitious (Pol)	Electricity generation based on CEA's projection for 2030 that takes into account target of adding 275 GW RE capacity by 2027

The scenarios were obtained from the following sources –Planning Commission (2014), IEA (2015), NITI Aayog (2017), and CEA (2019a). The 'reference' scenario for CEA 2019 has been estimated by authors based on their own calculations.

Figure 4 presents the electricity generation for each of the four scenario discussed in table 2.2.

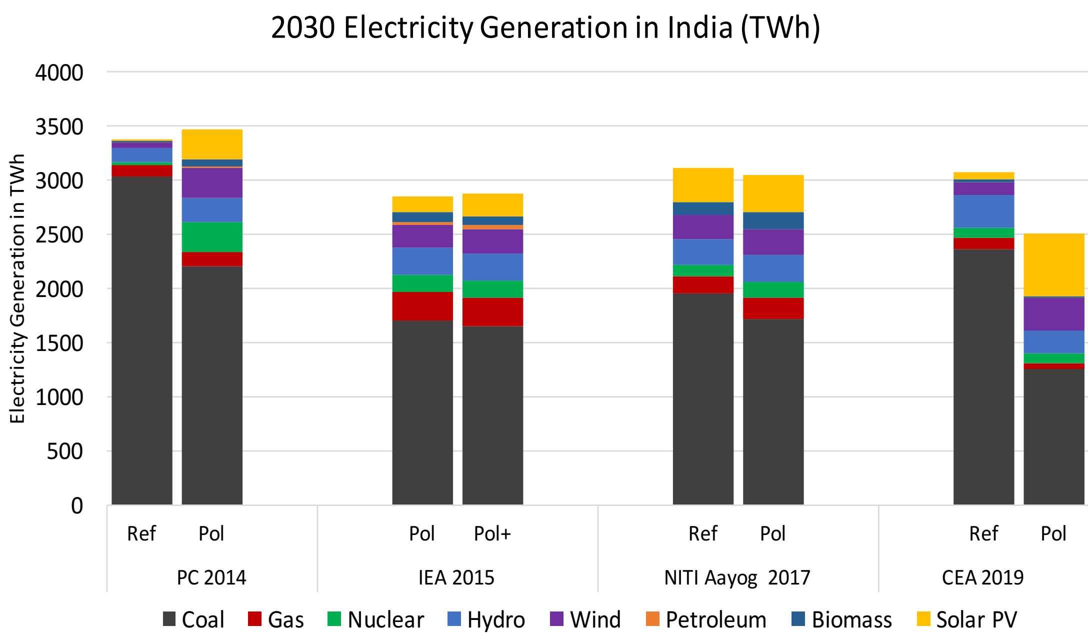

Figure 2.4: Electricity generation for 2030 in India under four different scenarios

The scenarios were obtained from the following sources –Planning Commission (2014), IEA (2015), NITI Aayog (2017), and CEA (2019a). The 'reference' scenario for CEA 2019 has been estimated by authors based on their own calculations.

The projections for electricity generation for 2030 vary from 2500 to 3500 TWh. It can be observed that the 2014 projections by an expert group for the Planning Commission, GoI are higher than the latest projections by Central Electricity Authority, GoI by ~1000 TWh.

This difference is a reflection of the trend of reduced growth in electricity demand, and thus electricity generation, that has been observed for India in the past few years. An important point to note here is that the table 2.2 presents only a subset of the different studies on future trajectories of electricity demand and supply in India. For the input-output analysis, I required projections for source-wise electricity generation in the target year i.e. 2030. There are many studies that provide projections for electricity demand in India. A 2018 Brookings India report, titled 'The Future of Indian Electricity Demand', provides a concise overview of demand-oriented projections for the electricity sector in India. However, as many of these study provide projections for electricity demand for different sectors such as buildings, transportation etc., I relied on the studies that provided source-wise electricity generation projections for the year 2030 for input scenarios.

Figure 2.5 presents the share of different fuels in the generation mix for the four studies.

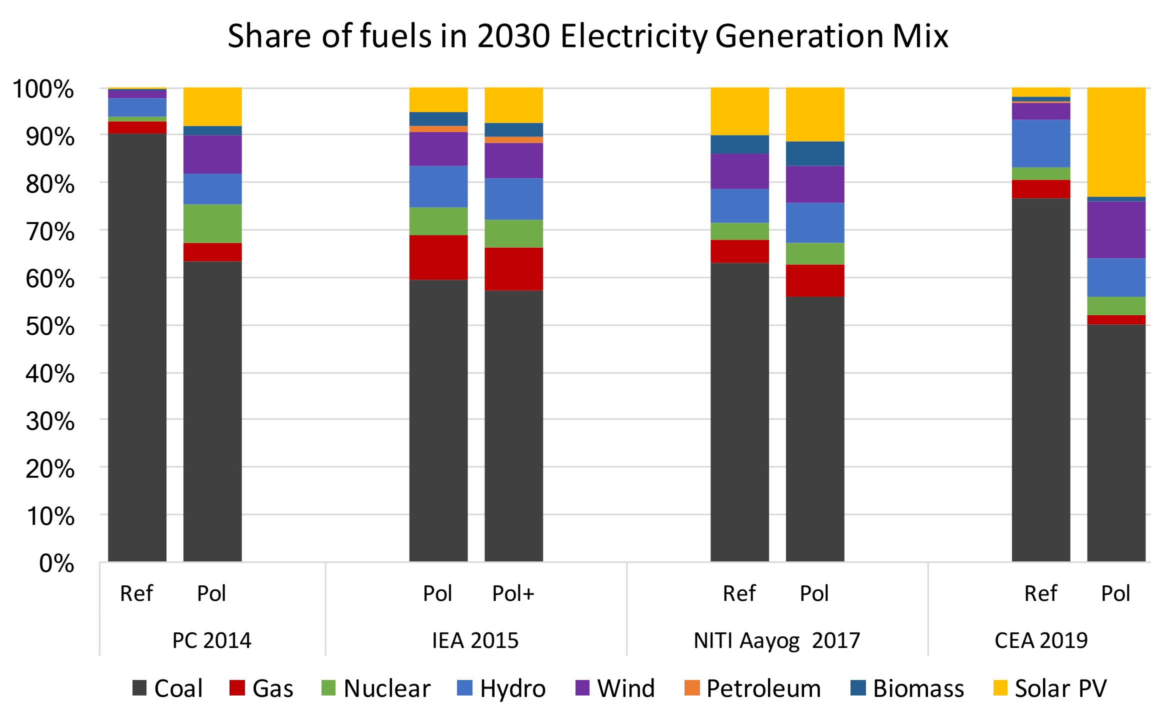

Figure 2.5: Share of different fuels in the 2030 electricity generation mix for India

The scenarios were obtained from the following sources –Planning Commission (2014), IEA (2015), NITI Aayog (2017), and CEA (2019a). The 'reference' scenario for CEA 2019 has been estimated by authors based on their own calculations.

Till 2030, coal remains the primary fuel for electricity generation under both reference and policy scenarios for all four studies. Among reference scenarios, the share of coal varies from 77% to 90% across the four studies, while among policy scenarios, its share varies between 50% and 63%. The share of RE, particularly solar, is higher in 'policy' scenarios. The latest CEA study (CEA, 2019a) makes the most optimistic projections for RE sources in India's electricity generation mix. It projects ~50% of the total electricity generation in 2030 to be met by RE sources that include solar, wind, biomass, hydro, and nuclear. Solar accounts for 23% of the total generation in this study, which is the highest projected share of solar in total electricity generation across the four studies. Overall, the share of solar in the generation mix varies between 8% and 23% across the four studies.

The total electricity generation values, and the values for the share of different fuels in total electricity generation under different scenarios are presented in appendix A2.

2.5 Results

2.5.1 Total jobs in power sector

The input-output analysis for the power sector suggests that coal will remain the major source of direct and indirect employment in power generation sector in India in 2030. This is because coal remains the primary fuel for electricity generation in India in 2030, under both business-as-usual scenarios as well as the scenarios that are based on accelerated deployment of RE. Total number of direct and indirect jobs from coal based power generation across the four studies vary between 17-26 million under reference scenarios, and 11-19 million under policy scenarios. The total direct and indirect employment from power generation varies between 21-28 million under reference scenarios, and 16-25 million under policy scenarios[4]. The number of jobs generated in policy scenarios is relatively lower as the total output i.e. electricity generation in these scenarios is estimated to be lower than reference scenarios. This is because policy scenarios are based on assumptions that include increased energy efficiency, and reduced T&D losses. Figure 2.6 presents the results of the analysis of the direct and indirect jobs in the sector by fuel source. It can be observed that the breakdown of jobs in the two IEA scenarios. This is because both IEA scenarios, i.e. 'Pol', and 'Pol+', assume rapid deployment of RE and the total electricity generation from different fuels is similar under both scenarios for the year 2030.

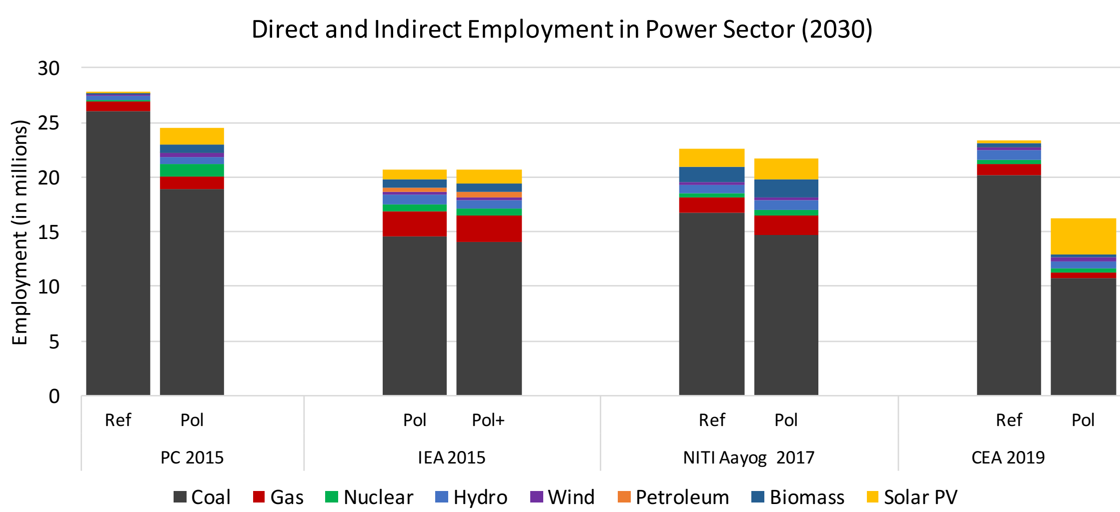

Figure 2.6: Direct and indirect jobs in electricity generation sector in India in 2030

[4] As per World Bank, India's total workforce stands at ~520 million in 2019 (source: https://www.indiaspend.com/only-4-75-million-join-indias-workforce-annually-not-12-million-as-claimed-70548/). India needs to generate ~10 million jobs annually till 2030 to provide employment to its growing working age population (FICCI, 2018).

Figure 2.7 presents the shares of different fuels in power sector jobs in India in 2030. In the case of NITI Aayog study, it can be observed that the share of different fuels in the total jobs created under reference and policy scenarios is similar. This is because this study assumes rapid deployment of RE, particularly solar and wind, under both the scenarios. Thus, the share of different fuels in the total electricity generation for the two scenarios is similar for the year 2030, leading to similar labor impacts.

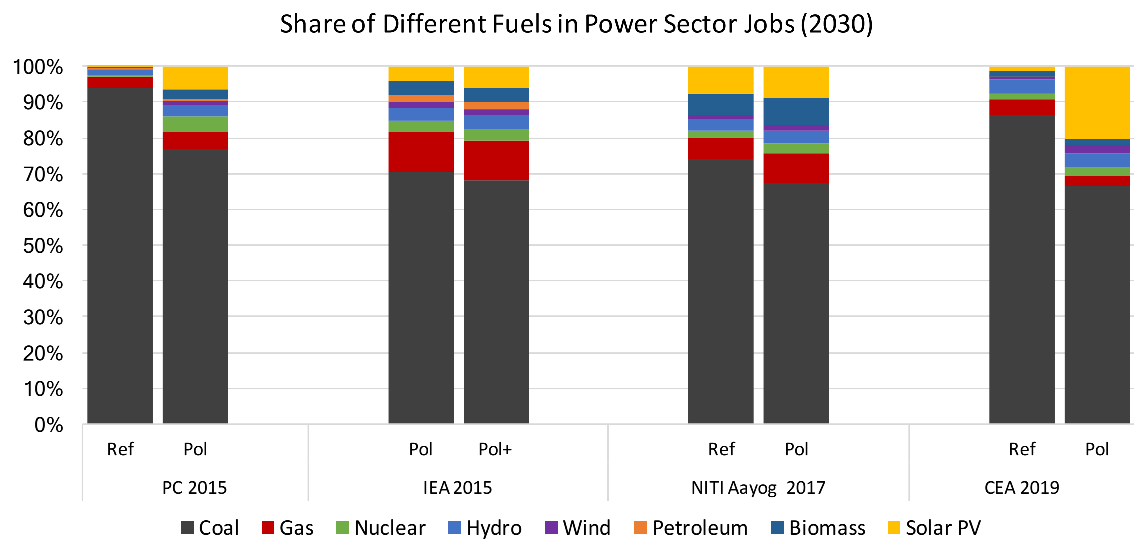

Figure 2.7: Share of different fuels in in direct and indirect jobs from electricity generation in India in 2030

It can also be observed that the share of RE sources is higher in policy scenarios, and solar constitutes majority of the jobs among RE sources. Among the 'policy' scenarios that represent accelerated deployment of RE, the share of solar in the total jobs varies between 6-20%. However, given the heavy reliance on coal for power generation even under policy scenarios, coal accounts for 66-77% of the total direct and indirect jobs from power generation in India in 2030 under different 'policy' scenarios. The share of coal jobs is even higher in reference scenarios, and varies between 70-95%.

The employment coefficients for different fuels, total direct and indirect employment values, and the share of different fuels in employment under different scenarios are presented in appendix A3. I used the LCOE values from table 1 to calculate the total output. For the results presented in this section, I used the '2030_a' values. Job estimates for 2018 are also provided for comparison.

2.5.2 Total jobs in solar and wind sectors

Figure 2.8 presents the total number of direct and indirect jobs associated with solar power generation in India in 2030. Across the four studies, the total number of solar-related jobs vary between 50,000 – 2 million jobs under reference scenarios, and 1.2-3.3 million jobs under policy scenarios. The CEA 2019 policy scenario projects the highest solar job gains across the four studies at 3.3 million direct and indirect jobs in 2030.

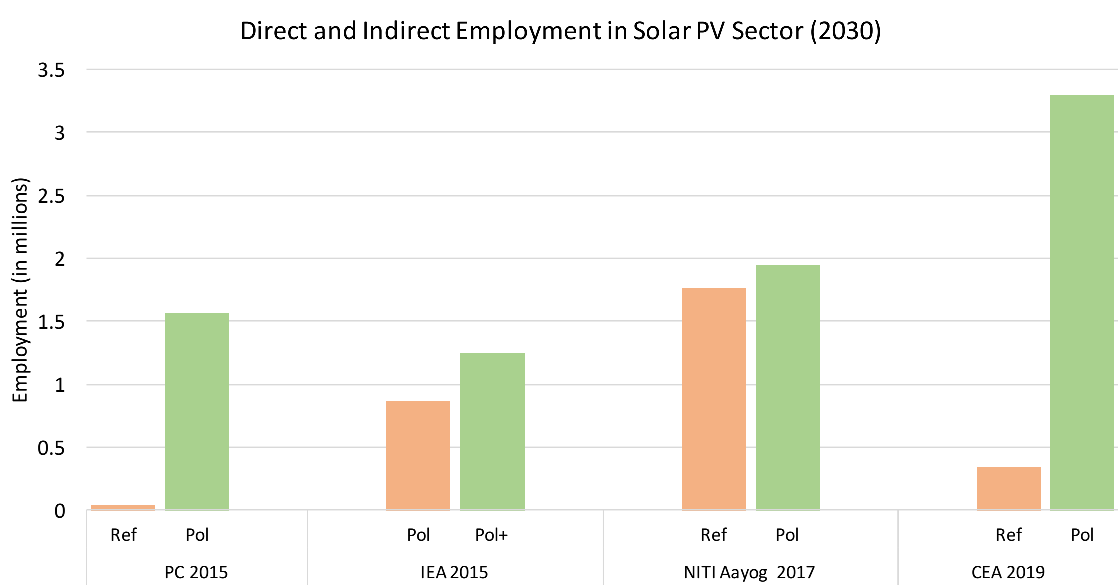

Figure 2.8: Total direct and indirect jobs from solar PV in India in 2030

Figure 2.9 presents the direct and indirect job gains associated with wind sector. It can be observed that the total number of wind-related jobs are relatively lower than solar-related jobs. Across the four studies, wind-related job numbers vary between 70,000-300,000 jobs under reference scenarios, and 300,000-400,000 jobs under policy scenarios.

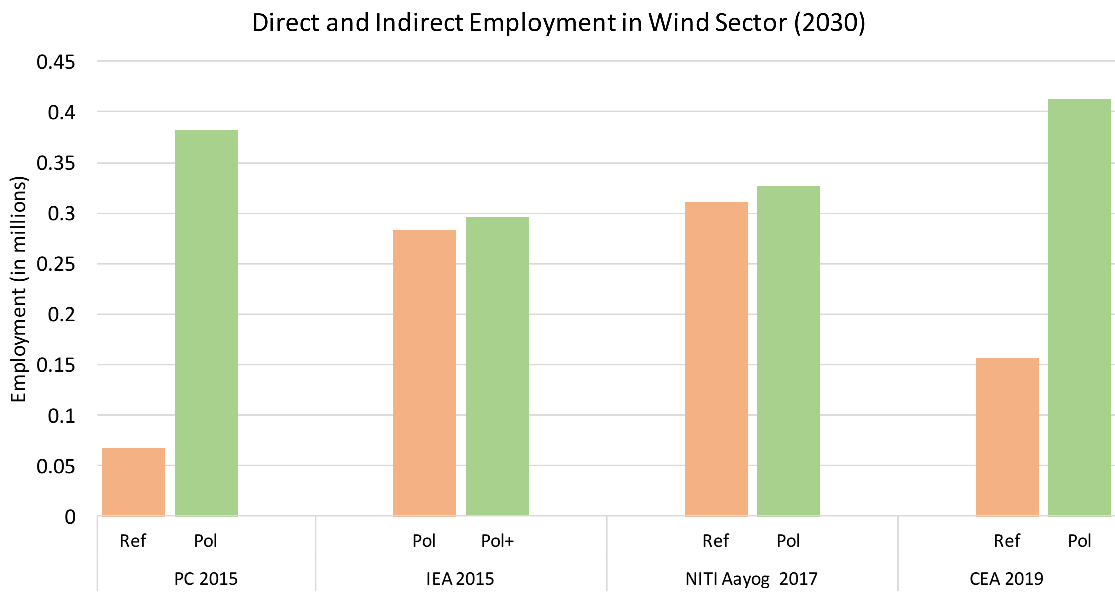

Figure 2.9: Total direct and indirect jobs from wind in India in 2030

2.5.3 Job share by sector

Figure 2.10 breaks down the major sectors for direct and indirect employment associated with power generation from coal and solar respectively. Here, I present job numbers based on CEA 2019 policy scenario only. It can be observed that direct jobs associated with production of electricity constitute majority of the jobs for both coal and solar at 67% and 74% of the total jobs respectively. For coal-based power generation, mining constitutes another 20% of the jobs. Other sectors where indirect jobs are generated due to power generation include transport, financial services, and manufacturing. In figure 2.10, the percentages do not add to 100% as I have only included the major sectors where direct and indirect jobs are generated.

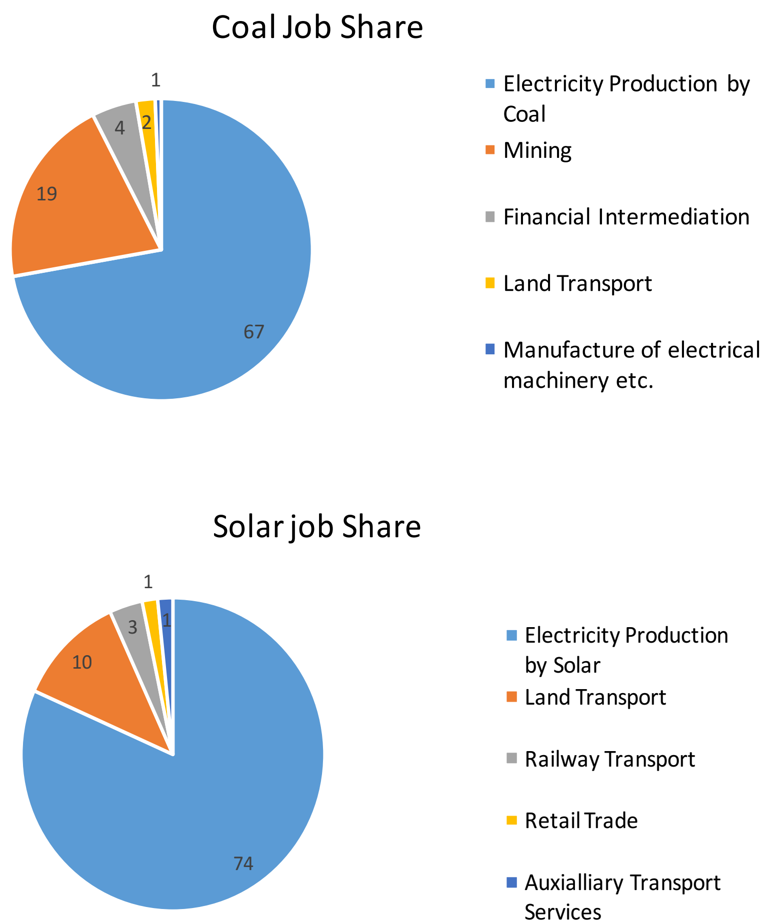

Figure 2.10: Share of different sectors in direct and indirect jobs from coal and solar power generation in 2030

2.6 Discussion

Employment generation associated with climate mitigation is an important co-benefit of climate action. Studies on the labor impacts of clean energy transitions in the power sector generally provide an optimistic assessment of the job creation potential of renewable energy. This paper also projects a substantial increase in RE employment in India due to the accelerated deployment of RE in the power sector. Using an input-output based model, the total number of direct and indirect jobs from solar and wind generation in India in 2018 were found to be 0.2 million, and 0.1 million respectively. These job numbers are likely to rise to 0.3-0.4 million wind jobs and 1.2-3.3 million solar jobs by 2030 under different decarbonization scenarios.

Increase in the employment in RE sectors is expected as RE technologies are deployed at an increasing rate in the power sector. However, in order to understand the economy-wide labor impacts of clean energy transitions in the power sector, it is important to study the labor impacts associated with all the fuels used for power generation, and not just RE technologies such as solar and wind. Many clean energy labor impact studies only focus on estimating the labor impacts for RE sectors. In this paper, I addressed this gap and assessed the labor impacts associated with power generation in India in 2030 under different decarbonization scenarios. The results of the input-output analysis show that the total direct and indirect jobs created due to power generation in scenarios with accelerated deployment of RE (i.e. 'policy' scenarios) are lower than business-as-usual scenarios, indicating a net loss in jobs from power generation in India in 2030 due to clean energy transitions when compared to the business-as-usual scenarios. This net job loss is the result of lower projections for power generation under policy scenarios on account of measures such as energy efficiency, reduction in T&D losses, as well as relatively higher direct and indirect employment impact of the coal sector in comparison to RE technologies.

In a 2019 report, the Central Electricity Authority (CEA) of India projects that renewable energy sources solar and wind will account for 35% of the total power generation in India in 2030. This study is based on assumptions of rapid deployment of RE in the power sector in India, and its projections meet India's NDC target of increasing the share of non-fossil fuels to 40% of the total installed capacity by 2030. In fact, this study assumes a much higher penetration of non-fossil fuels in India's power grid by 2030 as non-fossil fuels account for 65% of the total installed capacity as per this study. The total number of direct and indirect jobs created from power generation in this case is between 13-16 million. In comparison, in the scenario where power generation is assumed to increase following the 'business-as-usual' trajectory, with non-fossil fuels accounting for 35% of the total installed capacity in 2030, the total number of direct and indirect jobs generated from power generation in 2030 is higher, and varies between 18-24 million. The details of the two scenarios are provided in appendix A4.

The findings from the scenario analysis suggest that the employment gains associated with RE-heavy scenarios is likely to be lower in comparison to coal-heavy business as usual scenarios in India. These results highlight that the direct and indirect jobs associated with electricity generation from cleaner sources of such as solar, and wind are unlikely to compensate for the total number of jobs associated with the coal sector in India, and hence, it is important to broaden the scope of sectors and strategies than can help India meet its twin targets of clean energy transitions, and employment generation. Some sectors that are not included in the analysis in the paper are energy efficiency, and manufacturing of clean energy which implies that the estimates for total number of job gains associated with clean energy transitions are likely to be an underestimate in this paper, and inclusion of these sectors can provide a more comprehensive analysis.

A recent paper, Joshi et al. (2019), studied the impact of domestic content requirement (DCR) policies for solar manufacturing on employment generation in India. DCR has been one of the most important policy measure used in India to support domestic manufacturing of solar PV, specifically to support crystalline silicon industry. They found that the total number of direct and indirect jobs associated with solar deployment with DCR was 333 jobs/MW, which was almost 35% higher than the jobs generated in the case without DCR i.e. 211 jobs/MW. While employment analysis of scenarios involving increased domestic manufacturing of RE technology is important, it should be noted that some of the major policies followed by the Indian government to boost RE manufacturing, such as DCR, have not been able to deliver expected outcomes. In the case of solar energy, DCR has not resulted in globally competitive solar PV manufacturing in India, especially cell manufacturing (Shrimali and Sahoo, 2013; Johnson, 2013), In fact, DCR-focused policies resulted in leakage to thin-film cells, and trade disputes at WTO that have forced India to reassess its DCR strategy (Jha, 2017; Sahoo and Shrimali, 2013). Researchers have argued that instead of solely focusing on price distortion mechanisms to stimulate solar manufacturing, the focus should be on improving India's innovation and R&D capacities (Sahoo, 2016; Chaudhary et al., 2014).

As per World Bank, India's total workforce stands at ~520 million in 2019[5] , and India needs to generate ~10 million jobs annually till 2030 to provide employment to its growing working age population (FICCI, 2018). Assessing the projections of 13-16 million total jobs in the power sector in year 2030 (under RE heavy scenarios) in the light of the overall employment target for the Indian economy suggests that electricity generation constitutes a small proportion of the total number of jobs in India. Hence, meeting the overall employment target for the Indian economy requires policies that can help develop labor-intensive sectors such as the manufacturing sector.

Projections of green jobs are affected by methodological and data challenges. In this study, I conducted input-output based modeling to assess the labor impacts of clean energy transitions in the power sector in India. In order to make projections for 2030, I only updated the electricity sector of the available 2015 input-output table for the target year of analysis i.e. 2030. Updating the entire input-output table would require data projections for all sectors of the economy which is both highly data-intensive as well as time-intensive exercise. However, by updating only the electricity sector coefficients, I assumed the coefficients for other sectors of the economy to remain static between 2015 and 2030. As calculations that are done based on current coefficients fail to take into account emergence of new production methods, or the technological advancements that might happen in the future, this is an important drawback of this analysis.

[5] Source: https://www.indiaspend.com/only-4-75-million-join-indias-workforce-annually-not-12-million-as-claimed-70548/).

Apart from these methodological factors, the results of this analysis are also impacted by parameters used for analysis. In appendix A5, I provide employment estimates for the different values of LCOE as outlined in table 1. For the 2019 CEA 'policy' scenario, the total number of direct and indirect jobs vary between 18-24 million under the BAU scenario, and 13-16 million under the policy scenario. The results of this analysis can be made more robust with better data on current levels of employment in RE sectors. RE sectors such as solar and wind are not included separately in employment surveys in India. From a policy perspective, it is important to regularly collect data for RE industries in order to understand and highlight the scope and trends of employment in these industries. Without relevant data, it is difficult to assess the job creation potential of renewable technologies.

2.7 Conclusion

In this paper, I explored the labor impacts of clean energy transitions in the power sector in India. First, I reviewed the secondary literature on green jobs in India. I found that while there exists optimism about the employment potential of RE technologies, data on the current levels of employment in RE sectors such as solar and wind remains limited in India. Most projections for labor impacts of clean energy transitions focus only on estimating direct labor impacts of solar and wind energy. As per secondary literature, which includes government and think-tank reports, between 200,000-800,000 jobs are likely to be generated in solar and wind sectors in India by 2022, the year by which India aims to add 175 GW of RE capacity into its power grid. The estimates across different studies vary widely because of differences in types of jobs accounted for in the analysis, and methodology followed.

Second, I assessed the economy-wide labor impacts under different decarbonization scenarios using input-output modeling. The results show that that the total job creation in scenarios with accelerated RE deployment is relatively lower than business-as-usual scenarios on account of lower total power generation in the former scenarios, and greater economy-wide labor impacts associated with the coal sector. Moreover, even with accelerated RE deployment, coal jobs constitute 65-75% of the total jobs from power generation as coal remains the major fuel for power generation in India for the next decade. Majority of the jobs in RE sectors are created from solar generation. Estimates for total number of jobs from solar PV under different scenarios with accelerated RE deployment vary between 1.2-3.3 million, whereas wind jobs vary between 0.3-0.4 million.

The results suggest that coal is likely to remain an important source of employment generation for a developing country like India as it remains an important source of electricity generation in the country. Data on current levels and nature of employment in RE sectors remains limited making it difficult to assess the scope and trends of employment in clean industries. It is important to collect data for RE industries regularly so that assessment of the job potential of these industries can be improved.

3 Spatial Distribution Analysis of the Labor Impacts of Clean Energy Transitions

3.1 Abstract

This paper presents an analysis of the spatial distribution of the labor impacts of clean energy transition in India. While there exists optimism about the job creation potential of clean energy industries, just transitions literature has emphasized that the costs and benefits of energy transitions will not be distributed equally within regions. Aggregate labor estimates can hide regional inequalities that might surface sub-nationally as energy transition related job gains and job losses do not always occur at the same location. In this paper, I explore the case of the power sector in India.

Using an analytic spreadsheet-based model, I estimate the state-wise labor impacts associated with capacity addition plans till 2027 in India. The results suggest that Indian government's 2027 target of installing 250 GW of solar and wind capacity will generate jobs primarily in western and southern parts of India as 60% of the total jobs will be located in the states of Maharashtra, Rajasthan, Gujarat, Tamil Nadu, Andhra Pradesh, and Karnataka. Job gains due to RE capacity addition in coal-rich eastern states of the country are minimal as limited solar and wind capacity is planned to be installed in these states till 2027. However, short to medium-term power sector plans for India include addition of coal capacity as well. If plans for net coal capacity addition are also taken into account, overall job gains are relatively higher for coal-rich states - such as Chhattisgarh, Odisha, Jharkhand, and Madhya Pradesh - highlighting that coal sector is a major source of employment in power sector in India. This analysis serves as the first step for designing just transition plans in India. State-wise assessment of the labor impacts allows us to

identify the workers and regions that are likely to lose out in clean energy transitions, and can be used to design plans for providing economic opportunities and compensation to the affected parties.

Key words: energy transitions, just transitions, electricity, India, distributive energy justice

3.2 Introduction

Creation of 'green jobs' is a significant co-benefit of the transition to low-carbon energy systems. As per the International Labor Organization (ILO, 2018), global employment can increase by net 18 million jobs by working towards the Paris Agreement target of limiting global warming to 2 deg. C. Measures to mitigate climate change such as deployment of cleaner sources of energy, improved efficiency of energy systems and buildings, and adoption of electric vehicles could generate 24 million new jobs while around 6 million jobs are likely to be lost due to the scaling down of carbon-intensive industries (ILO, 2018). Optimistic estimates for green jobs not only indicate that positive economic outcomes can potentially be achieved while decarbonizing the economy, they also provide an opportunity to forge popular and political support for climate action. Researchers have argued that positive feedback loops such as job creation helps to create 'sticky' policies for low-carbon energy transitions i.e. policies that enjoy broad political support (Sebastian et al., 2019).

Several studies have assessed the labor impacts of clean energy transitions across the world (Garrett-Peltier, 2017; Pollin & Chakraborty, 2015; Wei et al., 2010). It is broadly agreed that clean energy transitions will have a net positive impact on labor i.e. the new green jobs created in renewable energy (RE) sectors will compensate for the jobs lost in fossil-fuel sectors. However, the labor impact studies remain primarily focused on estimating country-level aggregate labor impacts. Few studies have focused on understanding the distribution of these labor impacts by ‘location’. It is possible that the new green jobs that are generated during clean energy transitions are not located in areas where the fossil-fuel based jobs are lost. In the energy justice literature, this is characterized as the distributive injustices that are associated with energy transitions (Williams & Doyon, 2019). It is important to study the distributional labor impacts of energy transitions because if a particular location is only going to experience negative labor impacts, it can reduce political support for climate action in those areas. Moreover, from a justice perspective, it is essential that those who are likely to lose their livelihoods because of energy transitions are provided with alternative training and employment opportunities, or compensation. The preamble of Paris Agreement asked the parties to account for ‘just transition of the workforce and the creation of decent work and quality jobs’ while working towards climate action. Since 2015, the concept of Just Transition has gained further traction, and, in fact, was a key theme at the 2018 COP at Katowice, Poland. At this COP, more than 50 leaders and parties across the world signed the Silesia Declaration for Solidarity and Just Transition to highlight political support for the fair transition of workers who are likely to lose their jobs due to climate action.

In this paper, I present a spreadsheet-based analysis of the spatial distribution of the labor impacts associated with clean energy transitions in power sector in India. I find that ~60% of the jobs associated with the 2027 target of adding 250 GW of solar and wind capacity will be concentrated in the western and southern states of Rajasthan, Gujarat, Andhra Pradesh, Karnataka, and Tamil Nadu. However, short to medium-term power sector plans for India include addition of coal capacity as well such as addition of ~48 GW coal capacity between 2017 and 2022. If plans for net coal capacity addition are also taken into account, overall job gains are relatively higher for coal-rich states - such as Chhattisgarh, Odisha, Jharkhand, and Madhya Pradesh - highlighting that coal sector is a major source of employment in power sector in India. This analysis can serve as a pre-requisite for just transition policies and plan in India. It allows for identification of workers and regions that are likely to lose out in clean energy transitions, and thus can be used to design plans for providing economic opportunities and compensation to the affected parties.

The next section provides an overview of academic literature on the estimation of the labor impacts of clean energy transitions, and specifically the literature on spatial distribution of labor impacts. Then in section 3.4, I discuss the analytical framework used for analysis. I then present the methodology in section 3.5, and results in section 3.6. In section 3.7, I discuss the findings, and then present the conclusions in the final section.

3.3 Literature Review

3.3.1 Defining green jobs

In order to assess the labor impact of clean energy transitions, it is important to first identify the nature of jobs that are likely to get created in a low-carbon economy. Often, 'green jobs' is used as a blanket term to describe jobs associated with low-carbon transitions.

Despite its widespread use, there is no single definition for green jobs[6]. As per the ILO, green jobs are 'decent jobs in sectors that either produce green products or provide green services such as the clean transportation sector, or jobs in sectors that contribute to environmentally friendly processes such as improved recycling'[7].

In academic literature, the most commonly used classification scheme to assess the labor impact of clean energy transitions is direct, indirect, and induced jobs. This classification scheme is also used by IRENA (International Renewable Energy Agency (IRENA, 2012):

3.3.2 Overview of literature

Methods used for analysis

There are three commonly used methods to assess the labor impacts associated with clean energy transitions – Analytical method, Input-Output modelling, and Computational General Equilibrium (CGE) modelling. The analytical method involves spreadsheet based models that use surveys or secondary data to estimate the labor impact of clean energy transitions. These models are best suited for measuring the direct labor impacts at the regional level. To estimate the labor impact on the whole economy (i.e. direct as well as indirect, and induced impacts), input-output tables or CGE models are more suitable[8].

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[6] Other commonly used definitions of green jobs are those provided by the OECD/Eurostat, and the US Bureau of Labor Statistics.

[7] This definition has been accessed from the ILO website (URL: https://www.ilo.org/global/topics/green-jobs/news/WCMS_220248/lang--en/index.htm, Accessed on: 09/23/2019). ILO guidelines on Decent Work Management inform the decent work dimension of this definition.

[8] There are some crucial differences between Input-Output and CGE models. The details of those differences are beyond the scope of this paper.

Optimism about green jobs

The power sector, specifically the transition to solar & wind energy, and energy efficiency improvements in the power systems, constitutes the focus of the labor impact assessment studies. The general consensus is that clean energy transitions are likely to have a positive impact on employment generation (Garrett-Peltier, 2017; Markandya et al., 2016; Pollin & Chakraborty, 2015; Oliveira et al., 2014; Cai et al., 2011; Wei et al., 2010; Sastresa et al., 2010). Most of the literature assesses the labor impacts for developed countries. Relatively lesser empirical evidence is available for emerging and developing economies.

Metrics used for labor impacts

Many studies do not distinguish jobs based on whether they are short-term or long-term, and use 'person-years per MW' & 'jobs/MW' interchangeably (Camron and van der Zwaan, 2015). This can hide the fact that most of the jobs in RE sectors are short-term jobs, and can lead to an over-estimation of the of the labor potential of clean energy technologies. Using different units makes it difficult to compare job estimates across different phases of RE deployment. One of the strategies to counter this problem is to convert the person-year per MW estimates into jobs/MW estimates by averaging the former over the lifetime of the facility (Wei et al., 2010).

Lack of emphasis on distributional labor impacts

An important critique of the labor assessment studies is the lack of emphasis comparing the job gain estimates with the direct and indirect jobs that will be lost due to the shutdown of fossil-fuel based sectors. Most of the studies only focus on estimating the 'employment factors' (EF) i.e. jobs/MW for RE technologies. Corresponding employment factors for conventional technologies such as coal are not estimated in most of the studies (Cameron and van der Zwaan, 2015)

Moreover, most labor assessment studies only provide aggregate job gain (and loss) estimates. Cai et al. (2014) have argued that it is crucial to assess the 'distributional employment impacts' in order to evaluate whether the current labor force possesses the necessary skills and educational levels required for RE industries. Defined broadly, 'distributional employment impacts' can include assessment of green jobs based on their distribution by gender, education & skills requirement, or the spatial distribution of job gains and losses associated with energy transitions (Azad & Chakraborty, 2019; Sastresa et al., 2010; Blanco & Rodrigues, 2009; Moreno & López, 2008). Distributional impacts can also include impact of energy transitions on wages, and economic inequality but labor assessment studies on this topic remain sparse.

3.3.3 Spatial dimension of labor impacts

The transition to cleaner sources of energy is shifting the location of energy value chains across the world and within countries. Over the last decade, China has emerged as the world's leading solar manufacturer. In 2018, it accounted for almost 75% of the world production of PV cells and modules (IEA PVPS, 2018). Apart from China, other important solar manufacturing countries include Japan, South Korea, Taiwan, and Malaysia. In 2018, these countries together accounted for 3 million or 85% of the global solar jobs (IRENA, 2019). Given that solar manufacturing facilities are mainly concentrated in these Asian countries, other countries in the world procure solar PV cells and modules via imports. From the labor perspective, countries importing solar cells and modules from other countries are likely to create new solar jobs only in the downstream sectors such as construction of solar power plants, installation of panels and modules, and O&M.

Taking into account both import and export of RE equipment can provide a clearer assessment of the labor impact of energy transitions. In their study of Brazil's wind industry, Simas and Pacca (2014) found that if the import of wind equipment was included in the analysis, job creation estimates would reduce by 40%. Dalton & Lewis (2011) analyzed the wind industry in Denmark and found that the sector was characterized by high levels of manufacturing. But most of the manufactured equipment was exported, and deployment levels for wind energy in the country were low. Hence, the national statistics were found to be inflated because high export rates were not taken into account. For their study of the labor impacts of RE in a province in Spain, Sastresa et al. (2010) created a cumulative 'quality factor' for jobs in RE sectors that included 'location' as one of the factors. To identify the local benefits of RE deployment, they categorized the RE-related jobs into two categories on the basis on location: i) Technology development related jobs that were more likely to be foreign, and ii) Installation and O&M jobs that were considered local.

The spatial distribution of the labor impacts, especially at the sub-national level, have received greater attention from studies focused on exploring the justice, and politics of energy transitions. ‘Distributive’ justice forms one of the three tenets of ‘energy justice’. This stream of energy justice literature is primarily concerned with understanding the distribution of the loss and benefits of energy transitions. In their review of energy justice, Jenkins et al. (2016) consider the distributional impacts of the siting of new energy infrastructure to be an important theme of enquiry in the energy justice literature. Fossil-fuel based communities are likely to be disproportionately impacted during clean energy transitions as the location of new clean technology plants is decided based on natural conditions and expected economic performance (Jenniches, 2018). New RE plants are not always located in areas where fossil-fuel plants will be shut down. This asymmetric impact of energy transitions can reduce support for climate policies in areas that are being negatively impacted by energy transition (Vona, 2019), as highlighted by (Olson-Hazboun, 2018) through their interviews of fossil-fuel based communities in Utah, USA. The interviewed fossil-fuel based community members expressed skepticism and anger towards RE technologies as they perceived them to be a threat to their local economy and identity.

However, greater attention needs to be given to the spatial distribution of the labor impacts of clean energy transitions. Clean energy transitions are likely to create spatial inequalities due to the asymmetric job gain and job loss impacts across regions. Planning of just energy transition policies, especially for those who stand to lose in the clean energy transitions, would require assessment of the positive and negative labor impacts at a regional scale as the first step. The state-wise labor analysis in this paper provides the estimates that can be used for designing just transition plans. In the next section, I present the analytical framework used to analyze the spatial distribution of the labor impact associated with clean energy transitions at sub-national level.

3.4 Framework of analysis

3.4.1 Details of analytical framework

Figure 3.1 presents the analytical framework used to study the magnitude, and spatial distribution of the labor impacts associated with clean energy transitions. This framework accounts for two types of labor impacts: a) jobs that are created because of new RE technology, b) jobs that are lost in the process of setting up new RE plants, and due to the closure of fossil-fuel based power plants. For this paper, I focused on solar and wind renewable energy technologies for the analysis.

While new RE technology is not necessarily replacing fossil-fuel capacity in the case of power sector in India, I included the possibility of closure of fossil-fuel based plants in the framework to account for all the probable labor impacts associated with clean energy transitions. The framework presented in figure 3.1 is generic, and can be modified or extended to account for other kinds of labor impacts or labor impacts in other sectors as well. In section 3.4.2, I discuss in detail the labor impacts that I have focused on in this paper.

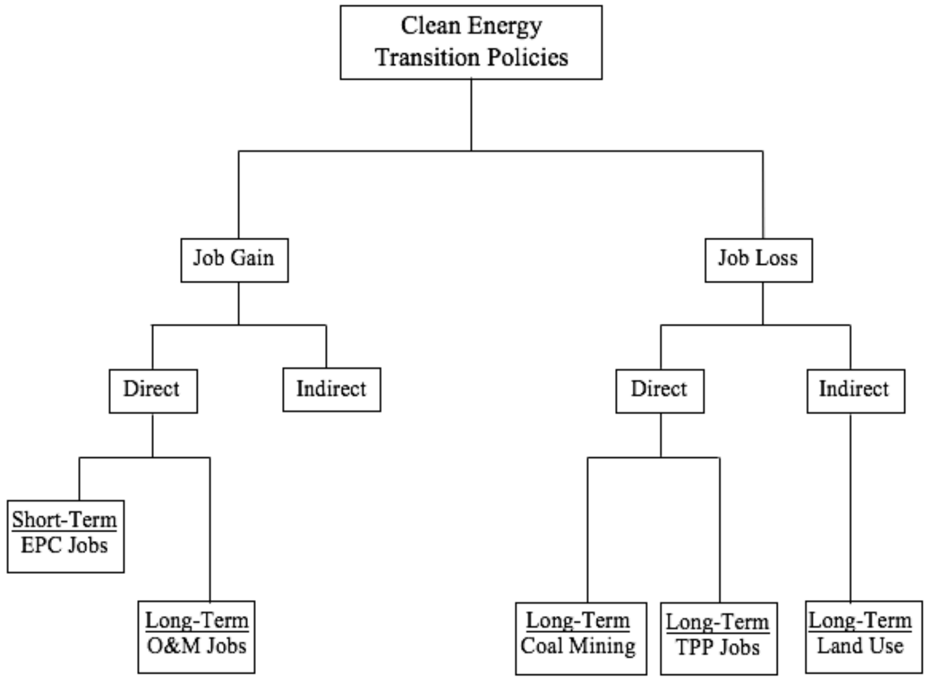


Figure 3.1: Analytical framework to study spatial distribution of labor impacts

3.4.2 Labor impacts studied

Job gain due to RE capacity addition: As expected, addition of new RE capacity leads to job gains. These job gains can be categorized as direct, and indirect jobs. The job impacts can also include induced jobs but I have only included direct and indirect jobs here for the sake of simplicity. I focused on calculating direct jobs created in solar and wind sectors that are most relevant for India, which includes jobs in downstream sectors. Jobs in the downstream sectors can been categorized as follows: 1) Engineering Procurement Construction (EPC) jobs i.e. jobs generated in engineering, procurement, and construction phases of project development, and 2) Operations and Maintenance (O&M) jobs i.e. jobs that are generated in maintaining the power plant. EPC jobs tend to be one-time jobs which means that the jobs in these phases are terminated after the completion of the project. Only

O&M jobs are considered long-term jobs are they last for the lifetime of the RE power plant. I have made this distinction between short-term and long-term jobs in Figure 3.1, and also in the estimates.

Job loss due to change in land use: Setting up a new RE plant could also lead to job loss during procurement of land for setting up the plant. Though the Indian government has mandated prioritizing 'waste lands' for setting up RE power plants (MNRE, 2016), the land that is categorized as wasteland might actually be in use for grazing, or farming purposes by marginal farmers (Yenneti et al., 2016). Thus, it is possible that procurement of wastelands can result in job loss for shepherds and marginal farmers, without any compensation. In instances where the procured land is not a wasteland, the Indian government has been following different modes of land procurement. For example, to procure about 4500 hectares of land for a 2000 MW solar park project in the southern state of Karnataka, the state solar power corporation leased agricultural land from farmers across five villages for a period of 28 years (TERI, 2017). While such a leasing arrangement provides compensation to land-holding farmers, it can still result in job loss for agricultural laborers working on the leased land as they do not own land themselves. Since land is a long-term source of livelihood for farmers, I categorized this job loss as long-term loss.

Labor impacts associated with thermal power plants and coal mining: The National Electricity Plan (NEP) prepared by the Central Electricity Authority (CEA) of India has provisions for both closure of thermal capacity – on account of retirement of thermal power plants or lack of space for installation of FGD (Flue Gas Desulphurization) units – as well as addition of new thermal capacity – to meet the rising electricity demand – between 2017 and 2027 (CEA, 2018). I took both proposed retirements as well as capacity additions into account, and calculated two types of direct fossil-fuel related labor impacts for the analysis. Firstly, the number of jobs associated with operating thermal power plants (TPPs) depends upon addition and retirement of thermal capacity. Secondly, jobs in coal mining sector are also likely to be impacted based on coal requirement by TPPs, and thus were included in the labor estimates. As both these jobs are long-term jobs i.e. they last as long as the thermal power plant is in operation, I categorized them as long-term jobs.

The framework in figure 3.1 does not account for job gains due to addition of new thermal capacity as the primary focus of the framework is to highlight the probable labor impacts associated with clean energy transition policies i.e. policies aimed at reducing carbon emissions. However, it could be the case that while new RE capacity is being installed, it does not replace fossil-fuel based capacity, and new thermal capacity continues to get installed as well because of financial and technical reasons. This is the case for India as per the National Electricity Plan 2018, and that's why I also estimated job gains due to thermal capacity addition.

3.5 Methodology

3.5.1 Employment equations

In the analysis, I focused on estimating labor impacts for three sectors – i) RE – EPC, and O&M jobs, ii) land, and iii) coal – TPP, and coal mining jobs. I did spreadsheet-based estimation of the labor impacts using employment factors (EF). I relied on estimates for power capacity installation between 2017-2027 as per the National Electricity Plan (NEP) by the Central Electricity Authority (CEA) of India for the analysis. The equations used for analyses are provided below. These equations were used to calculate the average *change* in jobs associated with power sector due to the changes in installed capacity of different power generation sources.

Average job gains associated with addition of RE capacity:

The average number of jobs gained due to addition of new RE installed capacity (IC) were calculated using equation 1. I distinguished between the jobs gained in different phases of RE, i.e. EPC, and O&M, by multiplying by their respective EFs with the total installed capacity. Since the jobs generated in the EPC phase of RE are short-term in nature and calculated in 'person-years per MW', I converted these estimates to jobs/MW by taking an average over the life of the RE power plant. This allowed me to arrive at the average number of jobs generated in the EPC phase throughout the lifetime of the RE power plant, allowing comparison with other long-term labor impacts. As O&M jobs are long-term, multiplying the installed capacity with employment factor for O&M jobs provided the total number of O&M jobs generated over the lifetime of the RE power plant.

I estimated the job gains for each state based on the solar and wind installation planned for the states, and aggregated the state-level job gains to arrive at the national level estimates. For the period 2017-2022, the Ministry of New and Renewable Energy (MNRE) of the government of India has provided state- and technology-wise breakdown of the RE capacity addition targets. However, for the period between 2022-2027, only the overall targets are available. I arrived at the state- and technology-level estimates for 2022-2027 by assuming the same distribution of capacity among states as in the 2017-2022 period. The state-level breakdown for installed capacity is presented in appendix B1.

$$\text{Average RE Job Gain} = \sum \left[\left(\frac{\text{ICs,t x EFi}}{life\ of\ RE\ power\ plant} \right) + (IC_{s,t} \text{ x } Ef_{k}) \right] \quad (1)$$

IC = Installed Capacity

EF = Employment Factor

s = state

t = technology – rooftop, ground mount, wind

i = EPC, k = O&M

Average job losses associated with change in land use:

I estimated the average job loss associated with change in land use, such as grazing or farming land being diverted for setting up RE power plants (for solar groundmount, and wind), using equation 2. I first estimated the total land area required to set up the RE capacity by multiplying the proposed installed capacity with average land area required per MW to set up an RE power plant. I then assumed that a proportion 'p' of the land required for setting up the RE power plant has been in use for other activities such as farming or grazing. I calculated the average job loss associated with change in land use by multiplying the land area in use with the average number of full-time jobs per unit land. This provided an estimate of the average number of land-related jobs that are likely to be lost for the duration of the operation of the RE power plant. I aggregated the state-level estimates to arrive at national level land-related job losses.

$$\text{Average Land Job Loss} = \sum [(IC_{RE} \times Land_{RE})* p * (\text{Jobs per unit land})] \qquad (2)$$

IC_{RE} = Installed Capacity for solar/wind capacity installed

$Land_{RE}$ = Land required per unit solar/wind capacity installed

p = Proportion of land in use for other activities such as farming, grazing

Job loss due to change in land-use or dispossession from land is not likely to be the same in each case as it would depend on the land-use prior to its procurement for setting up the RE power plant. In the analysis, I assumed that 10% of the procured land had been in use for farming purposes by those who do not own that land, i.e. p = 10%. I then used the estimate for the average number of full-time workers per hectare of farm-land to calculate the total number of people who are likely to lose their livelihood without any compensation. I have considered a conservative assumption of only 10% of the land being used for farming given the government mandate to prioritize 'waste lands' for setting up RE power plants. However, the results of land-related job loss analysis will change based on the assumption made for the value of 'p'. For example, if the value of 'p' is considered to be 5%, i.e. only 5% of the land procured for the construction of an RE power plant is in use for farming purposes, then the land-related job loss will be half of what is estimated when 'p' is assumed to be 10%. However, if we assume that 25% or $1/4^{th}$ of the total land that is procured for the construction of an RE power plant is being used for farming purposes, in that case land-related job losses will be 2.5 times of the job numbers that are estimated when 'p' is assumed to be 10%. This highlights that the land-related job loss is sensitive to the assumption of the value of 'p'. These estimates can be improved primary data on land procurement for construction of RE power plants.

Labor impacts associated with Thermal Power Plants (TPP):

Equation 3 gives an estimate of the average number of TPP-related jobs that are that are likely to be lost or gained due to the closure or addition of new thermal capacity respectively. I used manpower required per MW i.e. the EF for running for TPPs to estimate the job losses. Equation 3 also requires state-wise changes (addition and/or retirement) in thermal capacity. I arrived at these based on plans for thermal capacity retirement and addition outlined in the NEP 2018. I estimated the job changes associated with thermal capacity addition, and retirement separately. The details are provided in appendix B2. Again, I aggregated state-level TPP job-loss estimates to arrive at the national impact.

$$\text{Average Job Change at TPP} = \sum (\text{Thermal Capacity Change}_s \text{ x } EF_{TPP}) \qquad (3)$$

Thermal Capacity Change$_s$ = for each state, thermal capacity change refers to the addition and/or retirement of thermal capacity based on NEP 2018.

EF_{TPP} = Employment Factor for thermal power plant

Labor impacts associated with coal production:

I estimated labor impacts for the coal mining sector by first calculating the change in annual coal production due to the changes thermal capacity. To calculate coal production change, I multiplied the annual electricity generation associated with the thermal capacity with the amount coal required to generate one unit of electricity. I estimated the annual generation based on equation 4. The amount of coal required per unit of electricity depends on the ratio of heat rate or efficiency of the thermal power plants to the heat content of the coal used. I multiplied this ratio with the annual generation to estimate the annual coal production change. Then, I used coal mining productivity estimates to calculate the average number of jobs that are likely to be lost or gained in the coal mining sector due to changes of coal-based thermal capacity (equation 6). I attributed these job changes to states based on their share in annual coal production in 2019.

$$\text{Annual Generation (AG)} = \text{Thermal Capacity Change}_s \times PLF_{th} \times 8760 \qquad (4)$$

$$\text{Annual Coal Production Offset} = AG \times \left(\frac{\text{Heat Rate of TPP}}{\text{GCV of coal}}\right) \qquad (5)$$

$$\text{Average Job Change in Coal Mining} = \frac{\text{Annual Coal Production Offset}}{\text{Coal Mining Productivity}} \qquad (6)$$

GCVcoal = Gross Calorific Value of Coal

3.5.2 Variables used for calculation

Details about the variables, and their values used in employment calculations are given in table 3.1. An important point to note here is that the employment factors (EF) for the solar and thermal power plants are only available at the national level for India. Hence, I used the same EF for all states.

Table 3.1: Details of variables used for analyzing spatial distribution

Variable	**Unit**	**Value**	**Source**
RE Variables			
Lifetime of RE power plants	years	25	(CEA, 2018)
Thermal Variables			
Thermal PLF All India (PLF_{th})	%	60%	(CEA, 2019b)

Heat Rate of TPP India (HR)	kcal/kWh	2500	(CEA, 2019c)
Gross Calorific Value of Coal All India (GCV_{coal})	kcal/kg	3900	(CEA, 2019c)
Employment Factors			
Solar Rooftop			(Kuldeep et al., 2019)
Rooftop EPC (EF_{EPC})	FTE Jobs/MW	24.22	
Rooftop O&M (EF_{OM})	FTE Jobs/MW	0.5	
Solar Groundmount			(Kuldeep et al., 2019)
Groundmount EPC (EF_{EPC})	FTE Jobs/MW	2.95	
Groundmount O&M (EF_{OM})	FTE Jobs/MW	0.5	
Thermal Power Plant (EF_{TPP})	FTE Jobs/MW	1.065	(CEA, 2018)
Coal Mining Productivity All India ($Prod_{mining}$)	Tonnes/man year	2126	(CIL, 2019)
FTE jobs per hectare farmland ($Labor_{hectare}$)	FTE jobs/ hectare	1[9]	
Land Variables			
Land required for solar and power plants ($Land_{solar}$ / $Land_{wind}$)	Hectares/MW	2/1.5	(TERI, 2017)

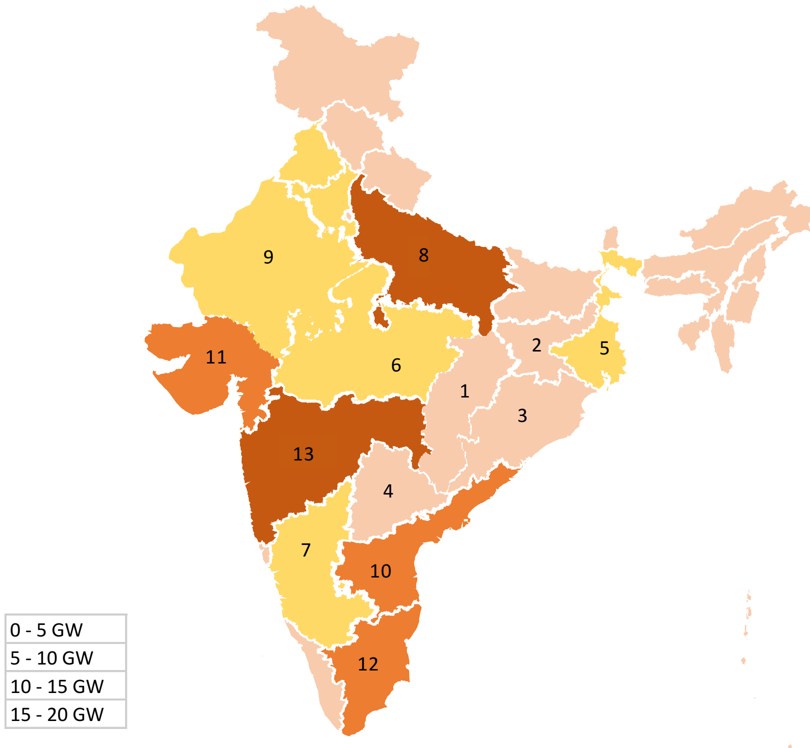
3.6 Results

I present here analysis of the distributional labor impacts of energy transitions in two cases.

[9] The average size of landholding in India is about 1 hectare where an operation landholding is defined as "as all land used wholly or partly for agricultural production and is operated as one technical unit by one person alone or with others, without regard to title, legal form, size or location." (Agricultural Census Portal) I have assumed that an average landholding provides full-time employment to 1 person throughout the year.

Case 1

In case one, I present the state-wise labor impacts associated addition of 150 GW of solar capacity, and 100 GW of wind capacity in India by 2027. Based on the state-level targets for solar and wind capacity installation as detailed in appendix B1, I estimated the average job gains for each state using equation 1. Figure 3.2 presents maps for proposed solar and wind capacity addition in India between 2017 and 2022.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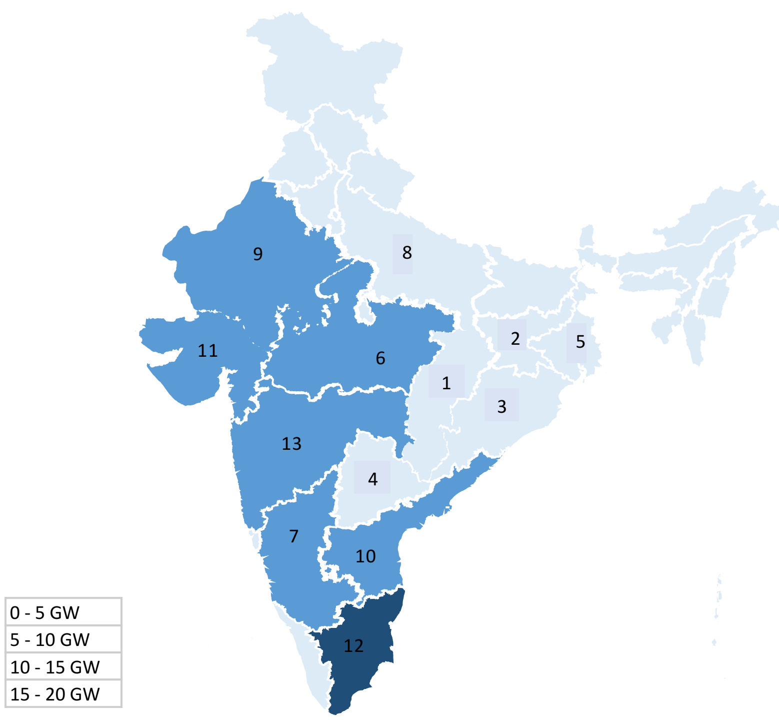
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10 - 15 GW
15 - 20 GW

1	Chhattisgarh
2	Jharkhand
3	Odisha
4	Telangana
5	West Bengal
6	Madhya Pradesh
7	Karnataka
8	Uttar Pradesh
9	Rajasthan
10	Andhra Pradesh
11	Gujarat
12	Tamil Nadu
13	Maharashtra

Figure 3.2: Proposed state-wise solar and wind capacity in India between 2017-2027

Figure 3.3 presents the results of this analysis. About 2/3rd of the direct job gains from installation of wind and solar are concentrated in the western and southern states of Maharashtra, Tamil Nadu, Gujarat, Andhra Pradesh, Rajasthan, and Karnataka. Northern state of Uttar Pradesh also accounts for substantial solar job gains because of the high proposed installation of solar capacity in the state. In total, the 150 GW solar target will generate 145,000 full-time direct jobs, and 100 GW of wind target would generate 53,000 full-time direct jobs that will last throughout the lifetime of the RE projects. The employment estimates for each state for this case are provided in appendix B3.

It can be observed that the job gains presented in figure 3.3 follow the trend of installed capacity observed in figure 3.2 with states with higher proposed RE capacity addition gaining majority of the new green jobs. The important point to note here is that plans for RE installation are dependent on meteorological conditions such as solar irradiation and wind speed and thus, can vary between locations. In India, potential for solar and wind energy is relatively higher in the western and southern states, making it more economically more viable to set up solar power plants in these parts of the country. The setting up of big solar parks in the western and southern states such as Gujarat, Rajasthan, Telangana, Andhra Pradesh, Karnataka, and Tamil Nadu is an indication of the same. Little grid-connected solar capacity has come in the Eastern part of India, also the coal-belt of the nation, because of the poor potential for RE.

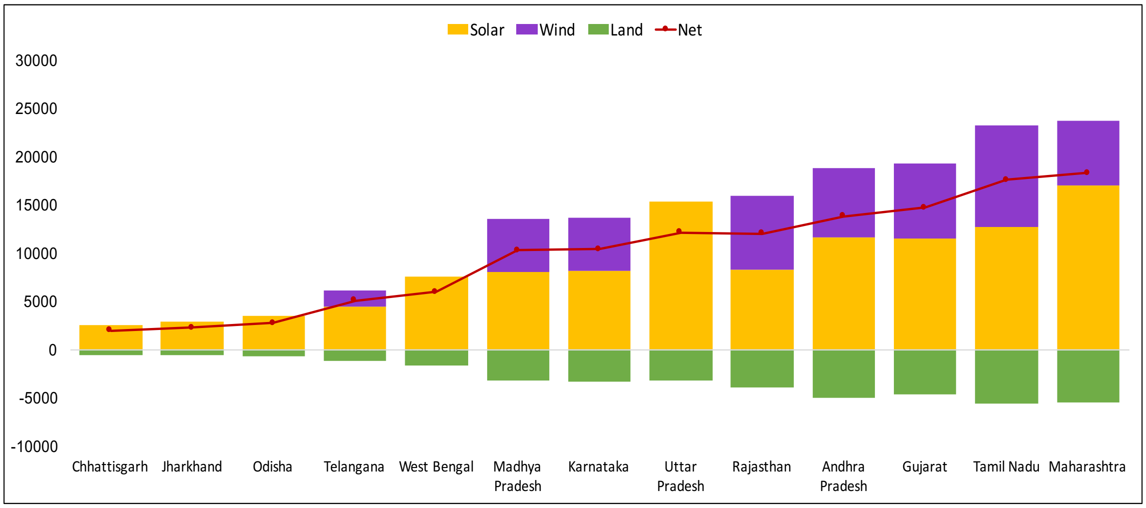


Figure 3.3: State-wise labor impacts due to 250 GW RE capacity addition

State-wise labor impacts associated with addition of 150 GW of solar capacity, and 100 GW of wind capacity between 2017 and 2022. The labor impacts have been estimated in terms of average number of full-time jobs. The location of states included in this analysis can be identified from figure 2.

Case 2

In case two, I present the state-wise labor impacts associated with installed capacity changes between 2017 and 2022. Between 2017-2022, India has RE capacity addition target of 175 GW that includes 60 GW of groundmount solar, 40 GW of rooftop solar, and 60 GW of wind capacity. In this period, India also plans to add ~48 GW of new coal-based thermal capacity while retiring 22.7 GW of old thermal capacity. In India, RE capacity is being installed as new thermal capacity also continues to get added to the grid. This is because coal-based thermal capacity is crucial for a developing country like India where electricity demand is still rising, and provision of affordable electricity is an important to increase the electricity access in the country.

To estimate the labor impacts for this case, I followed the methodology used in case 1 to estimate RE-related labor impacts. To estimate TPP- and mining-related job changes, I used equations 3 and 6. I attributed the location to TPP job losses based on the location of the individual thermal power plants, and the location details of thermal capacity are presented in appendix B2. As I did not have information on the location of the mines from which each of the retiring or new TPP would source its coal, I estimated the total annual coal production changes, and attributed it to the major coal-mining states in India based on their most recent share in annual coal production. By doing so, I made an implicit assumption that all the coal was being procured from within India.

Figure 3.4 presents the results of this analysis. It can be observed that if addition thermal capacity changes are also taken into account, coal-rich states such as Chhattisgarh, Odisha, and Madhya Pradesh gain more jobs relative to some southern and western states on account of job gains due to increased coal-mining. These trends in figure 3.4 are contrasting to the trends observed in figure 3.3, and highlight the importance of coal-related jobs in power-sector jobs in India. The net RE-related direct job gains in this case are 100,000 jobs. This includes addition of new 97,000 solar-related and 32,000 wind-related jobs, and loss of 29,000 jobs due to change in land-use. The thermal power related net direct job gains in this case are 27,000, and net mining related job gains are about 40,000. The overall labor impact is positive in this case, at around 165,000 jobs. The details of the employment estimates for each state are provided in appendix B4.

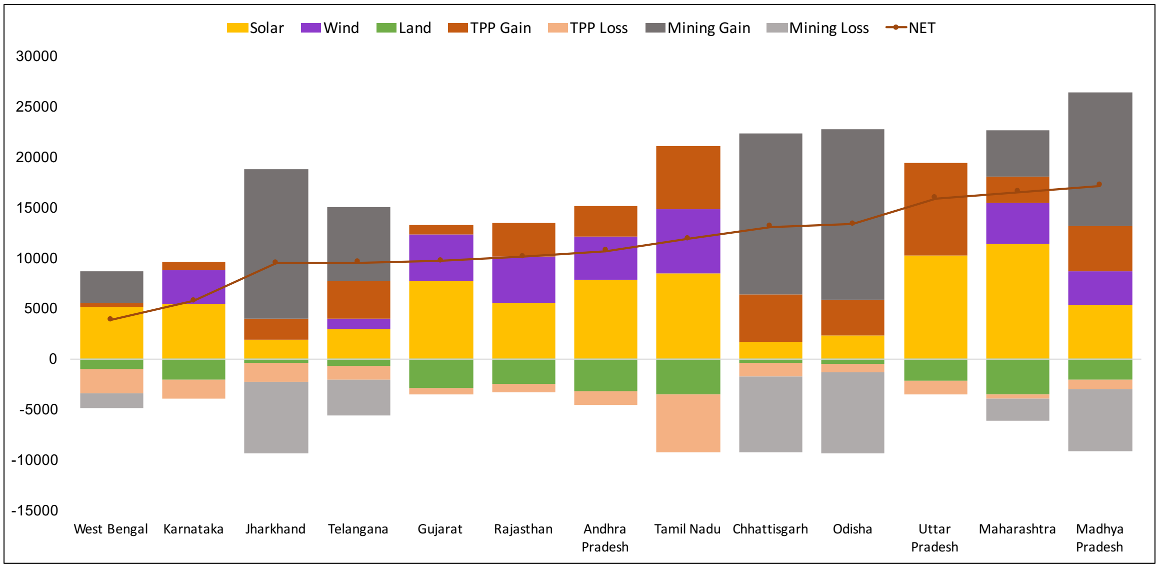


Figure 3.4: State-wise labor impacts due to changes in power installed capacity between 2017-2022

State-wise labor impacts associated with installed capacity changes between 2017 and 2022 which include – addition of 100 GW solar, 60 GW of wind, 47.8 GW of coal-based thermal capacity, and retirement of 22.7 GW of coal-based thermal capacity. The labor impacts have been estimated in terms of average number of full-time jobs. The location of states included in this analysis can be identified from figure 2.

3.7 Discussion

Majority of the labor impact studies only focus on estimating the national-level aggregate labor impacts of clean energy transitions. However, it is likely that the distribution of the benefits and losses of clean energy transitions will not be equitable within countries. As clean energy plants are sited based on meteorological and economic factors; they are not always located in the areas where fossil-fuel power plants are likely to shut down because of clean energy addition.

In this paper, I show that the job gains associated with increased installation of RE in India will not be distributed equally across the country. In India, new RE-based power plants are primarily proposed to be set up in the economically viable western and southern parts of the country. Almost 60% of the potential job gains from increased capacity addition of solar and wind between 2017 and 2027 will be concentrated in the states of western and southern states of Maharashtra, Rajasthan, Gujarat, Tamil Nadu, Andhra Pradesh, and Karnataka. These are also the states with higher GDPs in comparison to states in other parts of the country, particularly the coal-rich states located in eastern India that will experience very limited job growth in solar and wind jobs in the coming decade. In 2016-17, the top three states in terms of GDP were Maharashtra, Tamil Nadu and Gujarat respectively. Appendix B5 provides more detail about state GDPs.

As India does not plan to retire the existing thermal power plants in the near future, loss of jobs in the coal mining sector is not an urgent policy concern. However, when India retires its thermal capacity, it will result in direct as well as indirect job losses in the coal-rich eastern states, particularly in the coal mining sector. In addition to job loss, the decline of coal sector will also reduce the royalties that are obtained from coal mining, negatively impacting the GDP of coal-rich states. In 2015-16, for two of the biggest coal-rich states in India, i.e. Jharkhand and Chhattisgarh, mining accounted for 11% and 8% of the total state revenues respectively. Based on the Finance Accounts available for the states of Chhattisgarh and Jharkhand (Government of Chhattisgarh, 2016; Government of Jharkhand, 2016), non-ferrous mining and metallurgical industries accounted for INR 3709 crores and INR 4384 crores of the total state revenues in 2016 respectively. As other minerals are also mined in these states, it is difficult to disaggregate the royalties received solely from coal based on the financial accounts data available for these states. However, given that coal is one of the most important minerals extracted in these states, the share of mining royalties in the total state revenue suggests that closure of coal-mines can have substantial negative economic impacts in the coal-mining states.

Though questions about the distribution of the winners and losers of energy transitions form a core theme of the energy justice and just transitions literature, labor impact studies on this topic are limited. Only relying on aggregate national-level labor impacts can hide how the fossil-fuel based communities i.e. the likely losers of energy transitions, will not necessarily benefit from the positive labor impacts of clean energy transitions. Estimating the region-wise magnitude of job gains and job losses can then aid in the formulation of just transition policies at the national level. These policies can include plans for setting up new industries at locations that will experience net job losses due to energy transitions, or provision of support for training and migration for energy sector workers to work in RE or other industries.

An important limitation of this study is that it does not account for all the indirect labor impacts associated with clean energy transitions. The trends of labor impacts might change if all the indirect impacts are also taken into account. Here, I have constructed a spreadsheet based model for the analysis, and relied on secondary data sources for employment factors to estimate the labor impacts. The results would be more robust if region-specific values region-specific or project-specific employment values were used for calculation. It is difficult to estimate indirect job loss using analytical methods. Estimation of economy-wide labor impacts at the state-level can be done using state Input-Output tables. This would require state-level input-output tables that are currently not available for all states in India.

The labor impacts estimated in this paper are not directly comparable with the labor estimates from chapter 2. In chapter 2, I estimated the *total* number of direct and indirect jobs associated with different sources of power generation in India for the year 2030. In this chapter, I have estimated the *change* in direct jobs related to coal, solar, and wind sectors on account of changes in their installed capacity between 2017-2027. I discuss these estimates in more detail in chapter 4.

3.8 Conclusion

In this paper, I examined the spatial distribution of the labor impacts of clean energy transitions, and highlighted that the direct job gains due to clean energy transitions in the power sector in India will be largely concentrated in the western, and southern parts of the country.

I constructed an analytical framework to explore the spatial disaggregation of the labor impacts associated with clean energy transitions in the power sector in India. I found that the Indian government's target of adding 150 GW solar capacity, and 100 GW of wind capacity by 2027 will generate jobs primarily in western and southern states of Maharashtra, Rajasthan, Gujarat, Tamil Nadu, Andhra Pradesh, and Karnataka. Job gains due to RE capacity addition in coal-rich eastern states of the country are minimal as limited solar and wind capacity is planned to be installed in these states till 2027. However, short to medium-term power sector plans for India include addition of coal capacity as well. If plans for net coal capacity addition are also taken into account, overall job gains are relatively higher for coal-rich states - such as Chhattisgarh, Odisha, Jharkhand, and Madhya Pradesh - highlighting that coal sector is a major source of employment in power sector in India. These states are likely to lose out on jobs and economic revenue when India does start retiring thermal capacity. Hence, it is important to design policy support mechanisms in order to support the states that are expected to lose out in terms of employment, and economic revenue.

It is important that the policymakers take this regional differentiation into account which will only widen as India installs more RE and starting retiring coal-based power plants in the future. Estimation of spatially-disaggregated labor impacts of energy transitions is the first step towards designing just transition policies and fulfil one of the primary objectives of these policies i.e. providing compensation and economic opportunities to those who will be losing out in clean energy transitions.

The analytical framework that I constructed in this paper can be used in the context of other industries or countries as well. For example, labor impacts of shifting manufacturing from petrol/diesel based vehicles to electric vehicles for any specific region can be explored using this analytical framework. This can be helpful assessing the spatial inequalities that are likely to accompany clean energy transitions, and thus plan appropriate just transition plans especially for the negatively affected communities.

4 Skills Requirement Analysis of the Labor Impacts of Clean Energy Transitions

4.1 Abstract

Most of the studies assessing the labor impacts of clean energy transitions focus on estimating national-level, aggregate job numbers. Assessments of 'distributional labor impacts' i.e. distribution of jobs on the basis of location, gender, education, and skill requirements remain limited. As lack of appropriately skilled workforce has been identified as an important barrier for RE sectors in India, in this paper I explore the skill requirements for the labor impacts associated with clean energy transitions in the power sector in India. Using secondary data sources, I first construct a database of power sector jobs in coal, solar, and wind sectors. I then arrive at the distribution of these jobs across three skill categories – semi-skilled, skilled, and high-skilled – using the National Skill Qualification Framework (NSQF) for India. Using these skill estimates, I compare the skill requirements for direct jobs in coal, solar, and wind sectors in India under two scenarios – business-as-usual (reference) and accelerated deployment of RE (policy) – for the year 2027. I also assess the state-wise skill requirements for green jobs in solar and wind sectors.

The results of this analysis show that under both reference and policy scenarios, majority of the jobs in the power sector are created in the 'skilled' category. As per the classification used, skilled jobs require short- or long-term diplomas or graduate degrees. Clean energy transitions in the power sector will decrease the number of semi-skilled, and skilled jobs required to run coal-based thermal power plants, and in the coal mining sector. It will increase the requirement of semi-skilled, and skilled jobs in the solar sector which includes jobs as site surveyors, structural design engineers, mechanical and electrical draughtsman, solar PV installers, market research analysts, site engineers, HSE engineers, and QA

engineers etc. Most of the direct jobs in the solar and wind sectors will be generated in the states of Maharashtra, Rajasthan, Gujarat, Tamil Nadu, Andhra Pradesh, and Karnataka on account of the solar and wind capacity proposed to be installed in these states. Thus, these states should be considered the priority locations for setting up RE training institutes.

Key words: skills, green jobs, power sector, India

4.2 Introduction

Jobs in renewable industries would not be filled unless workers have the necessary skills for those jobs. Skills gap, i.e. lack of appropriately skilled workforce, has been identified as major challenge for renewable industries across the world. Cai et al. (2014) argue that it is important to assess these 'distributional employment impacts' (DEI) in order to evaluate whether the current labor force possesses the skills and educational levels that are required for RE sectors. Using secondary sources, Consoli et al. (2016) constructed profiles for green and non-green jobs in the US and found that green jobs require higher levels of education, and work experience in comparison to the non-green jobs. In India as well, skills gap is recognized as a challenge for hiring in RE industries such as solar. This has been highlighted in government reports such as the Skills Gap report that was released by the Skills Council for Green Jobs in 2016 (SCGJ, 2016).

In this paper, I specifically look into the skill requirements for power sector in India. As there is no standardized database available for the skill requirements in the power sector for India, I first construct a database of power sector jobs in coal, solar, and wind sectors in the country. I then distribute these jobs across three skill categories – semi-skilled, skilled, and high-skilled – using the National Skill Qualification Framework (NSQF) for India. The NSQF is a framework used by the government of India that allows organization of the skills required for different industries on a standardized scale of 1 to 10. I categorize jobs between levels 1-3 as semi-skilled, 4 and 5 as skilled, and 6 and above as high-skilled. Thus, using this framework, I arrive at comparable skill requirements for different power generation sources. I use these estimates to compare the skill requirements for direct jobs in coal, solar, and wind sectors in India under two scenarios – business-as-usual (reference) and accelerated deployment of RE (policy) – for the year 2027. I also assess the state-wise skill requirements for green jobs in solar and wind sectors.

The results of this analysis show that under both reference and policy scenarios, majority of the jobs in the power sector are created in the 'skilled' category. As per the classification used, skilled jobs require short- or long-term diplomas or graduate degrees. Clean energy transitions in the power sector will decrease the number of semi-skilled, and skilled jobs required to run coal-based thermal power plants, and in the coal mining sector. It will increase the requirement of semi-skilled, and skilled jobs in the solar sector which includes jobs as a site surveyor, structural design engineer, mechanical and electrical draughtsman, solar PV installer, market research analyst, site engineer, HSE engineer, and QA engineer etc. Most of the direct jobs in the solar and wind sectors will be generated in the states of Maharashtra, Rajasthan, Gujarat, Tamil Nadu, Andhra Pradesh, and Karnataka on account of the solar and wind capacity proposed to be installed in these states. Thus, these states should be considered the priority locations for setting up RE training institutes.

The next section provides an overview of academic literature on the skill requirements associated with clean energy transitions. Then in section 4.4, I present the methodology, and results in section 4.5. In section 4.6, I provide a comparison of the labor estimates across the three chapter (ch.2-4). In section 4.7, I discuss the findings, and then present the conclusions in the final section.

4.3 Literature Review

4.3.1 Skills required for jobs in RE sectors

As per the ILO, the skilling requirements for 'green jobs' can be classified as 'retraining', and 'skill upgrading'. Table 1 provides a snapshot of the skill requirements for green jobs as per the ILO. Green jobs, as defined by ILO, include all those jobs that are decent, and reduce the consumption of energy and raw materials, reduce greenhouse gas emissions, minimize waste and pollution, and protect and restore the ecosystems.

Table 4.1: Skill Upgrading & Retraining Requirements for Green Jobs

Industry	Employment Effect	Training Need
Renewable Energies: Wind, Solar	Gaining	Skills Upgrading: energy efficient solutions, project management skills Retraining from other manufacturing sectors Retraining for installers, engineers, technicians, O&M Specialists
Green Building and Retrofitting	Stable or Gaining	Skill Upgrading: energy efficiency, green technologies, new materials, energy auditing/certification
Transport	Stable or Gaining	Retraining and skills upgrading into various public transport jobs
Recycling and waste management	Gaining	Retraining from waste collection to recycling, skills upgrading in methane and energy recovery

Waste Resource Management	Gaining	Skills upgrading: water conservation and efficient use, wastewater management

Source based on (Sastresa et al., 2010)

For this paper, as the focus is on the power sector, the most relevant industry category in table 4.1 is the renewable energies category. Table 4.1 suggests that clean energy transitions will require skill upgradation and retraining of the workforce to meet the job requirements of RE industries. Other studies have also used the term 'training' as RE industries would require learning of new skills as well. Moreover, if those who get employed in RE industry were previously unemployed or employed in a different industry, they would require training to join the RE industries.

There are no standardized databases available for the skill requirements for power sector in India. However, CEEW & NRDC (2016) provide information on the phase-wise training requirements for solar industry in India (table 4.2). They categorize most of the jobs in solar sector in India as highly skilled jobs, which they define as jobs that require engineering or advanced degrees.

Table 4.2: Skills requirement for Solar Industry in India

Phase	Skill Level	Degree/Diploma Required
Manufacturing	Highly skilled	Photovoltaics engineering
Business Development	Highly skilled	Masters or diploma in business management
Design and Pre-Construction	Highly skilled	Engineering degree in civil, mechanical or electrical engineering
Construction and Commissioning	High, semi, and low-skilled	Engineering degree in civil, mechanical or electrical engineering (for highly skilled)
O&M	High, semi, and low skilled	Engineering in electrical systems (for highly skilled)

4.3.2 Reasons for skills gap and policies to address those gaps

Skills gap is a crucial barrier to hiring in RE industries. Mismatch between educational and training programs and the skills requirements of RE jobs is one of the most commonly identified reasons for the skills gap.

In 2008, Blanco and Rodrigues (2008) conducted surveys across wind companies in the EU in order to better understand the reasons behind the shortage of skilled workers as that was being reported by wind energy companies. Based on their interviews, they found pre-university level educational systems to be particularly lacking in providing students the skills necessary for wind industries – such as site management for O&M, and health & safety logistics. In order to address this issue, they suggested standardization of qualifications, and creation of certificate programs to increase the pool of skilled workforce that could join the wind industry in EU.

Moreno and Lopez (2008) compared the skill requirements for emerging RE job opportunities in Asturias region in Spain with the professional courses that are available for skill development in the region and concluded that the syllabus must be modified in order to prepare the workforce for upcoming employment opportunities.

Sooriyaarachchi et al. (2015) also arrived at similar conclusions, and suggested that the training programs should be modified to include RE sectors specific content such as training regarding technological, regulatory, and legal aspects of RE.

In their survey of solar industries in India, CEEW and NRDC (2016) found that in addition to lack of training facilities, poor quality of training and long distances of training centers from sites of job opportunity as resulted in skills gap.

Though skills gap is recognized as an important barrier to hiring in RE industries in India, limited empirical work has been done on this topic. There is no standardized database available for the skill requirements for power sector in India. Moreover, studies that assess skills for power sector primarily focus on solar and wind sectors. In order to understand how skill requirements will change because of clean energy transitions, it is important to assess skill requirements for not only green jobs, but also non-green jobs. Assessment of skills for non-green jobs can allow us to evaluate the scope of transition from non-green jobs to green jobs. In order to address these research gaps, in this paper, I first constructed a database of power sector jobs in coal, solar, and wind sectors. I used this database to compare the skill requirements for direct jobs in coal, solar, and wind sectors in India under two scenarios – business-as-usual (reference) and accelerated deployment of RE (policy). I also explored the location of the skill requirements by assessing the state-wise distribution of green jobs for solar and wind sectors.

4.4 Methodology

As there is no standardized database available for the skill requirements for power sector jobs in India, I first reviewed secondary literature to construct a database for power sector jobs. I only focused on direct jobs in the following three sectors – coal, solar, and wind. For coal sector, I assessed the skill requirements for jobs in coal mining, and operating thermal power plants (TPP). For both solar, and wind, I assessed skill requirements for engineering, procurement, & construction (EPC), and operations & maintenance (O&M) jobs.

For coal mining, solar, and wind sectors, information on the NSQF levels of different job profiles, and the share of different job profiles in the total jobs in the sectors was available. This allowed me to construct an NSQF-based database of jobs in these sectors. For each of these sectors, I estimated the share of jobs corresponding to each NSQF level. I narrowed down the 10 NSQF levels to 3 skill categories by classifying jobs requiring skills between levels 1-3 as 'semi-skilled', levels 4-5 as 'skilled', and levels 6 and above as 'high-skilled'. I obtained coal mining related information from the report 'Human Resource & Skill Requirement Study for Indian Mining Sector' which was released by the Skill Council for Mining Sector (SCMS) in 2016 (SCMS, 2016). Information for solar, and wind sectors was obtained from the report 'Skill Gap Report for Solar, Wind, and Small Hydro Sector' which was released by the Skill Council for Green Jobs (SCGJ) in 2016 (SCGJ, 2016). Both SCMS and SCGJ are the apex bodies supported by the Indian government with the mandate of meeting the skill requirements for mining, and green jobs respectively.

For TPP jobs, no detailed information regarding the job profiles was available. However, information of the share of 'technical' and 'non-technical' jobs was available in the National Electricity Plan (NEP) that was released by the Central Electricity Authority of India in 2018. I arrived at the skill distribution for TPP jobs by categorizing 'non-technical' jobs are 'semi-skilled' jobs, and 'technical' jobs as 'skilled jobs'. However, because of the absence of detailed information on job profiles, and their NSQF levels, I could not construct a database for TPP jobs similar to the ones constructed for mining, solar, and wind jobs.

The details of the of the job profiles, and the skill requirements for direct jobs in coal, solar, and wind sectors are provided in appendix C1.

After arriving at the skill distribution for the four job types, I estimated the skill requirements for direct jobs in the power sector in India under two scenarios – business-as-usual (reference), and accelerated deployment of RE (policy) – for the year 2027. I chose 2027 as the year of analysis because the Indian government plants to add 150 GW of solar capacity, and 100 GW of wind capacity into the power grid by 2027 as per the National Electricity Plan. I included these targets under the 'policy' scenario. For the 'reference' scenario, I assumed business-as-usual growth in the installed capacity with no efforts to ramp up installation of solar, and wind. The details of the total installed capacity from the three power sources – coal, solar, and wind – are presented in appendix C2.

As the focus of the analysis was on estimating the skill requirements for direct jobs, I first estimated the total number of direct jobs in coal, solar, and wind sectors in 2027. I relied on the following equation for estimating the direct jobs in solar, and wind sectors for the year 2027 (equation 1). RE jobs in the EPC phase for a particular year depend on the amount of new capacity that is added into the system in that year. However, as O&M jobs are long-term jobs, the total number of O&M jobs in a particular year depend on the total (i.e. cumulative) RE capacity in that year.

$$\text{RE Jobs in 2027} = (IC_{t,\,2027} \times EF_{EPC}) + (TC_{t,2027} \times EF_{OM}) \qquad (1)$$

‘t’ refers to technology – solar, wind

To estimate the jobs associated with TPP and coal-mining in the year 2027, I used the same method as used in chapter 3. Below, I present the equations used to estimate TPP and coal-mining jobs:

$$\text{TPP Jobs in 2027} = TC_{t,2027} \times EF_{TPP} \qquad (2)$$

‘t’ refers to technology - coal

$$\text{Coal Mining jobs in 2027} = \frac{\text{Annual Coal Production}}{\text{Coal Mining Productivity}} \qquad (3)$$

The details of these equations are discussed in chapter 3.

Having arrived at the direct job estimates, I calculated the distribution of the jobs based on skill-levels using the following equation.

$$\text{Jobs by skill}_{t,\,i} = \text{Total Job}_t \times \text{Skill Share}_i \qquad (4)$$

‘t’ refers to technology – coal, solar, wind

‘i’ refers to the skill category – semi-skilled, skilled, high-skilled

I also estimated the distribution of skill requirements for solar and wind jobs in each state in India by plugging the total direct job estimates for solar, and wind in each state as calculated in chapter 3 into equation 4.

4.5 *Results*

Table 4.3: Database of direct jobs in coal mining, solar, and wind sectors in India

NSQF Level	Mining	Solar EPC and O&M	Wind EPC and O&M
1	Skilled Helper		
2		Project Helper	Project Helper
3	Explosive handler, Sampler, Timberman,		
4	Bankman, Mine electrician, HEMM operator, Dewatering plant operator	Assistant site surveyor, Assistant structural design engineer, CAD/Draughtsman (mechanical, electrical), Assistant design engineer, Solar PV installer (civil, electrical), Maintenance technical (electrical, civil)	Assistant planning engineer, Construction technician, Crane operator, O&M Electrical and Instrumentation technician
5	Mining engineer, Material engineer, Mining geologist, Mineral processing engineer	Market research analyst, Business development executive, Structural design engineer, Procurement executive, Grid interconnection engineer, Site engineer, HSE engineer, QA engineer, O&M engineer	Assistant site surveyor, Planning engineer, Procurement executive, CMS engineer, Construction engineer, HSE engineer, O&M engineer (mechanical, electrical, CMS)
6	Geophysicist, Mining economist, Remote sensing specialist	Liaison officer, Site surveyor, Energy modeller, Procurement manager, Solar site-in charge, Rooftop solar entrepreneur	Site surveyor, System planning engineer, Site manager/sub-contractor, HSE manager
7		Solar proposal evaluation specialist, Solar PV BD manager, Solar PV designer/design consultant, Project manager, O&M manager	Wind Resources Assessment manager, Project design manager, Wind land acquisition officer, Procurement
8		Project head, O&M head	Project head, O&M head
9		Power Plant Operations head	Power Plant Operations head
10		MD/ Director	MD/ Director

Database of the direct jobs in coal mining, EPC and O&M job for solar, and wind in India categorized by NSQF levels. This table has been constructed by the author based on reports by SCMS (2016), and SCGJ (2016).

Table 4.3 presents the database for direct jobs in coal mining, and EPC and O&M jobs in the solar and wind sectors in India. From this table, it can be observed while jobs as 'helpers' constitute majority of the jobs at the NSQF levels 1-3, jobs in managerial positions such as 'project heads' and 'managing director' constitute the jobs at NSQF levels

8-10 for all three job types. The job types at NSQF levels 4-7 do vary between the different electricity sources with coal mining requiring mining engineers, mineral processing engineers, material engineers, geologists etc., whereas solar and wind plants requiring more mechanical, electrical, and civil engineers.

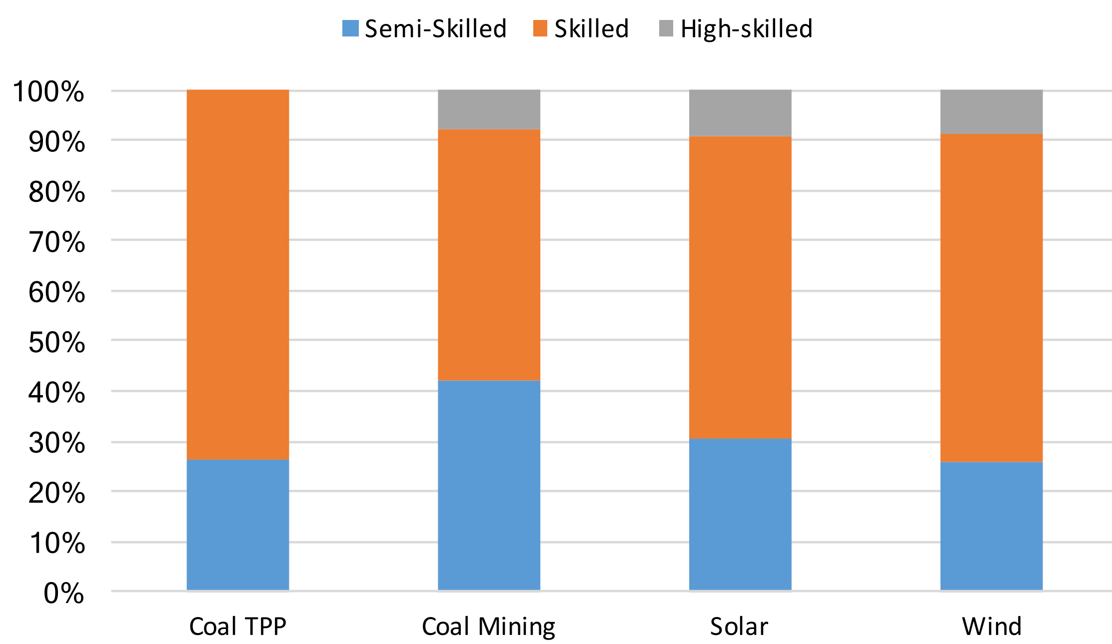


Figure 4.1: Distribution of jobs by skill requirements for direct jobs in coal, solar, and wind sectors in India

This distribution is based on author's own calculations.

I narrowed down the 10 NSQF levels to 3 skill categories by classifying jobs requiring skills between levels 1-3 as 'semi-skilled', levels 4-5 as 'skilled', and levels 6 and above as 'high-skilled'. For TPP jobs, I arrived at the skill distribution for TPP jobs by categorizing 'non-technical' jobs are 'semi-skilled' jobs, and 'technical' jobs as 'skilled jobs'. The results of the skill distribution for the four job types are presented in figure 4.1. It can be observed that jobs at NSQF levels 4 and 5 i.e. the 'skilled' jobs constitute majority of the jobs. Across the four power sector job types considered in this study, skilled jobs constitute 50-75% of the total jobs. The category of 'skilled' jobs is followed by 'semi-skilled' jobs, with their share varying between 26-42%. The share of semi-skilled jobs in coal mining is relatively higher than the other three job types.

Figure 4.2 presents the results of the scenario analysis for the year 2027.

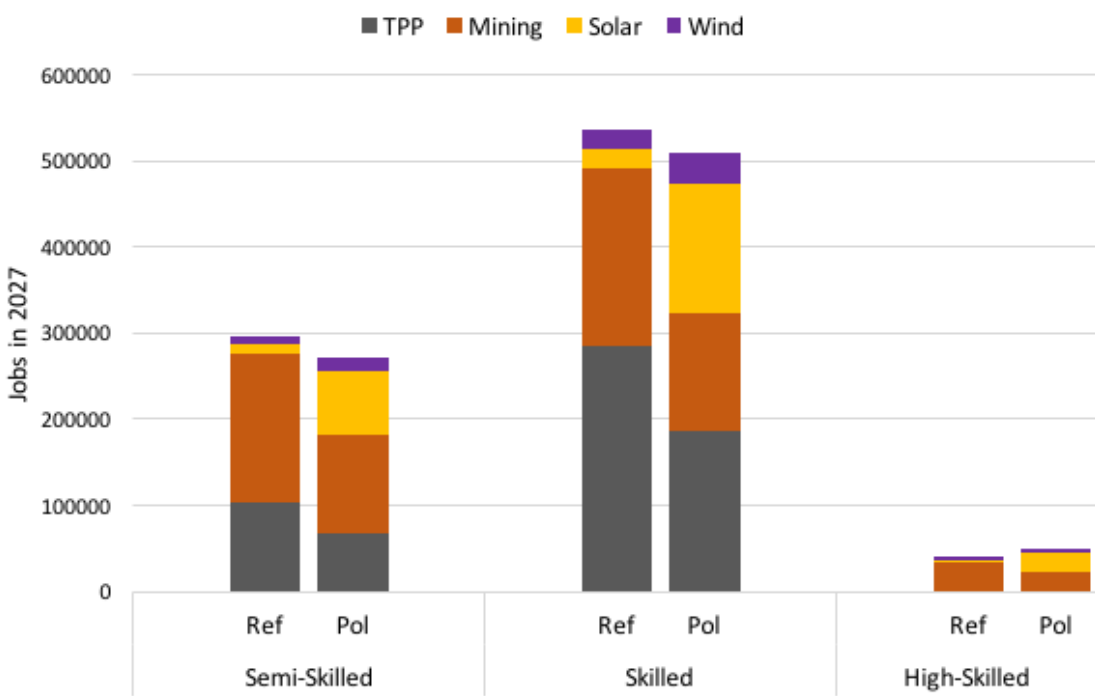


Figure 4.2: Distribution of skill requirements for direct coal, solar, and wind jobs under different scenarios

Distribution of the direct jobs in coal-based thermal power plants, coal mining, solar EPC and O&M, and wind EPC and O&M by skill levels under two scenarios – reference and policy. This analysis for the year 2027.

It can be observed that the total number of direct jobs is relatively higher in the 'reference' scenario as compared to the 'policy' scenario. Moreover, under the 'policy' scenario, the highest job gains occur in the solar sector. These observations are in line with the findings in chapter 2.

However, in both the 'reference' as well as 'policy' scenarios, majority of the job requirements are in the 'skilled' category, which is followed by the semi-skilled category. When compared to the reference scenario, the share of both semi-skilled, and skilled solar jobs is higher. This implies that clean energy transitions will increase the skill requirements for solar sector, particularly for solar jobs at NSQF levels 1-5. At the same time, clean energy transitions will decrease the requirement of semi-skilled, and skilled jobs associated with coal mining, and operating TPPs. In the semi-skilled category, it might be possible for the workers in non-green jobs to transition to green jobs as these jobs do not require vocational education. However, jobs between NSQF levels 3 to 5 require industry specific training in the form of short-term or advanced diploma or graduate degree. Clean energy transitions will require a change in the training programs designed for the power sector, with a greater emphasis on skills training for solar jobs at NSQF levels 4 and 5.

In order to understand the location of skill requirements for green jobs in India, I estimated state-wise skill distribution for solar and wind EPC and O&M jobs in the country. I used the state-level solar and wind job estimates from chapter 3 for the analysis. As the western, and southern states of Maharashtra, Gujarat, Tamil Nadu, Rajasthan, and Andhra Pradesh are expected to see the highest increase in direct solar and wind jobs, the skill requirements will be highest in these states. The state-wise job distribution by skills is presented in appendix C3.

4.6 Comparing the estimates with chapters 2 & 3

In this section, I compare the labor estimates across the three chapters i.e. chapter 2 to 4.

In chapter 2, I estimated the total direct and indirect labor impacts associated with power generation in India in 2030 under different decarbonization scenarios.

In chapter 3, I estimated the changes in state-level direct jobs associated with coal, solar, and wind sectors in India on account of changes in installed capacity between 2017 and 2027.

In this chapter, chapter 4, I estimated the skill distribution of direct jobs in coal, solar, and wind sectors in India. Using these estimates, I compared the skill requirements for direct jobs under 'reference' and 'policy' scenarios in India for the year 2027. I also estimated the state-wise share of skill requirements for direct jobs in solar and wind sectors.

As the target year of analysis in chapter 2 was 2030, I estimated labor impacts associated with coal, solar, and wind based power generation for the year 2027 for the comparison. Though input-output based models provide both direct as well indirect labor impacts, I have only considered direct job estimates i.e. jobs from electricity production, here. For coal, I have considered mining jobs as well.

In the following table, I present the labor estimates from the three chapters:

Table 4.4: Direct job estimates for coal, solar, and wind sectors for 2027 from chapter 2, 3, and 4

Direct Jobs 2027	**Chapter2**	**Chapter 3**	**Chapter 4**
Coal	9261068		524796
Solar	720690	143277	249475
Wind	136798	52722	56116

While I estimated cumulative job numbers for the scenario analysis in chapters 2 and 4, the labor estimates in chapter 3 are for *changes* in installed capacity between 2017 and 2027. That's why, the estimates for chapter 3 are relatively lower than chapters 2 and 4. However, even though the estimates from both chapter 2 and 4 are for direct jobs in coal, solar, and wind sectors in India for the year 2027, there is a substantial difference in the job numbers, especially for the coal sector. One important reason for these variations is the difference in data sources used to estimate the employment impacts in the two chapters. In chapter 2, I used the employment numbers associated with coal power generation as available in the EXIOBASE database. EXIOBASE database provides employment numbers in jobs per million Euros metric. For chapter 4, I obtained employment factors associated with coal power generation, and coal mining from secondary sources. It is likely that the types of jobs accounted for in these employment factors is a subset of the total number of jobs in the sector. For example, for coal mining, I relied on labor productivity estimates from Coal India Limited (CIL). The labor productivity estimates from CIL only account for the permanent employees, and does not include workers who are employed contractually.

Nonetheless, these variations highlight the need for data on power sector employment in India. The focus should be on both green, as well as fossil-fuel sectors. The impact of transitioning away from coal is also likely to have a pronounced impact on other sectors and workers of the economy that are indirectly associated with coal sectors, for eg. Railways, as it depends on coal for a significant proportion of its freight. Hence, it is important to have information on total employment associated with the sector.

Another important point to highlight here is the differences in estimates of direct jobs in solar and wind sectors between chapter 3 and 4. In chapter 3, I estimated the *change* in direct employment in solar and wind sectors between 2017-2027. Even though I estimated the *change* in employment in this chapter, these job numbers should be comparable to the total direct jobs in solar and wind in India in 2027, as estimated in chapter 4. This is because as per the RE capacity installation plans till the year 2027, majority of the solar and wind capacity in India is proposed to be added between the years 2017 and 2027. However, there are differences in the estimates between chapters 3 and 4. This is because in chapter 3, I estimated average employment numbers over the lifetime of RE projects, whereas in chapter 4, I estimated total employment for one year i.e. 2027.

In chapter 3, I wanted to compare job creation across different technologies. As the duration of jobs across different phases of RE vary – with EPC jobs being short-term that are calculated in 'person-years per MW', and O&M jobs lasting for the lifetime of RE projects that are calculated in 'jobs/MW' – I converted these estimates of short-term EPC jobs from 'person-years per MW' metric to 'jobs/MW' metric by dividing the EPC job estimated by the average lifetime of the RE power plant. This allowed me to arrive at the average number of jobs generated in the EPC phase throughout the lifetime of the RE power plant, allowing comparison with other long-term labor impacts. As O&M jobs are long-term, multiplying the installed capacity with employment factor for O&M jobs provided the total number of O&M jobs generated over the lifetime of the RE power plant. Without adjusting the estimates for the short-term jobs, I would be comparing EPC jobs that will last for the duration of one year with O&M jobs that will last for the lifetime of the RE power plant.

However, for the scenario analysis in chapter 4, I required estimates for the direct jobs in coal, solar, and wind sectors for a particular year i.e. 2027. As I was not concerned about comparing jobs of different duration, and from different technologies, and instead wanted estimates only for a particular year, I did not divide the EPC jobs by the average lifetime of an RE power plant. Instead, I estimated the number of EPC jobs generated in the year 2027 based on the new RE capacity installed into the grid in the year 2027. I estimated the O&M jobs based on the total (i.e. cumulative) RE capacity installed in the grid by 2027. I did not estimate the EPC jobs based on the cumulative capacity because in doing so, I would have assumed that the total RE capacity as of 2027 was constructed in just one year. However, I did estimate the O&M jobs based on cumulative RE capacity for as O&M jobs are long-term jobs, and are dependent upon the total RE capacity in the power system.

4.7 Discussion

Though skills gap is recognized as an important barrier to hiring in RE industries, limited empirical work has been done on this topic. Most of the studies on this topic only look into the skill requirements for RE sectors i.e. green jobs. While it is important to assess the skills required for green jobs, attention should be given to the skill requirements for non-green jobs as well. Evaluating the skill requirements for non-green jobs can inform us about the potential of transition from non-green jobs to green job within a country.

In this paper, I assessed the skill requirements for direct jobs in coal, solar, and wind sectors for the year 2027 under two scenarios – business-as-usual (reference), and accelerated deployment of RE (policy). Results suggest that accelerated deployment of RE will increase the skill requirements, particularly for solar jobs at NSQF levels 1-5, in India. However, at the same time, clean energy transitions will decrease the requirement of semi-skilled, and skilled jobs associated with coal mining, and operating TPPs. In the semi-skilled category, it might be possible for the workers in non-green jobs to transition to green jobs as these jobs do not require vocational education, and can be performed by anyone with education level below Xth standard. However, an important challenge for this transition would be 'location'. The semi-skilled workers, especially in the coal mining sector, who will be losing jobs because of clean energy transitions are unlikely to be located in the same states which hold the highest potential from solar and wind jobs as highlighted in chapter 3. Because of these spatial differences, it is unlikely that these semi-skilled workers working in non-green jobs can be seamlessly absorbed in the green industries, and thus would require retraining or skill upgradation in order to find work in other industries. It is important to note here that semi-skilled workers constitute ~40% of the mining workforce.

An important limitation of this study is that I could not construct NSQF-based job database for the direct jobs at thermal power plants due to the unavailability of data. Building a database for TPP jobs, on lines with the one constructed for mining, solar, and wind jobs in this paper can be useful in understanding the differences in the skill requirements for non-green, and green jobs in the power sector in India. It can, in turn, help assess the potential of transition from coal to solar/wind jobs, and evaluate the retraining requirements as well.

4.8 Conclusion

In this paper I explored the skill requirements for the labor impacts associated with clean energy transitions in the power sector in India. Using secondary data sources, I first constructed a database of power sector jobs in coal, solar, and wind sectors. I then arrived at the distribution of these jobs across three skill categories – semi-skilled, skilled, and high-skilled – using the National Skill Qualification Framework (NSQF) for India. The NSQF is a framework used by the government of India that allows organization of the skills required for different industries on a standardized scale of 1 to 10. I categorized jobs between levels 1-3 as semi-skilled, 4 and 5 as skilled, and 6 and above as high-skilled. Using these skill estimates, I compared the skill requirements for direct jobs in coal, solar, and wind sectors in India under two scenarios – business-as-usual (reference) and accelerated deployment of RE (policy) – for the year 2027. I also assessed the state-wise skill requirements for green jobs in solar and wind sectors.

The results of this analysis showed that under both reference and policy scenarios, majority of the jobs in the power sector are created in the 'skilled' category. As per the classification used, skilled jobs require short- or long-term diplomas or graduate degrees. Clean energy transitions in the power sector will decrease the number of semi-skilled, and skilled jobs required to run coal-based thermal power plants, and in the coal mining sector. It will increase the requirement of semi-skilled, and skilled jobs in the solar sector which includes jobs as site surveyors, structural design engineers, mechanical and electrical draughtsman, solar PV installers, market research analysts, site engineers, HSE engineers, and QA engineers etc. Most of the direct jobs in the solar and wind sectors will be generated in the states of Maharashtra, Rajasthan, Gujarat, Tamil Nadu, Andhra Pradesh, and Karnataka on account of the solar and wind capacity proposed to be installed in these states. Thus, these states should be considered the priority locations for setting up RE training institutes.

5 Conclusion

The purpose of this quantitative study is to assess the labor impacts associated with clean energy transitions in the power sector in India. While creation of 'green jobs' is recognized as an important co-benefit of climate action, few studies have looked into the employment impacts of clean energy transitions in India. In this study, I assess the economy-wide labor impacts of power generation in India in 2030 under different decarbonization scenarios. I also examine the regional distribution of these labor impacts, and assess the skill requirements for clean energy transitions in the power sector.

In chapter 2, I estimated the total direct and indirect labor impacts associated with power generation in India in 2030 under different decarbonization scenarios.
In chapter 3, I estimated the changes in state-level direct jobs associated with coal, solar, and wind sectors in India on account of changes in installed capacity between 2017 and 2027.
In this chapter, chapter 4, I estimated the skill distribution of direct jobs in coal, solar, and wind sectors in India. Using these estimates, I compared the skill requirements for direct jobs under 'reference' and 'policy' scenarios in India for the year 2027. I also estimated the state-wise share of skill requirements for direct jobs in solar and wind sectors.

I found that while there exists optimism about the employment potential of RE technologies, data on the current levels of employment in RE sectors such as solar and wind remains limited in India. Most projections for labor impacts of clean energy transitions focus only on estimating direct labor impacts of solar and wind energy. Moreover, economy-wide labor impacts under different decarbonization scenarios suggest that even with accelerated RE deployment, coal jobs will constitute 65-75% of the total jobs from power generation as coal remains the major fuel for power generation in India for the next decade. Majority of the jobs in RE sectors are likely to be created from solar generation. Estimates for total number of jobs from solar PV under different scenarios with accelerated RE deployment vary between 1.2-3.3 million, whereas wind jobs vary between 0.3-0.4 million. Data on current levels and nature of employment in RE sectors remains limited making it difficult to assess the scope and trends of employment in clean industries. It is important to collect data for RE industries regularly so that assessment of the job potential of these industries can be improved.

For chapter 3, I constructed an analytical framework to explore the spatial disaggregation of the labor impacts associated with clean energy transitions in the power sector in India. I found that the Indian government's target of adding 150 GW solar capacity, and 100 GW of wind capacity by 2027 will generate jobs primarily in western and southern states of Maharashtra, Rajasthan, Gujarat, Tamil Nadu, Andhra Pradesh, and Karnataka. Job gains due to RE capacity addition in coal-rich eastern states of the country are minimal as limited solar and wind capacity is planned to be installed in these states till 2027. However, short to medium-term power sector plans for India include addition of coal capacity as well. If plans for net coal capacity addition are also taken into account, overall job gains are relatively higher for coal-rich states - such as Chhattisgarh, Odisha, Jharkhand, and Madhya Pradesh - highlighting that coal sector is a major source of employment in power sector in India. These states are likely to lose out on jobs and economic revenue when India does start retiring thermal capacity.

In chapter 4, I explored the skill requirements for the labor impacts associated with clean energy transitions in the power sector in India. Using secondary data sources, I first constructed a database of power sector jobs in coal, solar, and wind sectors. I then arrived at the distribution of these jobs across three skill categories – semi-skilled, skilled, and high-skilled – using the National Skill Qualification Framework (NSQF) for India. Using these skill estimates, I compared the skill requirements for direct jobs in coal, solar, and wind sectors in India under two scenarios – business-as-usual (reference) and accelerated deployment of RE (policy) – for the year 2027. The results of this analysis showed that under both reference and policy scenarios, majority of the jobs in the power sector are created in the 'skilled' category. Clean energy transitions in the power sector will increase the requirement of semi-skilled, and skilled jobs in the solar sector which includes jobs as site surveyors, structural design engineers, mechanical and electrical draughtsman, solar PV installers, market research analysts, site engineers, HSE engineers, and QA engineers etc. Most of the direct jobs in the solar and wind sectors will be generated in the states of Maharashtra, Rajasthan, Gujarat, Tamil Nadu, Andhra Pradesh, and Karnataka on account of the solar and wind capacity proposed to be installed in these

Appendices

A1

List of academic, and grey literature on green jobs in India, or labor impacts of clean energy transitions in the power sector in India. This is not an exhaustive list, but covers the important sources of literature on this topic for India, along with the methodology used for analysis.

Study	Source type	Method
MNRE and CII (2010)	Government report	Analytic
Jain and Patwardhan (2013)	Article	Analytic
Pollin and Chakroborty (2015)	Article	I/O
Skills Gap Report (2016)	Government report	Analytic
CEEW and NRDC India (2017,2019)	Report	Analytic
CPI India (2018)	Report	Regression-based model
ILO (2018)	Report	I/O
IRENA (2018,2019)	Report	Analytic
Azad and Chakroborty (2018)	Working paper	I/O

A2

The following table, table A2.1, presents the total electricity generation in India in 2030 under different scenarios.

		Coal	Gas	Nuclear	Hydro	Wind	Petroleum	Biomass	Solar PV	Total
	Ref	3038	95	32	131	50	3	13	8	3370
PC 2014	Pol	2200	128	280	230	279	3	70	275	3465
	Pol	1698	262	165	253	207	32	80	152	2849
IEA 2015	Pol+	1645	262	165	254	216	36	81	218	2877
	Ref	1958	149	112	228	228	0	126	308	3109
NITI Aayog 2017	Pol	1709	208	136	257	239	0	159	342	3049
	Ref	2358	112	86	305	114	4	31	60	3071
CEA 2019	Pol	1254	50	100	201	301	0	25	577	2508

The following table, table A2.2, presents the share of different fuels in total electricity generation in India in 2030 under different scenarios.

		Coal	Gas	Nuclear	Hydro	Wind	Petroleum	Biomass	Solar PV	Total
	Ref	90.15%	2.82%	0.95%	3.89%	1.48%	0.09%	0.39%	0.24%	100%
PC 2014	Pol	63.49%	3.69%	8.08%	6.64%	8.05%	0.09%	2.02%	7.94%	100%
	Pol	59.60%	9.20%	5.79%	8.88%	7.27%	1.12%	2.81%	5.34%	100%
IEA 2015	Pol+	57.18%	9.11%	5.74%	8.83%	7.51%	1.25%	2.82%	7.58%	100%
	Ref	62.97%	4.80%	3.59%	7.35%	7.33%	0.00%	4.05%	9.91%	100%
NITI Aayog 2017	Pol	56.04%	6.81%	4.45%	8.44%	7.83%	0.00%	5.22%	11.20%	100%
	Ref	76.78%	3.66%	2.82%	9.93%	3.72%	0.12%	1.02%	1.95%	100%
CEA 2019	Pol	50.00%	2.00%	4.00%	8.00%	12.00%	0.00%	1.00%	23.00%	100%

A3

The following table, table A3.1, presents the employment coefficients (jobs/ million Euros) for direct and indirect jobs for different fuel technologies.

Source	Jobs/Million Euros
Coal	142
Gas	97
Nuclear	81
Hydro	51
Wind	42
Petroleum	65
Biomass	92
Solar PV	120

The following table, A3.2, presents the fuel-wise total direct and indirect employment from electricity generation in India in 2030 under different scenarios. These employment numbers have been estimated using the analytical framework described in section 3.

		Coal	**Gas**	**Nuclear**	**Hydro**	**Wind**	**Petroleum**	**Biomass**	**Solar PV**	**Total**
2018		6.39	0.31	0.15	0.26	0.11	0.00	0.06	0.17	7.46
	Ref	26.07	0.84	0.13	0.41	0.07	0.04	0.13	0.05	27.73
PC 2014	Pol	18.88	1.13	1.14	0.71	0.38	0.04	0.72	1.57	24.57
	Pol	14.57	2.31	0.67	0.78	0.28	0.40	0.83	0.87	20.71
IEA 2015	Pol+	14.12	2.31	0.67	0.79	0.30	0.45	0.84	1.24	20.70
	Ref	16.80	1.32	0.45	0.71	0.31	0.00	1.30	1.76	22.65
NITI Aayog 2017	Pol	14.67	1.83	0.55	0.80	0.33	0.00	1.64	1.95	21.76
	Ref	20.24	0.99	0.35	0.94	0.16	0.05	0.32	0.34	23.39
CEA 2019	Pol	10.76	0.44	0.41	0.62	0.41	0.00	0.26	3.29	16.20

The following table, table A3.3, presents the share of different fuels in total direct and indirect employment from electricity generation in India in 2030 under different scenarios.

		Coal	Gas	Nuclear	Hydro	Wind	Petroleum	Biomass	Solar PV	Total
2018		85.68%	4.16%	2.03%	3.54%	1.49%	0.04%	0.81%	2.24%	100%
	Ref	94.02%	3.02%	0.47%	1.46%	0.25%	0.13%	0.48%	0.16%	100%
PC 2014	Pol	76.85%	4.59%	4.63%	2.90%	1.55%	0.15%	2.94%	6.39%	100%
	Pol	70.37%	11.15%	3.24%	3.78%	1.37%	1.92%	3.99%	4.19%	100%
IEA 2015	Pol+	68.18%	11.15%	3.24%	3.80%	1.43%	2.16%	4.04%	6.01%	100%
	Ref	74.18%	5.81%	2.00%	3.12%	1.38%	0.00%	5.74%	7.76%	100%
NITI Aayog 2017	Pol	67.39%	8.41%	2.53%	3.66%	1.50%	0.00%	7.55%	8.96%	100%
	Ref	86.52%	4.24%	1.50%	4.04%	0.67%	0.19%	1.39%	1.46%	100%
CEA 2019	Pol	66.45%	2.73%	2.52%	3.83%	2.54%	0.00%	1.60%	20.33%	100%

A4

The following table, table A4.1, presents the total installed capacity (in GW) under the two scenarios for the CEA 2019 study.

Source	BAU 2030	Policy 2030
Coal	445	267
Gas	56	24
Nuclear	15	17
Hydro	112	73
Wind	77	140
Petroleum	2	0
Biomass	20	10
Solar	49	300
Total	776	832

The following table, table A4.2, presents the share of different fuels in the total installed capacity (in GW) under the two scenarios for the CEA 2019 study. Here, non-fossil fuel category includes the following fuels: nuclear, hydro, wind, biomass, and solar.

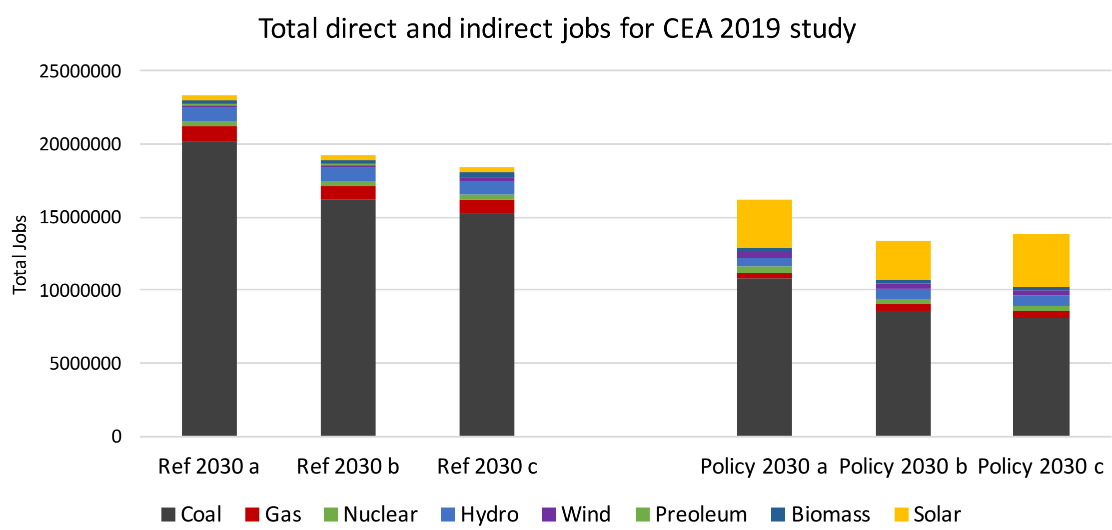
Source	BAU 2030	Policy 2030
Coal	57%	32%
Gas	7%	3%
Nuclear	2%	2%
Hydro	14%	9%
Wind	10%	17%
Petroleum	0%	0%
Biomass	3%	1%
Solar	6%	36%
Non Fossil Share	35%	65%

A5

The following table, table A5.1, presents to total number of direct and indirect jobs under the 'reference' and 'policy' scenarios for the CEA 2019 study for different values of LCOE as outlined in table 1 in the text.

	Coal	Gas	Nuclear	Hydro	Wind	Preoleum	Biomass	Solar	TOTAL
Ref 2030 a	20236020	990704	351263	943926	156450	45179	324653	341974	23390169
Ref 2030 b	16141670	990704	351263	943926	156450	45179	324653	272561	19226405
Ref 2030 c	15259145	990704	351263	943926	156450	45179	324653	376972	18448291
Policy 2030 a	10761386	441834	407395	621061	411678	0	258973	3293227	16195554
Policy 2030 b	8584037	441834	407395	621061	411678	0	258973	2624775	13349752
Policy 2030 c	8114715	441834	407395	621061	411678	0	258973	3630256	13885913

The following figure, figure A5.1, presents the total direct and indirect jobs under 'reference' and 'policy' scenarios for the CEA 2019 study for different values of LCOE as outlined in table 1 in the text.



B1

The following tables present the state-wise breakdown of solar and wind capacity targets between 2017 and 2027.

MNRE provides state- and technology-wise breakdown for the 2022 RE capacity addition target that includes 100 GW of solar capacity addition, and 60 GW of wind. The National Electricity Plan that was released in 2027 included target of increasing RE capacity to 275 GW by 2022, by adding 50 GW of solar, and 40 GW of wind between 2022 and 2027. However, the plan does not provide state-wise breakdown of the target for the 2022-2027 period. I estimated the state-wise breakdown for 2022-2027 by assuming the same distribution of solar and wind capacity across states as proposed for the 2017-2022 targets.

Table B1.1: State-wise breakdown of solar capacity addition targets between 2017 and 2027 (in MW):

	2017-2022			2022-2027		
State	**Rooftop**	**Groundmount**	**Total 100 GW**	**Rooftop**	**Groundmount**	**Total 50 GW**
Andaman & Nicobar Islands	20	7	27	10	3	13
Andhra Pradesh	2000	7834	9834	1000	3819	4819
Arunachal Pradesh	50	0	39	25	0	25
Assam	250	413	663	125	201	326
Bihar	1000	1493	2493	500	728	1228
Chandigarh	100	53	153	50	26	76
Chhattisgarh	700	1083	1783	350	528	878
D. & N. Haveli	200	249	449	100	121	221
Daman & Diu	100	99	199	50	48	98
Delhi	1100	1662	2762	550	810	1360
Goa	150	208	358	75	101	176
Gujarat	3200	4820	8020	1600	2350	3950
Haryana	1600	2542	4142	800	1239	2039
Himachal Pradesh	320	456	776	160	222	382
Jammu & Kashmir	450	705	1155	225	344	569
Jharkhand	800	1195	1995	400	583	983
Karnataka	2300	3397	5697	1150	1656	2806
Kerala	800	1070	1870	400	522	922
Lakshadweep	10	0	4	5	0	5
Madhya Pradesh	2200	3475	5675	1100	1694	2794
Maharashtra	4700	7226	11926	2350	3523	5873
Manipur	50	55	105	25	27	52
Meghalaya	50	111	161	25	54	79
Mizoram	50	22	72	25	11	36
Nagaland	50	11	61	25	5	30
Orissa	1000	1377	2377	500	671	1171
Puducherry	100	146	246	50	71	121
Punjab	2000	2772	4772	1000	1351	2351
Rajasthan	2300	3462	5762	1150	1688	2838
Sikkim	50	0	36	25	0	25
Tamil Nadu	3500	5384	8884	1750	2625	4375
Telangana	2000	0	2000	1000	0	1000
Tripura	50	55	105	25	27	52
Uttar Pradesh	4300	6397	10697	2150	3119	5269
Uttrakhand	350	550	900	175	268	443
West Bengal	2100	3236	5336	1050	1578	2628
Total	40000	61534	101534	20000	30015	50015

Table B1.2: State-wise breakdown of solar capacity addition targets between 2017 and 2027 (in MW):

State	**2017-2022**	**2022-2027**
Andaman & Nicobar Islands		
Andhra Pradesh	8100	5455
Arunachal Pradesh		
Assam		
Bihar		
Chandigarh		
Chhattisgarh		
D. & N. Haveli		
Daman & Diu		
Delhi		
Goa		
Gujarat	8800	5926
Haryana		
Himachal Pradesh		
Jammu & Kashmir		
Jharkhand		
Karnataka	6200	4175
Kerala		
Lakshadweep		
Madhya Pradesh	6200	4175
Maharashtra	7600	5118
Manipur		
Meghalaya		
Mizoram		
Nagaland		
Orissa		
Puducherry		
Punjab		
Rajasthan	8600	5791
Sikkim		
Tamil Nadu	11900	8013
Telangana	2000	1347
Tripura		
Uttar Pradesh		
Uttrakhand		
West Bengal		
Total	59400	40000

B2

The following table presents the state-wise thermal capacity changes between 2017-2022. The National Electricity Plan 2018 provides information about thermal power plants that are proposed to be retired (due to age or lack of space for FGD units), as well as new thermal capacity under construction. Between 2017 and 2022, while 47,855 MW of new thermal capacity is proposed to come up, 22,715 MW is marked for closure. I arrived at state-level coal capacity to be added and retired between 2017 and 2022 based on the plant-level data provided in NEP 2018.

Table B2: State-wise thermal capacity changes between 2017 and 2022 (in MW)

State	**Coal Addition**	**Coal Retirement**
Andaman & Nicobar Islands		
Andhra Pradesh	2900	1260
Arunachal Pradesh		
Assam	250	
Bihar	5210	430
Chandigarh		
Chhattisgarh	4420	1280
D. & N. Haveli		
Daman & Diu		
Delhi		840
Goa		
Gujarat	800	540
Haryana		210
Himachal Pradesh		
Jammu & Kashmir		
Jharkhand	1980	1790
Karnataka	800	1720
Kerala		
Lakshadweep		
Madhya Pradesh	4240	830
Maharashtra	2430	380
Manipur		
Meghalaya		
Mizoram		
Nagaland		
Orissa	3270	810
Puducherry		
Punjab		1700
Rajasthan	3140	850
Sikkim		
Tamil Nadu	5905	5310
Telangana	3480	1283
Tripura		
Uttar Pradesh	8580	1313
Uttrakhand		
West Bengal	450	2170
Total	**47855**	**22716**

B3

The following table, table B3, presents the state-wise solar and wind sectors related direct labor impacts associated with capacity addition of 250 GW – including 150 GW of solar, and 100 GW of wind – in India between 2017-2027.

State	Solar Gain	Wind Gain	Land Loss
Andaman & Nicobar Islands	50	0	-8
Andhra Pradesh	11608	7189	-4964
Arunachal Pradesh	110	0	-13
Assam	930	0	-198
Bihar	3576	0	-744
Chandigarh	269	0	-46
Chhattisgarh	2538	0	-532
D. & N. Haveli	670	0	-134
Daman & Diu	311	0	-59
Delhi	3951	0	-824
Goa	522	0	-107
Gujarat	11481	7811	-4603
Haryana	5862	0	-1236
Himachal Pradesh	1124	0	-232
Jammu & Kashmir	1640	0	-345
Jharkhand	2861	0	-596
Karnataka	8190	5503	-3257
Kerala	2746	0	-558
Lakshadweep	22	0	-2
Madhya Pradesh	8042	5503	-3250
Maharashtra	16998	6746	-5467
Manipur	161	0	-31
Meghalaya	212	0	-48
Mizoram	130	0	-22
Nagaland	120	0	-18
Orissa	3469	0	-710
Puducherry	355	0	-73
Punjab	6955	0	-1425
Rajasthan	8250	7633	-3879
Sikkim	110	0	-12
Tamil Nadu	12661	10562	-5639
Telangana	4406	1775	-1102
Tripura	161	0	-31
Uttar Pradesh	15355	0	-3193
Uttrakhand	1277	0	-269
West Bengal	7602	0	-1593
Total	144725	52722	-45220

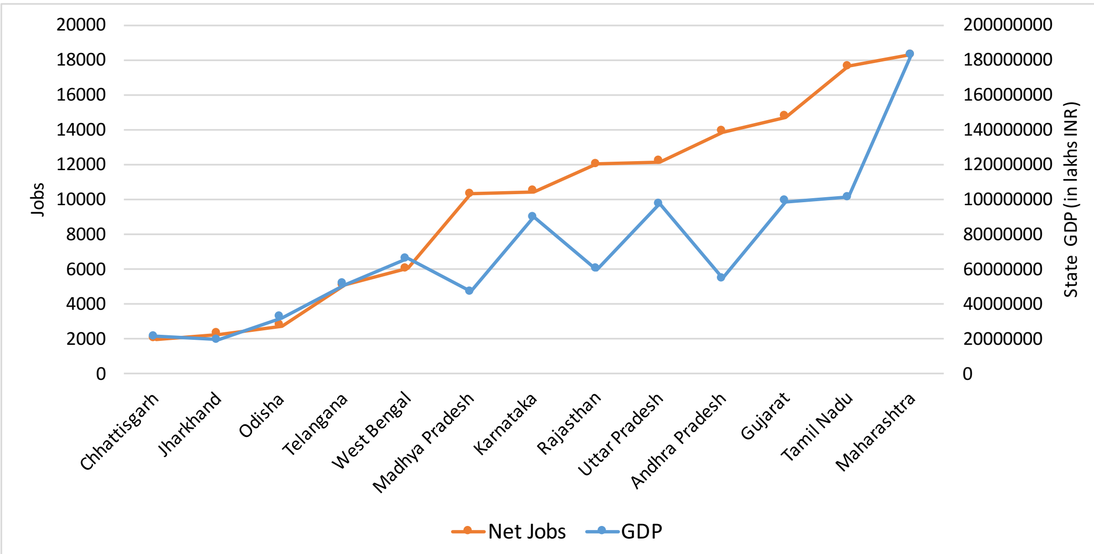
B4

The following table presents the state-wise direct labor impacts associated with changes in the installed capacity of coal, wind, and solar in India between 2017 and 2022.

				TPP			Mining			
State	**Solar**	**Wind**	**Land**	**Gain**	**Loss**	**Net**	**Gain**	**Loss**	**Net**	**Overall net**
Andaman & Nicobar Islan	34	0	-5	0	0	0	0	0	0	28
Andhra Pradesh	7779	4296	-3182	3089	-1342	1747	0	0	0	10640
Arunachal Pradesh	73	0	-8	0	0	0	0	0	0	66
Assam	622	0	-133	266	0	266	0	0	0	756
Bihar	2391	0	-499	5549	-458	5091	0	0	0	6984
Chandigarh	180	0	-31	0	0	0	0	0	0	149
Chhattisgarh	1697	0	-357	4707	-1363	3344	15916	-7555	8361	13046
D. & N. Haveli	448	0	-90	0	0	0	0	0	0	358
Daman & Diu	208	0	-40	0	0	0	0	0	0	168
Delhi	2643	0	-552	0	-895	-895	0	0	0	1196
Goa	349	0	-72	0	0	0	0	0	0	277
Gujarat	7679	4668	-2924	852	-575	277	0	0	0	9699
Haryana	3921	0	-828	0	-224	-224	0	0	0	2869
Himachal Pradesh	752	0	-155	0	0	0	0	0	0	597
Jammu & Kashmir	1097	0	-231	0	0	0	0	0	0	866
Jharkhand	1914	0	-399	2109	-1906	202	14754	-7003	7751	9467
Karnataka	5478	3288	-2069	852	-1832	-980	0	0	0	5717
Kerala	1836	0	-374	0	0	0	0	0	0	1462
Lakshadweep	15	0	-1	0	0	0	0	0	0	14
Madhya Pradesh	5379	3288	-2065	4516	-884	3632	13126	-6231	6896	17130
Maharashtra	11369	4031	-3525	2588	-405	2183	4674	-2218	2455	16513
Manipur	107	0	-21	0	0	0	0	0	0	86
Meghalaya	142	0	-32	0	0	0	0	0	0	110
Mizoram	87	0	-14	0	0	0	0	0	0	73
Nagaland	80	0	-12	0	0	0	0	0	0	68
Orissa	2320	0	-475	3483	-863	2620	16873	-8009	8864	13328
Puducherry	237	0	-49	0	0	0	0	0	0	188
Punjab	4651	0	-954	0	-1811	-1811	0	0	0	1886
Rajasthan	5518	4561	-2442	3344	-905	2439	0	0	0	10076
Sikkim	73	0	-7	0	0	0	0	0	0	66
Tamil Nadu	8468	6312	-3562	6289	-5655	634	0	0	0	11852
Telangana	2938	1061	-700	3706	-1366	2340	7358	-3493	3865	9504
Tripura	107	0	-21	0	0	0	0	0	0	86
Uttar Pradesh	10269	0	-2139	9138	-1398	7739	0	0	0	15869
Uttrakhand	854	0	-180	0	0	0	0	0	0	674
West Bengal	5084	0	-1067	479	-2311	-1832	3138	-1490	1649	3834
Total	96799	31506	-29217	50966	-24192	26774	75839	-35999	39840	165702

B5

The following figure shows the net direct jobs created due to addition of 250 GW RE capacity – including 150 GW solar, and 100 GW wind for selected states, and also the GDPs of those states for the year 2016-17. It can be observed that states that experience the highest gains in RE jobs are also the states with relatively higher GDP in comparison to the states where RE job gains are low.



C1

Distribution of jobs in mining sector by skill and education levels

Education Level	NSQF level	Distribution	Skill Code
Primary	1	4.30%	1
Upper Primary	1	16.30%	1
Secondary	1	6.80%	1
Higher Secondary	1	3.60%	1
Short/Med Diploma	3	11.00%	1
Diploma/ITI	4	37.00%	2
Graduate/Polytech	5	13.00%	2
Post Graduate	6	8.00%	3

Distribution of jobs in thermal power generation into technical and non-technical categories

Job type	Distribution	Skill Code
Non-Technical	26%	1
Technical	74%	2

Distribution of solar PV EPC and O&M jobs by skill levels

Job Description	Share in total jobs	NSFQ level	Skill Code
Solar Project Helper	30.35%	2	1
Solar PV Maintenance Technician (Electrical)- Ground Mount and Rooftop	13.78%	4	2
Solar PV Installer (Civil)	11.43%	4	2
Solar PV Installer (Electrical)	8.77%	4	2
Solar PV Engineer (Site/ QA/ HSE)	8.04%	5	2
Solar PV Installer (Suryamitra)*	5.10%	4	2
Solar PV O&M Engineer	3.97%	5	2
Solar PV Maintenance Technician (Civil/ Mechanical)	3.94%	4	2
Rooftop Solar Grid Engineer	0.97%	7	2
Solar PV Structural Design Engineer	0.86%	6	2
Solar PV Design Engineer (Electrical)	0.86%	7	2
Solar PV Business Development Executive	1.10%	7	2
Procurement Executive - Solar PV	1.01%	5	2
Market research analyst	0.15%	7	2
CAD/ Draughtsman- Solar PV	0.10%	5	2
Solar PV Assistant Design Engineer (Electrical)	0.05%	5	2
Solar PV Assistant Structural Design Engineer	0.05%	5	2
Assistant Site Surveyor	0.05%	5	2
Solar PV Engineer (Grid Interconnection)	0.08%	7	2
Solar PV O&M Manager	1.32%	7	3
Solar Site Incharge	1.89%	6	3
Rooftop Solar Photovoltaic Entrepreneur	1.68%	6	3
Solar PV Project Manager - E&C/ Project Execution Subcontractor	1.29%	5	3
Solar PV Designer	0.86%	4	3
Solar Proposal Evaluation Specialist	0.68%	4	3
Business Development Manager	0.72%	4	3
Procurement Manager- Solar PV	0.48%	6	3
Solar PV Site Surveyor	0.35%	4	3
Energy Modeller- Solar PV	0.05%	5	3
Solar Ground Mount Entrepreneur	0.02%	7	3

Distribution of wind EPC and O&M jobs by skill levels

Job Description	Share in total jobs	NSFQ level	Skills
Wind Project Helper – EPC and O&M	25.71%	2	1
O&M Electrical and Instrumentation Technician - Wind Power Plant	10.91%	4	2
Construction Technician (Electrical)- Wind Power Plant	7.86%	4	2
Construction Technician (Civil) - Wind Power Plant	5.90%	4	2
O&M Mechanical Technician - Wind Power Plant	7.27%	4	2
CMS Engineer (EPC and O&M)	5.24%	5	2
Construction Technician (Mechanical) - Wind Power Plant	3.93%	4	2
Crane Operator	3.93%	4	2
Procurement Executive- Wind	3.14%	5	2
Assistant Planning Engineer (Civil/ Mechanical and Electrical)	2.36%	6	2
Construction Engineer (Electrical)- Wind Power Plant	2.36%	4	2
Construction Engineer (Civil) - Wind Power Plant	1.97%	5	2
Construction Engineer (Mechanical)- Wind Power Plant	1.97%	5	2
O&M Engineer (Electrical) - Wind Power Plant	2.42%	5	2
O&M Engineer (Mechanical) - Wind Power Plant	2.42%	5	2
Assistant Site Surveyor (Civil)- Wind Power Plant	0.79%	5	2
Assistant Site Surveyor (Electrical)- Wind Power Plant	0.79%	6	2
Planning Engineer (Civil/ Structural)- Wind Power Plant	0.79%	7	2
Planning Engineer (Electrical)- Wind Power Plant	0.79%	5	2
HSE Engineer	0.79%	5	2
Site Surveyor (Civil and Electrical)	2.36%	7	3
O&M Manager- Wind Power Plant	1.21%	7	3
WRA – Wind Resource Assessment Manager	1.18%	5	3
Wind Land Acquisition Officer	0.79%	5	3
Procurement Manager- Wind	0.79%	6	3
Site Manager/ Subcontractor/ Entrepreneur- Wind Power Plant	0.79%	5	3
Project Design Manager - Wind Power Plant	0.39%	7	3
Project Manager- Wind Power Plant	0.39%	7	3
System Planning Engineer - Wind Power Plant	0.39%	6	3
HSE Manager	0.39%	6	3

C2

The following table presents the total installed capacity from coal, solar, and wind

Source	2019	Ref 2027	Pol 2027
Coal	200704	362931	238150
Solar	28181	39854	150000
Wind	35626	62668	100000

Ref Skills Distribution				
	Coal		**Solar**	**Wind**
	TPP	**Mining**		
Semi-Skilled	102347	173564	11122	8718
Skilled	284175	206624	22099	22243
High-skilled	0	33060	3424	2942
TOTAL	386522	413248	36645	33903

Pol Skills Distribution				
	Coal		**Solar**	**Wind**
	TPP	**Mining**		
Semi-Skilled	67158	113890	75717	14430
Skilled	186471	135583	150450	36816
High-skilled	0	21693	23308	4870
TOTAL	253630	271167	249475	56116

C3

The following table presents the state-wise distribution of solar and wind jobs in India by skill level.

	Solar Skill			Wind Skill		
	Semi	Skilled	Highly Skilled	Semi	Skilled	Highly Skilled
Maharashtra	5099	10199	1530	1754	4452	540
Tamil Nadu	3798	7596	1139	2746	6971	845
Gujarat	3444	6889	1033	2031	5155	625
Andhra Pradesh	3482	6965	1045	1869	4745	575
Rajasthan	2475	4950	742	1985	5038	611
Uttar Pradesh	4606	9213	1382	0	0	0
Karnataka	2457	4914	737	1431	3632	440
Madhya Pradesh	2412	4825	724	1431	3632	440
West Bengal	2280	4561	684	0	0	0
Punjab	2086	4173	626	0	0	0
Telangana	1322	2644	397	462	1172	142
Haryana	1759	3517	528	0	0	0
Delhi	1185	2371	356	0	0	0
Bihar	1073	2145	322	0	0	0
Orissa	1041	2081	312	0	0	0
Jharkhand	858	1717	258	0	0	0
Kerala	824	1648	247	0	0	0
Chhattisgarh	761	1523	228	0	0	0
Jammu & Kashmir	492	984	148	0	0	0
Uttrakhand	383	766	115	0	0	0
Himachal Pradesh	337	675	101	0	0	0
Assam	279	558	84	0	0	0
D. & N. Haveli	201	402	60	0	0	0
Goa	157	313	47	0	0	0
Puducherry	106	213	32	0	0	0
Daman & Diu	93	187	28	0	0	0
Chandigarh	81	161	24	0	0	0
Meghalaya	64	127	19	0	0	0
Manipur	48	96	14	0	0	0
Tripura	48	96	14	0	0	0
Mizoram	39	78	12	0	0	0
Nagaland	36	72	11	0	0	0
Arunachal Pradesh	33	66	10	0	0	0
Sikkim	33	66	10	0	0	0
Andaman & Nicobar Is	15	30	5	0	0	0
Lakshadweep	7	13	2	0	0	0
Total	43417	86835	13025	13708	34796	4218

Bibliography

Azad, R., & Chakraborty, S. (2019). *Policy Proposal for Green Jobs in India—A Quantitative Analysis on Inclusivity of Green Jobs*. 32.

Blanco, M. I., & Rodrigues, G. (2009). Direct employment in the wind energy sector: An EU study. *Energy Policy*, *37*(8), 2847–2857. https://doi.org/10.1016/j.enpol.2009.02.049

Cai, W., Mu, Y., Wang, C., & Chen, J. (2014). Distributional employment impacts of renewable and new energy–A case study of China. *Renewable and Sustainable Energy Reviews*, *39*, 1155–1163. https://doi.org/10.1016/j.rser.2014.07.136

Cai, W., Wang, C., Chen, J., & Wang, S. (2011). Green economy and green jobs: Myth or reality? The case of China's power generation sector. *Energy*, *36*(10), 5994–6003. https://doi.org/10.1016/j.energy.2011.08.016

Cameron, L., & van der Zwaan, B. (2015). Employment factors for wind and solar energy technologies: A literature review. *Renewable and Sustainable Energy Reviews*, *45*, 160–172. https://doi.org/10.1016/j.rser.2015.01.001

CEA. (2019b). *CEA Monthly Power Generation Report March 2019*. Central Electricity Autority, GoI. http://www.cea.nic.in/reports/monthly/generation/2019/March/actual/opm_16.pdf

CEA. (2019c). *CEA Norms for Coal Consumption in Thermal Power Plants 2019*. Central Electricity Autority, GoI. http://cea.nic.in/reports/others/thermal/tppd/acq_norms.pdf

CEA. (2019a). *Draft Report on Optimal Generation Mix for 2029-2030*. https://img.saurenergy.com/2019/07/optimal_generation_mix_report-by-cea.pdf

CEA. (2018). *National Electricity Plan*. Central Electricity Autority, GoI. http://www.cea.nic.in/reports/committee/nep/nep_jan_2018.pdf

CEEW & NRDC. (2016). *Filling the skill gap in India's Clean Energy Market: Solar Energy Focus*. https://www.nrdc.org/sites/default/files/renewable-energy-solar-skill-gap.pdf

CIL. (2019). *CIL Annual Report and Accounts*. Coal India Limited. https://www.coalindia.in/DesktopModules/DocumentList/documents/AnnualReportAccounts2018-19.pdf

Consoli, D., Marin, G., Marzucchi, A., & Vona, F. (2016). Do green jobs differ from non-green jobs in terms of skills and human capital? *Research Policy*, *45*(5), 1046–1060. https://doi.org/10.1016/j.respol.2016.02.007

Dalton, G. J., & Lewis, T. (2011). Metrics for measuring job creation by renewable energy technologies, using Ireland as a case study. *Renewable and Sustainable Energy Reviews*, *15*(4), 2123–2133. https://doi.org/10.1016/j.rser.2011.01.015

Deshmukh, R., Wu, G. C., & Phadke, A. (2017). *Renewable Energy Zones for Balancing Siting Trade-offs in India* (LBNL report number: 1007272). https://www.osti.gov/servlets/purl/1366450

Garrett-Peltier, H. (2017). Green versus brown: Comparing the employment impacts of energy efficiency, renewable energy, and fossil fuels using an input-output model. *Economic Modelling*, *61*, 439–447. https://doi.org/10.1016/j.econmod.2016.11.012

GoI. (2015). *India's Intended Nationally Determined Contribution*. https://www4.unfccc.int/sites/submissions/INDC/Published%20Documents/India/1/INDIA%20INDC%20TO%20UNFCCC.pdf

Government of Chhattisgarh. (2016). *Finance Accounts 2015-16 Volume I*. Government of Chhattisgarh. https://cag.gov.in/sites/default/files/account_report_pdf/Chhattisgarh_Finance_Account_2015_16.pdf?download=1

Government of Jharkhand. (2016). *Finance Accounts 2015-16 Volume-I*. Government of Jharkhand. https://cag.gov.in/sites/default/files/account_report_pdf/JH_Finance_Accounts_2015_16_0.pdf?download=1

Hafstead, M. A. C., Williams, R. C., Golub, A. A., Meijer, S., Narayanan, B. G., Nyamweya, K., & Steinbuks, J. (2018). *Effect of climate policies on labor markets in developing countries: Review of the evidence and directions for future research*. https://doi.org/10.1596/1813-9450-8332

Healy, N., & Barry, J. (2017). Politicizing energy justice and energy system transitions: Fossil fuel divestment and a "just transition." *Energy Policy*, *108*, 451–459. https://doi.org/10.1016/j.enpol.2017.06.014

IEA. (2015). *India Energy Outlook* [World Energy Outlook Special Report].

IEA. (2017). *Levelised cost of value-adjusted LCOE (VALCOE) for solar PV and coal-fired power plants in India in the New Policies Scenario, 2020-2040*. https://www.iea.org/data-and-statistics/charts/levelised-cost-of-value-adjusted-lcoe-valcoe-for-solar-pv-and-coal-fired-power-plants-in-india-in-the-new-policies-scenario-2020-2040

IEA PVPS. (2018). *PVPS Annual Report 2018*. International Energy Agency. https://tecsol.blogs.com/files/iea-pvps-ar-2018.pdf

ILO. (2018). *World Employment and Social Outlook 2018 – Greening with jobs* (p. 189).

IRENA. (2012). *Renewable Energy Jobs and Access* (p. 80).

IRENA. (2018). *Renewable Power Generation Costs in 2018*. International Renewable Energy Agency. https://www.irena.org/publications/2019/May/Renewable-power-generation-costs-in-2018

IRENA. (2019). *Renewable Energy and Jobs: Annual Review 2019*. 40.

Jenkins, K., McCauley, D., Heffron, R., Stephan, H., & Rehner, R. (2016). Energy justice: A conceptual review. *Energy Research & Social Science*, *11*, 174–182. https://doi.org/10.1016/j.erss.2015.10.004

Jenniches, S. (2018). Assessing the regional economic impacts of renewable energy sources – A literature review. *Renewable and Sustainable Energy Reviews*, *93*, 35–51. https://doi.org/10.1016/j.rser.2018.05.008

Joshi, S., Sharma, P., & Mishra, K. (2019). Green Growth & Trade Restrictions: Assessing Socio Economic Impacts of Local Content Requirements in Indian Solar Policy. *The Journal of Developing Areas*, *54*(1). https://doi.org/10.1353/jda.2020.0010

Kapoor, R. (2017). *Waiting for Jobs* (Working Paper No. 348). https://icrier.org/pdf/Working_Paper_348.pdf

Kuldeep, N., Joshi, M., Tyagi, A., Bishnoi, T., Kwatra, S., Jaiswal, A., & Saxena, P. (2019). *Powering Jobs Growth with Green Energy*. Council on Energy, Environment and Water, Natural Resources Defense Council, and Skill Council for Green Jobs. https://www.nrdc.org/sites/default/files/jobs-growth-green-energy.pdf

Lambert, R. J., & Silva, P. P. (2012). The challenges of determining the employment effects of renewable energy. *Renewable and Sustainable Energy Reviews*, *16*(7), 4667–4674. https://doi.org/10.1016/j.rser.2012.03.072

Lehr, U., Lutz, C., & Edler, D. (2012). Green jobs? Economic impacts of renewable energy in Germany. *Energy Policy*, *47*, 358–364. https://doi.org/10.1016/j.enpol.2012.04.076

Markandya, A., Arto, I., González-Eguino, M., & Román, M. V. (2016). Towards a green energy economy? Tracking the employment effects of low-carbon technologies in the European Union. *Applied Energy*, *179*, 1342–1350. https://doi.org/10.1016/j.apenergy.2016.02.122

Mehra, M. K., Mukherjee, S., Bhattacharya, G., & Azharuddin, S. (2018). An Assessment of India's Energy Choices: What it Means for the Economy, Jobs, and Energy Security. *Technical Report*, 93.

Miller, R. E., & Blair, P. D. (2009). *Input–Output Analysis: Foundations and Extensions, Second Edition*. 784.

MNRE. (2016). *Guidelines for Development of Solar Parks*. Ministry of New and Renewable Energy, GoI. https://www.eqmagpro.com/wp-content/uploads/2016/02/Solar-Park-Guidelines.pdf

MNRE & CII. (2010). *Human Resource Development Strategies for Indian Renewable Energy Sector*.

Moreno, B., & López, A. J. (2008). The effect of renewable energy on employment. The case of Asturias (Spain). *Renewable and Sustainable Energy Reviews*, *12*(3), 732–751. https://doi.org/10.1016/j.rser.2006.10.011

Newell, P., & Mulvaney, D. (2013). The political economy of the 'just transition.' *The Geographical Journal*, *179*(2), 132–140. https://doi.org/10.1111/geoj.12008

NITI Aayog. (2017). *Draft National Energy Policy*. http://niti.gov.in/writereaddata/files/new_initiatives/NEP-ID_27.06.2017.pdf

Oliveira, C., Coelho, D., & Silva, P. P. da. (2014). A prospective analysis of the employment impacts of energy efficiency retrofit investment in Portugal by 2020. *International Journal of Sustainable Energy Planning and Management*, *2*, 81–92. https://doi.org/10.5278/ijsepm.2014.2.7

Olson-Hazboun, S. K. (2018). "Why are we being punished and they are being rewarded?" views on renewable energy in fossil fuels-based communities of the U.S. west. *The Extractive Industries and Society*, *5*(3), 366–374. https://doi.org/10.1016/j.exis.2018.05.001

Pachouri, R., Thomas Spencer, & Renjith, G. (2017). *Exploring Electricity Supply-Mix Scenarios to 2030*. https://www.teriin.org/sites/default/files/2019-02/Exploring%20Electricity%20Supply-Mix%20Scenarios%20to%202030.pdf

Perrier, Q., & Quirion, P. (2018). How shifting investment towards low-carbon sectors impacts employment: Three determinants under scrutiny. *Energy Economics*, *75*, 464–483. https://doi.org/10.1016/j.eneco.2018.08.023

PIB. (2015). *Revision of cumulative targets under National Solar Mission from 20,000 MW by 2021-22 to 1,00,000 MW*. https://pib.gov.in/newsite/PrintRelease.aspx?relid=122566

Planning Commission. (2014). *The Final Report of the Expert Group on Low Carbon Strategies for Inclusive Growth*. http://www.cstep.in/drupal/sites/default/files/2019-02/CSTEP_Low_Carbon_Strategies_for_Inclusive_Growth_Report_2014.pdf

Pollin, R., & Chakraborty, S. (2015). *An Egalitarian Green Growth Program for India*. 51.

Sastresa, E., Usón, A. A., Bribián, I. Z., & Scarpellini, S. (2010). Local impact of renewables on employment: Assessment methodology and case study. *Renewable and Sustainable Energy Reviews*, *14*(2), 679–690. https://doi.org/10.1016/j.rser.2009.10.017

SCGJ. (2016). *Skill Gap Report for Solar, Wind, and Small Hydro Sector*. Skill Council for Green Jobs. http://sscgj.in/wp-content/uploads/2016/06/SCGJ-skill-gap-report.pdf

SCMS. (2016). *Human Resource & Skill Requirement Study for Indian Mining Sector*. Skill Council for Mining Sector. http://skillcms.in/wp-content/uploads/2019/08/Skill-Gap-Study-SCMS.pdf

Sebastian et al. (2019). *The Green New Deal Should Focus on Economic Opportunities: Lessons from the German Energy Transition – Public Administration Review*. https://www.publicadministrationreview.com/2019/07/16/gndsewerin/

Simas, M., & Pacca, S. (2014). Assessing employment in renewable energy technologies: A case study for wind power in Brazil. *Renewable and Sustainable Energy Reviews*, *31*, 83–90. https://doi.org/10.1016/j.rser.2013.11.046

Sooriyaarachchi, T. M., Tsai, I.-T., El Khatib, S., Farid, A. M., & Mezher, T. (2015). Job creation potentials and skill requirements in, PV, CSP, wind, water-to-energy and energy efficiency value chains. *Renewable and Sustainable Energy Reviews*, *52*, 653–668. https://doi.org/10.1016/j.rser.2015.07.143

Stevis, D., & Felli, R. (2015). Global labour unions and just transition to a green economy. *International Environmental Agreements: Politics, Law and Economics*, *15*(1), 29–43. https://doi.org/10.1007/s10784-014-9266-1

Strietska-Ilina, O. (2011). *Skills for green jobs: A global view: synthesis report based on 21 country studies*. International Labour Office.

Strietska-Ilina—2011—Skills for green jobs a global view synthesis re.pdf. (n.d.). Retrieved April 25, 2020, from https://www.ilo.org/wcmsp5/groups/public/---dgreports/---dcomm/---publ/documents/publication/wcms_159585.pdf

TERI. (2017). *Assessing Land Issues for Utility Scale Renewable Energy Development in India*. TERI Institute of Advanced Studies. https://shaktifoundation.in/wp-content/uploads/2018/01/Study-Report-Addressing-Land-Issues-for-Utility-Scale-Renewable-Energy-Deployment-in-India.pdf

Tourkolias, C., & Mirasgedis, S. (2011). Quantification and monetization of employment benefits associated with renewable energy technologies in Greece. *Renewable and Sustainable Energy Reviews*, *15*(6), 2876–2886. https://doi.org/10.1016/j.rser.2011.02.027

Vona, F. (2019). *Job losses and political acceptability of climate policies: Why the 'job-killing' argument is so persistent and how to overturn it: Climate Policy: Vol 19, No 4*. https://www.tandfonline.com/doi/abs/10.1080/14693062.2018.1532871

Wei, M., Patadia, S., & Kammen, D. M. (2010). Putting renewables and energy efficiency to work: How many jobs can the clean energy industry generate in the US? *Energy Policy*, *38*(2), 919–931. https://doi.org/10.1016/j.enpol.2009.10.044

Williams, S., & Doyon, A. (2019). Justice in energy transitions. *Environmental Innovation and Societal Transitions*, *31*, 144–153. https://doi.org/10.1016/j.eist.2018.12.001

Wood, R., Stadler, K., Bulavskaya, T., Lutter, S., Giljum, S., De Koning, A., Kuenen, J., Schütz, H., Acosta-Fernández, J., Usubiaga, A., Simas, M., Ivanova, O., Weinzettel, J., Schmidt, J. H., Merciai, S., & Tukker, A. (2015). Global Sustainability Accounting—Developing EXIOBASE for Multi-Regional Footprint Analysis. *Sustainability*, *7*(1), 138–163. https://doi.org/10.3390/su7010138

World Bank. (2018). *South Asia Economic Focus: Jobless Growth*. The World Bank. https://doi.org/10.1596/978-1-4648-1284-2

World Bank. (2020). *Poverty & Equity Brief India*. World Bank. https://databank.worldbank.org/data/download/poverty/33EF03BB-9722-4AE2-ABC7-AA2972D68AFE/Global_POVEQ_IND.pdf

Yenneti, K., Day, R., & Golubchikov, O. (2016). Spatial justice and the land politics of renewables: Dispossessing vulnerable communities through solar energy mega-projects. *Geoforum*, *76*, 90–99. https://doi.org/10.1016/j.geoforum.2016.09.004