Estimating the Social and Economic Impacts from Renewable Energy Developments in Emerging Energy Markets

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Master's Project for the Master of Environmental Management Degree in the Nicholas School of the Environment of Duke University

April 2020

Abstract

It is both well-understood and well-documented that household-level energy access introduces numerous social and economic benefits, including financial savings from fuel switching, increased study time for students, and increased ability to conduct income-generating activities within the household. Energy access specifically from renewable sources not only presents benefits due solely to the access to electricity they provide, but their elimination of fossil-based energy sources presents *additional* environmental, social, economic, and health-related benefits. Using Multi-Tier Framework (MTF) survey data from Myanmar and Nepal, and a statistical technique called "propensity score matching" (PSM), we establish regression models for predicting the social and economic impact from a renewable energy development in both Myanmar and Nepal. Ultimately, this tool provides users with data-backed information regarding optimal placement of renewable energy developments within Nepal and Myanmar to maximize social and/or economic benefits.

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AEPC	Alternative Energy Promotion Center
ESMAP	Energy Sector Management Assistance Program
GIS	Geographic Information System
HDI	Human Development Index
IEA	International Energy Agency
IRENA	International Renewable Energy Agency
LPG	Liquefied petroleum gas
MDI	Multidimensional Disadvantages Index
MPW	Minutes per week
MTF	Multi-Tier Framework
NEP	National Electrification Plant
PSM	Propensity score matching
SE4ALL	Sustainable Energy For All
UN	United Nations
WHO	World Health Organization

1. Introduction

According to the International Renewable Energy Agency (IRENA), approximately 11% of the total global population lacks access to electricity, with a majority of this population residing in South Asia and Sub-Saharan Africa (International Renewable Energy Agency, 2019). Although the number of people who *gain* energy access is increasing annually, meeting the United Nations' (UN) Sustainable Development Goal 7 of ensuring 100% access to safe and reliable modern energy sources by the year 2030 will require more vigorous efforts by the global community (The World Bank, 2018).

In areas without reliable sources of electricity, households rely on other fuel sources – such as kerosene, wood, charcoal and other traditional biomass – to support day-to-day needs. Usage of these resources is relatively inefficient, causes environmental degradation, and introduces significant health and safety implications (World Health Organization, 2014).

Providing access to reliable electricity via renewable energy developments can significantly improve the living standards of those communities lacking access to electricity. Not only do renewable energy developments present a plethora of benefits due solely to the access to electricity they provide, but their reliance on non-fossil-based energy sources presents *additional* environmental, social, economic, and health-related benefits.

Using Multi-Tier Framework (MTF) survey data and statistical analysis, our report seeks to establish a method for estimating the social and economic impact from a renewable energy development. The total benefits from a renewable energy development will incorporate both the social and economic benefits stemming from electrification, as well as those additional benefits stemming from the electrification being from renewable sources. As such, the total projected benefits will be significantly higher for non-electrified areas. Our report therefore calculates the projected benefits solely and specifically for non-electrified households in a given region.

Due to data availability, our report focuses on two countries: Myanmar and Nepal. Using a statistical technique called "propensity score matching" (PSM), we identify which household-level variables are significant in predicting a renewable energy development's impact on non-electrified households in a given region.

Ultimately, we seek to establish a method and model for determining the *magnitude* of social and economic impact a renewable energy development will have in a given area. In doing so, the user of the model (hereinafter referred to as "the User") is better equipped to make strategic decisions regarding the placement of future renewable energy developments (with the goal of maximizing social and/or economic benefits). This endeavor aligns with many companies' long-term goal of covering 100% of operations by renewable energy: by acquiring a method for strategic placement of future renewable energy developments, the User can both (1) work towards a goal of covering 100% of operations by renewable energy, and (2) maximize benefits to local communities.

1.1 Social and Economic Benefits of Energy Access

It is both well-understood and well-documented that energy access introduces numerous social and economic benefits. It is important to note, however, the indistinct lines and potential overlap between both social benefits, and economic benefits. For example, electrification is often associated with an increase in study time for students (as a result of increased lighting after sunset). At its surface, this cause-effect relationship most obviously displays a social benefit (as this could have an impact on a student's overall educational achievements). An increase in study time, however, could ultimately bolster the student's ability to generate income, which would be considered an economic benefit.

Among the many cited benefits of electrification include a decrease in time spent collecting household fuels (e.g. firewood), financial savings from fuel switching, increase in study time for students, increased ability to conduct income-generating activities within the household, etc. Location-specific benefits are demonstrated in a wide range of case studies, capturing various parameters to assess the cause-effect relationship of electrification across geographies.

One case study aimed to capture the effects of World Bank-financed rural electrification projects (implemented throughout the early 2000s) across rural provinces of Vietnam. Via survey data collected from over 1,000 households at varying levels of electricity access, and two methods of impact assessment, the study observed significant benefits from electrification. For one, the study found that, even using the more conservative impact assessment methodology, the average household total income increased by approximately

25%. Furthermore, school enrollment rates for males increased by 11% (an increase in enrollment rates was not observed for females) (Khandker, Barnes, Samad, & Minh, 2009).

Another case study on Sagar Dweep, an island in West Bengal, India, measured the impacts of electrification following the implementation of a decentralized solar photovoltaic power plant. The study found that, for those households that reported a decrease in cooking time following electrification from the plant, average daily cooking time decreased by 90 minutes. Ultimately, this allowed household members to use more time for other purposes such as income-generating activities, community development, education, and leisure. Furthermore, households reported that students were able to increase daily study time by up to 135 minutes (Chakrabarti & Chakrabarti, 2002).

It is important to note, however, that these benefits are largely contingent on the access to electricity being affordable, reliable, and safe.

1.2 Additional Benefits of Access to Clean Energy Resources

According to the World Health Organization's (WHO) 2012 Guideline for Indoor Air Quality: Household Fuel Combustion, over 3 billion people rely on solid fuels (e.g. wood, animal dung, charcoal, crop residue and coal) for household cooking, lighting, and/or heating purposes.

The harms associated with using solid fuels inside the household are numerous and potentially severe in nature, including respiratory and cardiovascular diseases, cancer, poisoning, and injuries from burns and/or fuel collection. Overall, diseases directly caused by exposure to household air pollution result in approximately 4 million premature deaths in both children and adults, accounting for 5% of the world's total diseases (World Health Organization, 2014).

This information is echoed via a 2016 study seeking to examine the relationship between household cooking fuels and the health of adult women in rural China. Using biomarker data from the China Family Panel Studies and the China Health and Nutrition Survey, the study assesses the use of three predominant cooking fuels (liquefied petroleum gas (LPG), wood, and coal) by 25,000 individuals. The study concluded that, compared to LPG (a non-solid fuel), the use of wood and/or coal (solid fuels) is associated with significantly lower lung

function and higher incidence of pulmonary and cardiovascular diseases (Nie, Sousa-Poza & Xue, 2016).

Not only do HAPs impact the health of residents *within* the household, but they also contribute significantly to outdoor air pollution-related deaths. Emissions from HAPs travel to the ambient environment, ultimately accounting for approximately 12% total ambient air pollution. This translates to about 0.4 million deaths annually (World Health Organization, 2014). Again, these conclusions are echoed by studies, including a 2010 study which estimates the proportion of one type of air pollutant – ambient particulate matter less than or equal to 2.5 μm in diameter ($APM_{2.5}$) – caused by household emissions from solid fuels ($PM_{2.5\_hh}$) in 170 countries. $APM_{2.5}$, which are microscopic particles produced from motor vehicles, airplanes, the burning of biomass, power plants and volcanic eruptions, remain suspended in the air for long periods of time, and are inevitably inhaled by humans. Ultimately, these particles can cause or exacerbate asthma, bronchitis, lung disease, and heart attacks. The study found that the percentage of $APM_{2.5}$ from $PM_{2.5\_hh}$ ranged from 0% in higher-income countries (with approximately 100% access to electricity), to 37% in lower-income countries, with a global average of 12% (Chafe et. al, 2014).

There is a strong correlation between electrification and adoption of modern cooking fuels (non-solid fuels). A 2004 study, which builds off previous findings, analyzes household-level survey data from eight developing countries (Brazil, Ghana, Guatemala, India, Nepal, Nicaragua, South Africa and Vietnam) to better understand this relationship between electrification and modern cooking fuel use. Using descriptive statistics, as well as regression techniques to eliminate potential for multicollinearity, it concludes that electrified households use significantly more modern fuels for cooking purposes. In rural Brazil and urban India, for example, electrification increased the probability a given household used LPG as the primary cooking fuel by 28% and 34%, respectively. Furthermore, the study identified that, in most countries, electrification's impact on modern fuel use was greater in urban areas, and smaller in rural areas (Heltberg, 2004).

1.3 Multi-Tier Framework (MTF) Surveys

In 2011, the Secretary-General of the United Nations, launched Sustainable Energy For All (SE4ALL), an initiative whose chief goal was to ensure 100% global access to modern energy services by the year 2030. Through collaborative efforts with numerous international

agencies including the World Bank and the International Energy Agency (IEA), SE4ALL developed the Multi-Tier Framework.

The MTF seeks to establish universal guidelines and standards for defining, evaluating and monitoring energy access. Instead of using the traditional approach of viewing energy access as binary (either having access or having no access), the MTF attempts to factor in *multiple* aspects of energy access, including reliability, affordability, quality, convenience, and safety. Ultimately, MTF assigns an area-of-interest a score on a spectrum, from Tier 0 (no access) to Tier 5 (highest level of access) according to the criteria listed in Table 1. In order to qualify as a certain Tier, the household and/or geographical area must meet *all* listed criteria (Multi-Tier Framework, 2019).

Table 1: Multi-Tier Framework criteria for measuring access to energy

Tier	0	1	2	3	4	5
Peak available capacity (Watts)	0	>1 W	>20 W	>200 W	>2000 W	>2000 W
Duration of daily electricity supply (hours)	0	>4 h	>4 h	>8 h	>16 h	>22 h
Evening electricity supply (6:00pm - 10:00pm) (hours)	0	>2 h	>2 h	>2 h	4 hrs	4 hrs

In an effort to collect relevant data for evaluating energy access, The World Bank, in collaboration with the Energy Sector Management Assistance Program (ESMAP), created the Global Survey on Energy Access. The survey, which is in accordance with the MTF approach, aims to collect household- and individual-level data on the following:

- Seven aspects of access to electricity: capacity, availability, reliability, quality, affordability, formality, and health/safety;
- Cooking practices, including cookstove fuel use and fuel availability, cookstove efficiency, and health and safety of the household's primary cookstove;
- Energy-related expenditures, energy consumption habits, willingness to pay for improvements in energy access, and general attitudes on the benefits of improved energy access;
- Other socioeconomic factors, such as household size, household income, age of all household members, etc. (Multi-Tier Framework, 2017).

The survey has already been administered in several countries with relatively low levels of energy access, including Myanmar and Nepal. It is important to note that, while the surveys administered in Myanmar and Nepal aim to capture the same *general* information on energy access, there are key differences in the actual *structure* of the survey (see examples in Table 2). For this reason, the methods for calculating the social and economic impacts of renewable energy developments in Myanmar and Nepal differ.

Table 2: Examples of differences between MTF surveys administered in Myanmar and Nepal

Myanmar		Nepal	
Survey Question/Prompt	**Survey Reference**	**Survey Question/Prompt**	**Survey Reference**
"Please indicate the typical monthly income for this activity"	*M_A04_06*	NA: Question is not asked	NA
"How many Domestic vehicle in (working condition or still healthy) does your household own? "	*M_B03a_01*	NA: Question is not asked	NA
"Of all the sources that you mentioned above, which is the source that you use the most in your household?" [One response option is "Pico hydro"]	*M_C06_01*	*"Is this household connected to a Pico hydro?"*	*N_C44*
NA: Question is not asked	NA	*"What is the main source you use to heat your house?"*	*N_K5*

For the purposes of this report, specific survey questions will be referenced accordingly:

- Question from Myanmar Survey: "*M_XX_XX*"[1]
- Question from Nepal Survey: "*N_XX_XX*"[2]

1.3.1 Defining Energy Access with MTF Survey Data

As highlighted in above sections, there is no internationally-recognized or internationally-adopted definition of energy access. Although various entities and case studies employ different definitions of energy access, there are important commonalities among them, including:

[1] https://energydata.info/dataset/myanmar-multi-tier-framework-mtf-survey

[2] https://microdata.worldbank.org/index.php/catalog/3532/related-materials

- Access to energy that enables economic activity;
- Household-level access to electricity;
- Access to safer and more sustainable forms of energy which minimize negative health impacts.

Additionally, as mentioned above, there are important differences in the MTF survey structure for both Nepal and Myanmar. For these reasons, we have devised the following criteria to distinguish between "electrified" and "non-electrified" households in both Myanmar and Nepal as shown in Table 3.

Table 3: Criteria for designating households as "electrified" and "non-electrified" for both Nepal and Myanmar

Myanmar		Nepal	
Electrified	**Non-electrified**	**Electrified**	**Non-electrified**
Receives electricity for at least 15 hours per day	Receives electricity for no more than eight hours per day	Receives electricity for at least 15 hours per day	Receives electricity for no more than eight hours per day
Receives electricity for no less than four hours during the hours of 6:00pm to 10:00pm	Receives two hours or less of electricity during the hours of 6:00pm to 10:00pm	Receives electricity for no less than four hours during the hours of 6:00pm to 10:00pm	Receives two hours or less of electricity during the hours of 6:00pm to 10:00pm
Receives electricity service for seven days per week		Receives the same quality of service throughout the year	
Has had a household electricity connection for at least two years			
Has weekly total outages and/or blackouts of no more than one hour			

1.3.2 Myanmar and Nepal Country Comparison with MTF Survey Data

Using MTF survey data, we compare a few key household-level demographic and socioeconomic indicators between Myanmar and Nepal. All analyses in this section are

conducted according to the definitions of "electrified" and "non-electrified" households in Section 1.3.1: Defining Energy Access with MTF Survey Data.

First, we compare the percentage of electrified households in rural areas and urban areas. We see that, in both countries, a greater percentage of electrified households are in urban areas. The magnitude of this disparity is highest in Nepal, in which approximately two thirds electrified households are in urban areas.

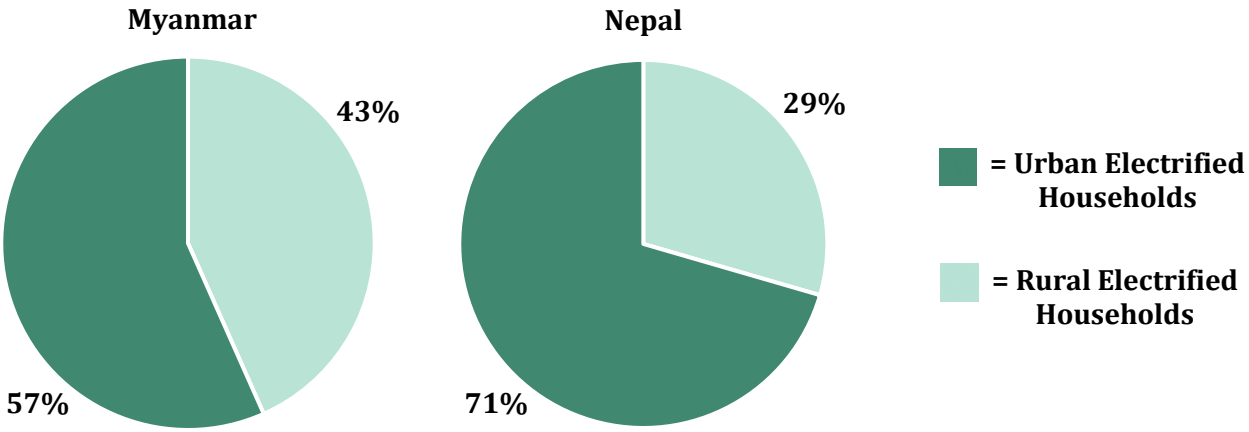

Figure 1: Portion of urban and rural electrified households In Myanmar and Nepal. Survey references: M_ID1_04 and N_LOCALITY.

Next, we observe country-level differences in education by analyzing the average percentage of household members (above age five) who have ever attended school. Myanmar, overall, appears to have a higher portion of residents who have ever attended school, with electrified households having a higher percentage (by 5%) than non-electrified households. In Nepal, however, a greater number of individuals from non-electrified households have attended school (72% vs. 66%). This difference, however, could be due to the relatively small sample size of electrified households in Nepal (n = 217). Additionally, it is important to note that this metric captures the portion of household members who have *ever* attended school, without capturing the longevity or current state of one's student status. The portion of household members *currently* attending schools is, in fact, higher for electrified households in Nepal than for non-electrified.

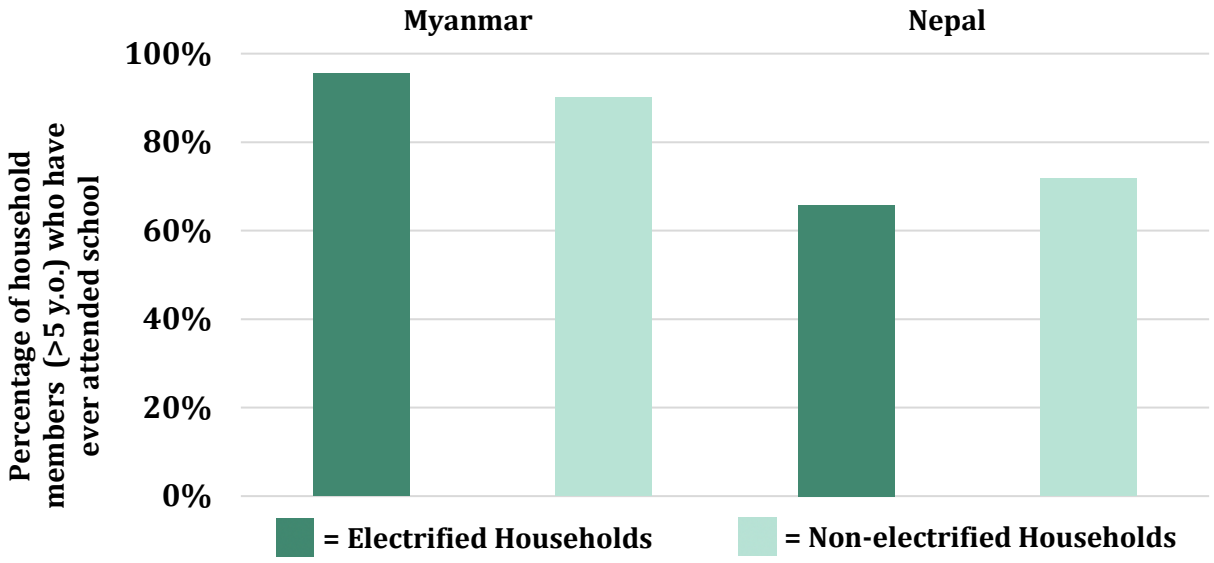

Figure 2: Percentage of household members from electrified and non-electrified households In Myanmar and Nepal who have ever attended school. Survey references: M_A03_02 and N_A7.

Next, we observe country-level differences in employment by analyzing the average unemployment rates. Overall, survey data shows Myanmar has greater unemployment rates, with a small difference between electrified and non-electrified households (2.9% and 3.0%, respectively). Nepal has a greater disparity in unemployment electrified and non-electrified households (2.0% and 2.5%, respectively).

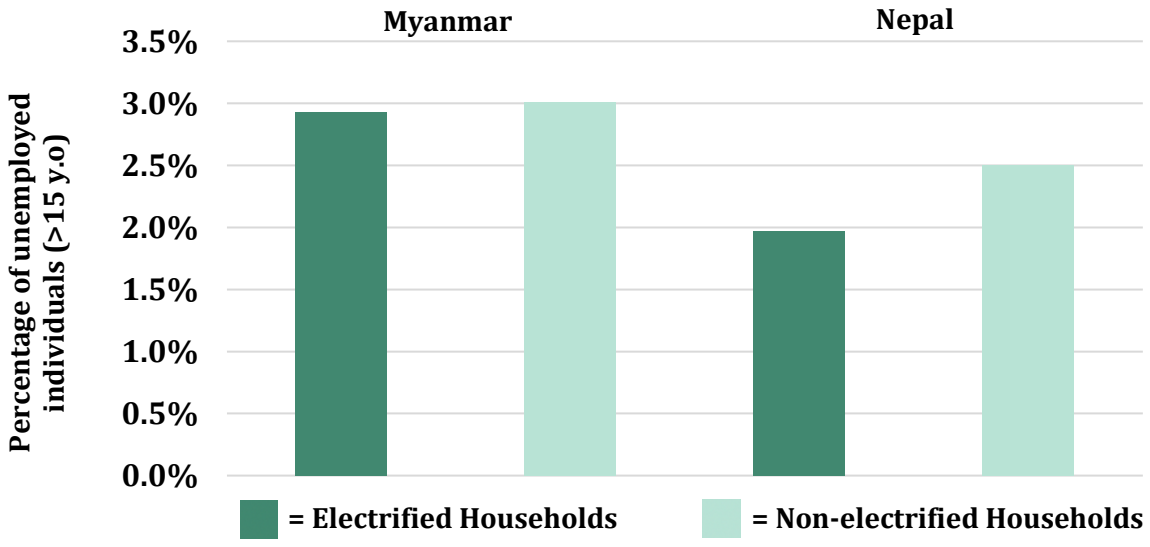

Figure 3: Portion of unemployed individuals from electrified and non-electrified households In Myanmar and Nepal. Survey references: M_A04_02 and N_A14.

Finally, we observe the percentage of total household expenditures allocated to electricity bills, food expenses, and other expenses for electrified households in Myanmar and Nepal. The percentage of household expenditures for electricity bills is similar between the two countries: approximately 2.8% in Myanmar, and 1.9% in Nepal. These percentages are comparable to developed countries such as the United States, in which total household expenditures allocated to electricity range from 1.2% in the state of Washington, to 4.5% in the state of Hawaii (Eisenbach Consulting, 2015). These relatively-low percentages for Myanmar and Nepal indicate that, in general, the *costs* associated with using electricity are not high enough to significantly influence either (1) whether a household adopts electricity (discounting any connection costs), or (2) whether a household uses electricity once connected to an electricity source. This last implication, however, assumes connected households either have flexibility in terms of budget, or have access to a relatively cheap form of electricity (e.g. renewable sources).

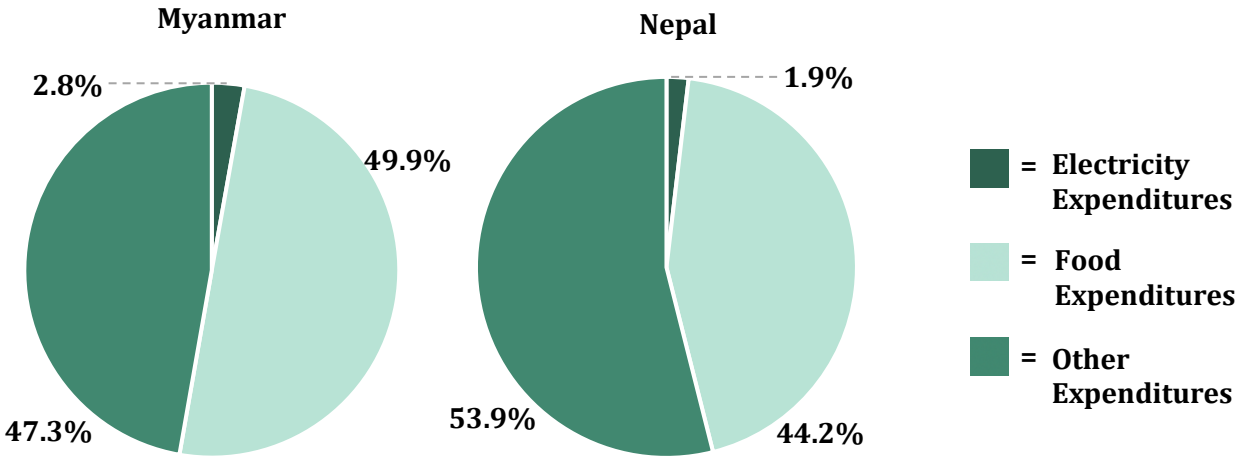

Figure 4: Expenditure profile for electrified households in Myanmar and Nepal.

1.4 Myanmar: Background and Electrification Status

Myanmar is a developing country located in Southeast Asia with a population of 55 million. 36% of the population lives in urban areas, while the other 64% lives in rural areas. As of 2017, Myanmar's poverty line was 1,590 Kyat (approximately $1.08 USD) per adult equivalent per day. Estimates from the 2017 Myanmar Living Conditions Survey indicate that about 24.8% of the total population lives under the poverty line, with a majority of those under the poverty line residing in rural areas (The World Bank, 2019).

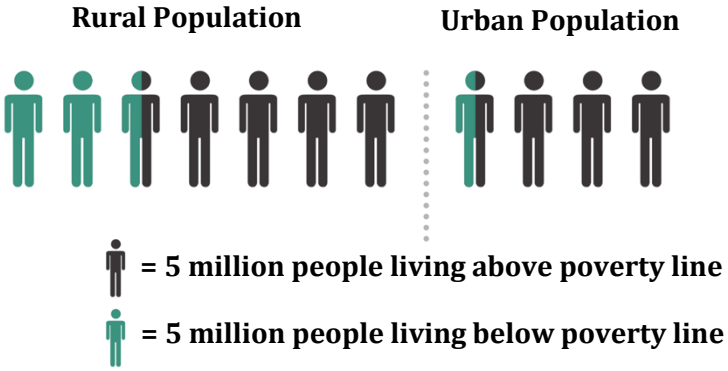

Figure 5: The proportion of individuals living below the national poverty line in both urban and rural areas of Myanmar.

The Human Development Index (HDI) was created by the United Nations as an internationally-adopted summary measure for assessing a region's progress in three distinct areas of development: (1) a long and healthy life, as measured by life expectancy at birth, (2) access to knowledge, as measured by expected years of schooling for children at school-entry age, and (3) a decent standard of living, as measured by gross national income per capita. As of 2018, Myanmar had an HDI value of 0.584, ranking it 145 out of 189 countries and territories (Advisors, 2014).

As access to energy is strongly correlated with health, economic and social benefits, we can assume that Myanmar's electrification status has significant implications for the country's overall HDI value. The most recent data reveals approximately 30.8% of Myanmar's population lacks access to electricity. Thanks to electrification programs throughout the country, however, the percentage of the population with access to electricity is rapidly growing: in 2014, only 52.0% of the population had access to electricity. By 2017, this percentage increased to 68.9% (about a 32% increase over three years) (The World Bank, 2017).

The Myanmar National Electrification Plan (NEP), implemented in 2014, has the ambitious goal of electrifying 76% of Myanmar households by 2025, and 100% by 2030. According to the population projections and geospatial analysis, this would involve connecting more than 7.2 million households between 2014 and 2020 (Advisors, 2014).

The NEP recognizes that a significant portion of electrification efforts must focus on rural areas, which have significantly lower availability and capacity than that for urban areas. MTF survey data mirrors this:

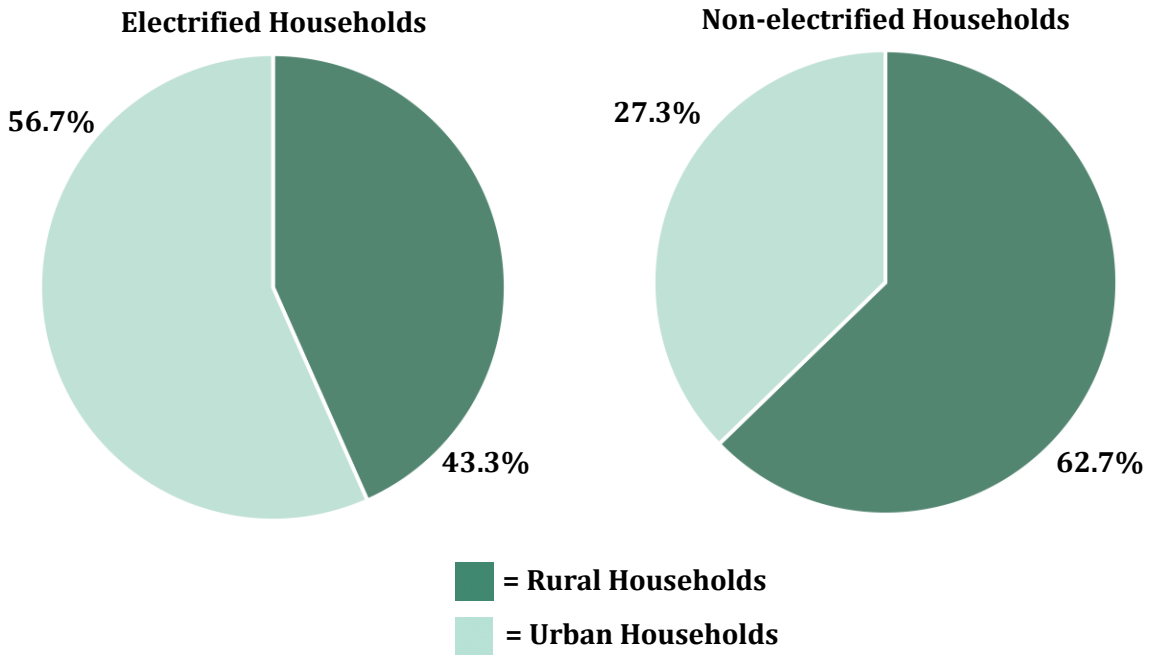

Figure 6: Portion of urban and rural electrified households and non-electrified households according to MTF survey data (according to the definitions of "electrified" and "non-electrified" households in Section 1.3.1: Defining Energy Access with MTF Survey Data).

1.5 Nepal: Background and Electrification Status

Nepal is a country in South Asia globally ranking 92nd largest in area, but 49th in population (with a total population of approximately 29.3 million). According to the latest data from Nepal's national statistics office, approximately 80% of the population resides in rural areas, with the other 20% residing in urban areas. Additionally, as of 2018, 25% of the population lived below the poverty line, which was approximately $0.50 USD per adult equivalent per day. This poverty line makes Nepal one of the poorest nations in the world (Trading Economics, 2018).

Nepal and Myanmar have similar HDI values: as of 2018, Nepal's HDI value was 0.579, positioning it at 147 out of 189 countries and territories (just two rankings behind Myanmar). This stems partially from a general lack of healthcare and education in regions

with high poverty rates. This *also* stems from the physical geography of the country: Nepal is landlocked and mountainous, which makes transportation of goods and resources – including food – very difficult (Human Development Report: Nepal, 2019).

Due to significant efforts by the Nepalese government, Nepal has become one of the fastest electrifying countries, alongside Cambodia and Afghanistan: in 2000, approximately 81% of the population lacked access to electricity. By 2010, this value decreased to about 65% and, as of 2018, only 6% of the population remains without any form of electricity access (International Energy Agency, 2019).

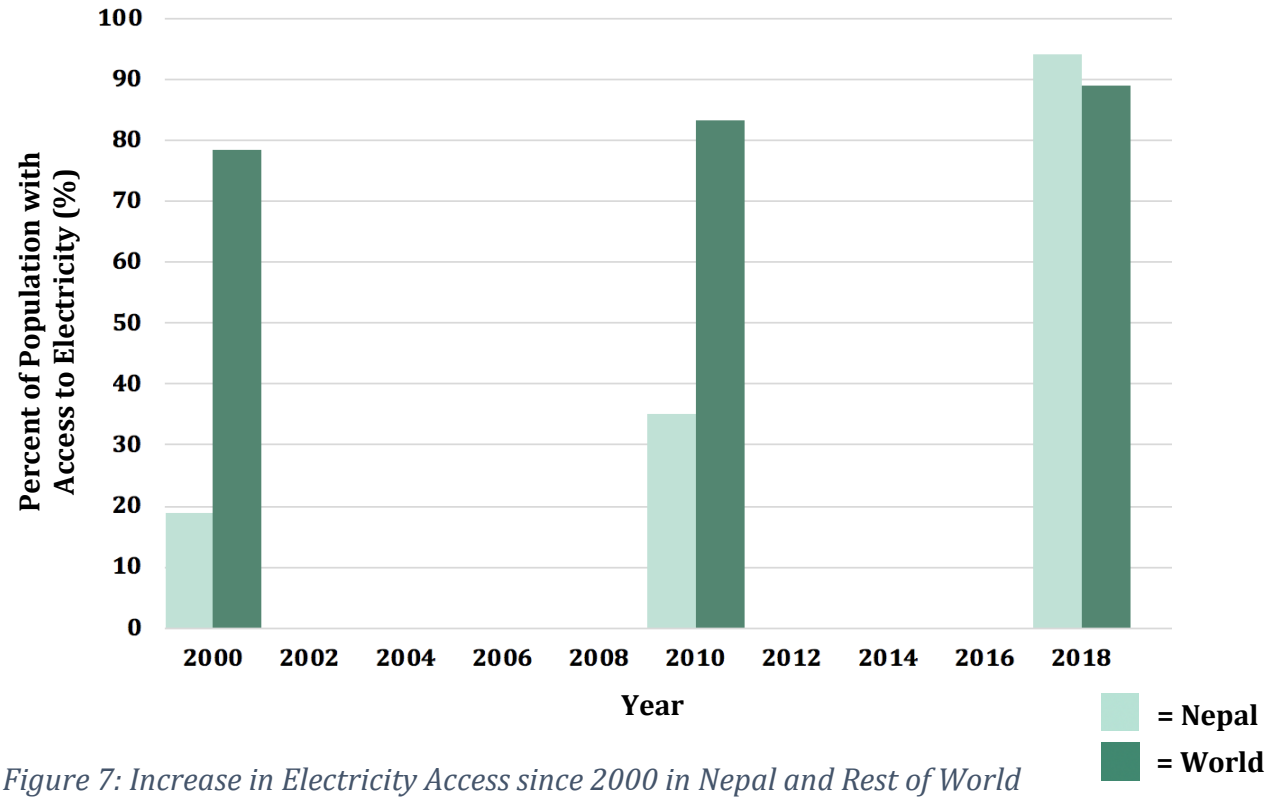

Figure 7: Increase in Electricity Access since 2000 in Nepal and Rest of World

Although nearly all households have some form of access to electricity, this access is not necessarily reliable; a majority of Nepal's installed electricity generation is from large, centralized hydropower plants which have significantly reduced output during Nepal's dry season (approximately October through May). In times of water scarcity, the Nepalese Electricity Authority (the largest state-run power company) cuts power from its customers for up to 16 hours per day. Additionally, there is a large disparity between the electricity access for citizens residing in urban and rural areas, with those in urban areas having greater, more reliable access (Energy in Nepal, 2016).

Despite its relatively large potential for hydro, solar and wind, Nepal has one of the lowest electricity generation per capita rates in the world. Instead, the country remains largely dependent on fossil fuels such as oil and kerosene, especially for residential heating, lighting and cooking. As of 2015, about 82% of households lacked access to a clean and safe cooking method, relying primarily on either imported kerosene, or firewood (Energy in Nepal, 2016).

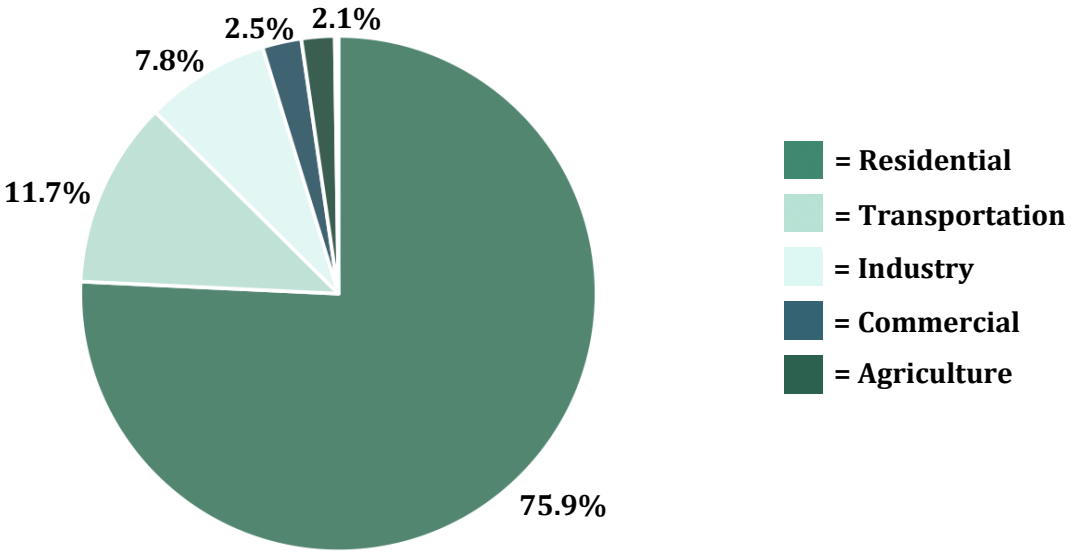

Figure 8: Energy Consumption by Sector in Nepal (2016)

1.6 Key Analysis Assumptions

As our model encompasses a wide range of potential renewable energy developments over a large geographic scope, a number of important assumptions were incorporated into our analysis:

1. ***Renewable energy projects undertaken by the User will allow recipient households to become "electrified," as defined in Figure 1.*** This is a noteworthy assumption, as it negates any differentiation between the various *types* of potential renewable energy developments (e.g. micro-hydropower, solar PV with storage, etc.); we assume that renewable energy development undertaken by the User will provide all applicable beneficiaries with reliable, safe, and clean energy access.
2. ***The User will absorb all capital expenditures associated with the renewable energy projects.*** All applicable upfront installment and connection costs associated with the renewable energy projects will not be passed down to beneficiaries.

3. ***Any addition or decrease in household expenditures for energy (for cooking, lighting, heating, etc.) following electrification from a renewable energy development will have little-to-no impact on overall household expenditures.*** Although income levels may certainly change following electrification, we make the assumption that changes in household expenditures specifically for energy uses will not significantly change following electrification. In other words:

   $$(\text{Cost of fuel}_{\text{before electrification}}) \approx (\text{Cost of fuel}_{\text{after electrification}}) + (\text{Cost of electricity})$$

4. ***Renewable energy projects undertaken by the User will cause households to significantly reduce their solid fuel use.*** While access to energy from renewable energy sources will decrease or eliminate household demand for solid fuels for lighting (e.g. kerosene), a significant portion of a household's solid fuel use is associated with its cooking practices and stove type. We make the important assumption that access to clean energy via renewable energy developments undertaken by the User will cause households to use non-solid fuels (e.g. electricity) for cooking purposes. As mentioned in the "Health Benefits" section above, a strong correlation exists between electrification and adoption of modern fuel use for cooking. Although correlation is identified and supported by literature, causation is not. For the purposes of this study, however, causation is assumed. In other words, we assume households with a stove that *does not* support non-solid fuels will acquire a stove that *does* support non-solid fuels following electrification.
5. ***All Economic and Social Impact sub-scores are calculated exclusively for non-electrified households.***

Note that more granular, sub-score-specific assumptions are mentioned and explained in Section 2: Methods.

1.7 Propensity Score Matching

Control groups are a vital part of any experiment seeking to establish a cause-effect relationship, as they provide a baseline comparison for the treatment group. In certain observational studies, however, there may lack a systematic method for maintaining – or even obtaining – a control group. In these cases, it is difficult to tease out the cause-effect relationship by comparing the treatment group with a "nonexperimental comparison group" (Dehejia & Wahba, 2002).

One such case occurs when measuring the social and/or economic impacts of electrification. An ideal observation study for measuring impacts could involve the following steps:

1) Randomly assigning all households in a completely unelectrified city into a treatment group and a control group,
2) Collecting key data points on each household in both the treatment and control groups
3) Providing 24/7 electricity access only to those households assigned to the treatment group
4) After approximately five years (enough time for electrification's impacts to be realized), collecting the same key data points (from Step 2) for each household
5) Directly comparing the data collected in Step 4 between the treatment (electrified) and control (non-electrified) groups.

The above theoretical study design is impractical and unrealistic for numerous reasons: firstly, political and social considerations would make it infeasible to only provide electricity access to certain households within a given city or area, while neglecting other households. Secondly, this study design is unrealistic in terms of grid and other infrastructure requirements; implementing costly energy infrastructure for an entire city or region, only to deliver power to a limited number of households, is financially inefficient. Lastly, significant resources and planning would be required to collect all needed data both before electrification, and years after electrification.

Considering this, studies seeking to capture the cause-effect impacts of electrification must often rely on data that is captured in a single point of time (i.e. "snapshot data"), which is commonly in the form of household-level survey data. Using such data, however, certainly comes with challenges. For one, there is an unclear distinction between electrified (treatment) and non-electrified (control) groups; assigning households to one of these groups will inevitably introduce researcher bias, as researchers must come up with definitions for what constitutes as an electrified and non-electrified household. Additionally, this snapshot data captures real-world data, meaning certain households are electrified not because of randomization, but because of other social, economic, or political factors. As such, it is extremely difficult to determine causation, or that a certain variable (e.g. an increase in income following electrification) is a result of *only* electrification, and not of other confounding factors.

One commonly-used method for overcoming this causation issue is the propensity score-matching (PSM) method. PSM is an econometric technique which first involves assigning a "propensity score" to all treatment and non-treatment subjects. This score indicates the probability an individual subject will have the treatment based on any number of pre-determined factors. Next, PSM pairs subjects from the treatment and non-treatment groups that have similar – or even identical – propensity scores. In doing so, subjects from the treatment and non-treatment groups can be directly compared while reducing the prevalence and/or impact of confounding factors.

A 2009 study on the welfare impacts of electrification in rural Bangladesh, for example, employs the PSM method to analyze survey data. First, the study determines each surveyed household's probability of being electrified (i.e. the propensity score) as a function of household and village demographic, geographical and socioeconomic characteristics. Next, it separates all surveyed households into two groups: electrified and non-electrified. Households with similar propensity scores are then matched (between these two groups) and compared to capture the household-level impacts of electrification. Using these econometric techniques, the study was able to quantify multiple effects of electrification: for example, households' income increased by as much as 30% due solely to electrification (Khandker, Barnes & Samad, 2009).

Another 2011 study utilizes the PSM method in assessing the impacts of electrification from micro-hydro mini-grid developments in rural Rwanda. The study first assigned a propensity score to each village included in the analysis based on factors such as population density, distance to Kigali (the capital), the distance to paved roads, and village structure. In other words, each village was assigned a probability of being electrified (regardless of whether or not it actually *was* electrified), based on the aforementioned factors. Next, electrified and non-electrified villages with similar propensity scores were matched together to for direct comparison. Among other things, the study concluded that electrification did, in fact, result in an increase in at-home study time for students (Bensch, Kluve & Peters, 2011).

1.8 Goals and Purpose

The purpose of this study is to, first, use MTF survey data to identify which variables affect a renewable energy project's *magnitude* of impact on a given area. Next, it seeks to, again, use

MTF survey data to assign sub-regions an "impact score" (based on the findings in step (1)). Our final model is presented via an online application with a map indicating high-priority and low-priority regions for a renewable energy development based on the development's estimated magnitude of impact.

The model is developed solely for Myanmar and Nepal for the following reasons:

- ***This is a data-driven project, and sufficient data on energy access and socioeconomic parameters is available for a limited number of countries (including Myanmar and Nepal).*** To ensure statistical significance of our results, it is imperative to analyze ample data points. The MTF surveys provides data that is highly granular in nature, making it a viable and ideal data source for the purposes of our study. As mentioned previously, MTF surveys have only been administered in a limited number of countries (including Myanmar and Nepal).
- ***A significant portion of the populations in both countries either lacks access, or has limited access, to electricity. This is especially true for the countries' rural populations.*** According to our definitions of electrified and non-electrified households (see Section 1.3.1: Defining Energy Access with MTF Survey Data), approximately 35.8% households in Myanmar are non-electrified; 54.6% households surveyed in Nepal are non-electrified. Again, these percentages differ from the country-level data reported in Sections 1.4 and 1.5 due to our model's particular criteria for designating households as "electrified." Our reported percentages demonstrate the significant potential to develop socially- and economically-valuable renewable energy projects in both countries.

The main goal of this project is two-fold: first, to provide Users with data-backed information regarding optimal placement of renewable energy developments within Nepal and Myanmar to maximize social and/or economic benefits. Second, to establish a sound method for distinguishing between regions within a given country based on the regions' propensity for tangible social and/or economic benefits as a result of electrification. In doing so, future researchers will have the tools and knowledge base necessary to continue this work for additional countries and/or regions.

2. Methods

To estimate the impacts of renewable energy developments, we deployed statistical analysis to build a quantitative model that produces a region-level impact score comprised of socioeconomic and health impact subscores. The selection of survey data points to include as subscores was based on: (1) literature review of studies on electrification's impacts, and (2) availability of MTF survey data. Given the distinctive nature of MTF survey data for Myanmar and Nepal, the statistical analysis was performed separately for each country.

We conducted statistical analysis based on two approaches: (1) a regression-based approach, and (2) a non-regression-based approach. The regression-based approach was utilized in calculating the socioeconomic subscores to ultimately capture the causal effect of electrification on socioeconomic metrics such as employment and school attendance. Ideally, we would use temporal survey data that captures conditions both before *and* after electrification to provide a straightforward measurement of the treatment effect. Given our limitations in resources to conduct surveys, however, coupled with the "snapshot" nature of MTF survey data, we employed propensity score matching (PSM) as a tool to help strengthen the causal inference from electrification.

PSM produces a matched set of households that simulates a "before-after" scenario. Regression analysis is then conducted using this matched dataset to measure the magnitude of electrification's impact. Electrification is considered a binary variable, with "0" denoting a non-electrified household, and "1" denoting an electrified household. In addition to the electrification binary variable, we have also included other predictor variables, which were selected using a heuristic approach. For example, electrification's impact on the number of household members who have ever attended school is also affected by the productivity and the economic welfare of the household.

Regression analysis ultimately produced a linear equation for each socioeconomic subscore. These equations were then used to calculate subscores for each region of Myanmar and Nepal using region-level average values for each predictor variable as inputs, and setting the electrification binary variable to "1." In doing so, we simulate how the subscore changes following electrification for a given household. The change in each subscore was measured by calculating the difference between the calculated value derived from the regression

equation and region-level average values derived from MTF survey data of non-electrified households.

A non-regression-based approach was applied to calculate the health impact subscore. Regression analysis was not applied to calculate this subscore because health impacts are closely tied to cookstove fuel consumption, which is available in MTF survey data. Electrification and tangible health benefits are correlated to household cookstove fuel-switching from solid fuels to non-solid fuels. We used the duration each household spends on solid cookstove fuel consumption as a proxy to estimate the potential health benefits of electrification.

The z-score of each socioeconomic and health impact subscores was then calculated for each region of Myanmar and Nepal. All subscores were then averaged to calculate each region's total impact score. The total impact score was then assigned a prioritization score to identify highest-priority regions for renewable energy developments. To enhance the User's experience with this model, a geographical visualization was performed using ArcGIS.

2.1 Regression-Based Method for Estimating Socioeconomic Impacts

2.1.1 Data Wrangling and Covariate Selection for Propensity Score Matching

The analysis began with a thorough data wrangling process on MTF survey data. Data wrangling consisted of formatting survey data by assigning codes to each survey question, and adjusting all monetary responses for inflation and currency conversion to 2018 U.S. Dollars.

Covariates are regressors used in the logistic regression to estimate the probability of a household to receive the treatment (i.e. electrification). In other words, covariates are variables that are correlated to the likelihood of a household to be electrified. The following steps were conducted to identify covariates that significantly predicted households' electrification status:

- A logistic regression was performed to identify which covariates were significant predictors of being recipients of electrification. The dependent variable was binary: "0" denoted the counterfactual (non-electrified) and "1" denoted the condition of receiving treatment (i.e. electrified). At this point in the analysis, all variables are

included, except for household ID (*HHID*), regions (*ID1_01*) , township (*TSP*), and grid connection status (*ID1_05*)

- A difference of means test (t-test) is conducted to identify which covariates are significantly different between the control group (non-electrified group) and the treatment group (electrified group).

Results for both tests are assessed to filter which variables can be assigned as covariates in the matching process. Significant variables (p-value < 0.05) in both tests are selected as covariates for PSM. In addition, we included covariates that were significant in either the differences in means test or the logistic regression. Some of these variables were also selected as covariates based on literature review of PSM in impact evaluation of energy access. Covariates ultimately selected for PSM for Myanmar and Nepal survey data is shown in Tables 4 and 5, respectively.

Table 4: Covariates used for propensity score matching of Myanmar survey data

Survey Reference	Category
A05_b04	Time household spends collecting fuel per day
A01_05	Total number of household numbers
A05_b06	Daily time household spends on cooking (min)
A01_05	Total number of household members
A_05_c02	Total minutes per day household spends on income generating activities outside the house
A_05_c03	Total minutes per day household spends on income generating activities inside the house
A01_09	Average number of children per household
I02_07	Monthly transportation costs (2018 USD)
I03_B	Average weekly expenditures (2018 USD)
C1_804	Total number of smartphones/tablets owned by household
E01_02_day	Days per month household uses candles for lighting
I0_09	Total regular non-food expenditures in the past 30 days
I03_A	Total non-food expenditures in the past 12 months
C1_501	Total number of radios owned by household

Table 5: Covariates used for propensity score matching of Nepal survey data

Survey Reference	Category
A01_09	Number of children
R_23A	Total minutes per day household spends on income generating activities outside the house (total for all household members)
J37_A	Expenditures for stove fuel in the last month (2018 USD)
MA	Value of consumed food in last 7 days (purchased food)
MB	Value of consumed food in last 7 days (produced/acquired)
M18	Transportation costs (fuel for own vehicles, public transportation, etc)
M19	Total regular non-food expenditures in the past 7 days
M29	Appliances and tools
M30	Vehicles (motorcycle and bicycle) purchase and repairs
M33	Other major expenses

2.1.2 Propensity Score Matching

Using the selected covariates from the previous step, propensity score matching was performed for survey data from both Myanmar and Nepal. The study followed these steps to match treatment (electrified) and non-treatment (non-electrified) groups:

1. Logistic regression was conducted to estimate the original propensity score – the probability of receiving treatment given the covariates we selected in Section 2.1.1.
2. The dependent variable was established as a binary variable (representing electrification status) and the independent variables were covariates selected from Section 2.1.1.
3. The R package "MatchIt" was used to produce the propensity scores and create a new dataset of matched data points.
    - The MatchIt package works by retaining all treated units, and selecting control units to include in the final data set (Ho, et. al., 2008)
    - We observed that the matching method "coarsened exact matching" performed best compared to other methods for Myanmar. For Nepal, however, the "nearest neighbor" method produced the best results. Final selection of matching method was based on analyzing histograms showing the distribution of propensity scores across the control and treatment groups.
    - "Coarsened exact matching" is a matching technique that matches on a specific covariate, while maintaining the original values of other covariates (Randolph

et. al., 2014). In the MatchIt package, this method is implemented by specifying method = "cem" in the MatchIt code.

- "Nearest neighbor matching" selects the best control matches for each household in the treatment group based on a distance measure which is the estimated propensity score obtained from the logistic regression model. Matches are chosen for each treated unit one at a time and at each matching step. In the MatchIt package, this method is implemented by specifying method = "nearest" in the MatchIt code.
- The matched dataset was then used for the follow-up analysis presented in section 2.1.3.

2.1.3 Outcome Model Using Matched Data

After successfully obtaining a data set containing all matched data points, a follow-up statistical analysis was performed to measure the treatment's effect. We selected linear regression as our statistical method for producing outcome models. The outcome variables were selected based on a t-test (between electrified and non-electrified groups) and literature review of similar case studies.

Correlation matrices were produced to rule out variables with significantly-high correlation to eliminate incidence of multicollinearity. Multicollinearity is a disturbance in a regression model due which results from high intercorrelations among independent variables. We included one variable for each pair of significantly correlated variables. Significant outcome variables were then regressed against electrification status and other covariates. We then fine-tuned the model by reducing insignificant independent variables to improve the R^2 values. The following table shows the outcome variables we analyzed using regression-based outcome models from each respective country's survey data.

Table 6: Impact subscores for Myanmar and Nepal

Subscore Code	Survey Reference	Country	Category
M_IS_1	A03_2A	Myanmar	School attendance
M_IS_2	A04_02B	Myanmar	Employment
M_IS_3	I03_15A	Myanmar	Expenditures
N_IS_1	A03_03	Nepal	School attendance
N_IS_2	A_14_B	Nepal	Employment

The equations that resulted from each regression are used to quantify the estimated impacts on a regional level for each country.

2.1.4 Socioeconomic Impacts Quantification

After consolidating all equations, we applied the base layer data (the regional average values of the independent variables of non-electrified households) to the equations. The study produces a pivot table to obtain the regional average values of all covariates with significant p-values from the prior section. In this step, only non-electrified cases are considered. Those values are then applied into the equation for each subscore. The results show the estimate of each subscore following the treatment effect – electrification. The equation for each subscore and the value of each impact score are presented in the Results section.

2.2 Non-regression Based Method for Estimating Health Impacts

As described in section 1.2, decreasing solid fuel usage within a household results in tangible health benefits. Furthermore, a strong correlation exists between electrification and adoption of modern cooking fuels (non-solid fuels). As such, we used the household's main cookstove fuel type (and the amount of time the stove is utilized) as a proxy for total household solid fuel usage in both Myanmar and Nepal.

The MTF survey conducted in Myanmar and Nepal asks households which of the following fuels they use primarily for their cookstove (*M_H01_19a and N_J20_A):*

Table 7: Options given in MTF survey for households' primary cook stove fuel

Myanmar	Nepal
Wood purchased	LPG/Cooking Gas
Charcoal	Wood
Solar	Charcoal
Kerosene	Solar
Piped Natural Gas	Kerosene
Coal	Animal Waste/Dung
Animal Waste/Dung	Crop Residue/Plant Biomass
Crop Residue/Plant Biomass	Saw Dust
Saw Dust	Coal Briquette
Coal Briquette	Biomass Briquette

Electric	Electric
Pellets/Woodchips	Pellets/Woodchips
Biogas	Biogas
Ethanol	Garbage
Garbage/Plastic	Other
Other	

Household were then asked how much *time* they used their cookstove via the following questions shown in Table 8.

Table 8: MTF survey questions for assessing how much time households used their cookstove

Myanmar	Nepal
In the last 7 days, on average, how much time did your household use the main cookstove per day to cook or reheat meals (do not include boiling water) in the morning? (M_H01_11a)	*In the last 7 days, on average, how much time did your household use the main cookstove per day to cook or reheat meals (do not include boiling water) in the morning? (N_J25)*
In the last 7 days, on average, how much time did your household use the main cookstove per day to cook or reheat meals (do not include boiling water) in the afternoon? (M_H01_11b)	*In the last 7 days, on average, how much time did your household use the main cookstove per day to cook or reheat meals (do not include boiling water) in the afternoon? (N_J26)*
In the last 7 days, on average, how much time did your household use the main cookstove per day to cook or reheat meals (do not include boiling water) in the evening? (M_H01_11c)	*In the last 7 days, on average, how much time did your household use the main cookstove per day to cook or reheat meals (do not include boiling water) in the evening? (N_J27)*
In the last 7 days, on average, how much time did your household use the main cookstove per day to boil water (for cooking, washing, and drinking and bathing)? (M_H01_11d)	*In the last 7 days, on average, how much time did your household use the main cookstove per day to boil water (for cooking, washing, and drinking and bathing)? (N_J28)*
	In the last 7 days, on average, how much time did your household use this cookstove per day to cooking cattle fodder? (N_J29)

The following steps were then taken in Microsoft Excel to calculate M_IS4 and N_IS3 (for non-electrified households):

1. The fuel types were separated into two categories: (1) solid fuels, and (2) non-solid fuels.
2. For each household, we identified whether their main cookstove fuel was solid or non-solid.
3. For each household, we calculated the total number of minutes per week (MPW) the main cookstove was used by summing the values reported from Table 8.
4. We calculated the percentage of households that used a solid fuel as the main cookstove fuel, and the percentage of households that used a non-solid fuel as the main cookstove fuel for each region.
5. For each region, we used AVERAGEIF functions (matching based on region name) to calculate the average MPW households used their main cookstove fuel for households using a solid fuel as the main cookstove fuel.
6. We calculated the total average MPW of solid fuel use for each region by multiplying the percentage of households that use a solid fuel as the main cookstove fuel (step 4) by the average MPW these households used their main cookstove (step 4).
7. We calculated the z-score for each region based on the results from step 6.

2.3 Calculating Impact Subscores via Z-scores

After each impact of electrification is calculated (e.g. a 4% increase in employment in Region X, or a $20 increase in household expenditures in Region Y), we obtain a z-score for that particular region.

The z-score is given by:

$$z = \frac{\left(\left(X_{Region}\right) - \left(Average\ X_{Country}\right)\right)}{\left(Standard\ Deviation\ X_{Country}\right)}$$

Each z-score therefore corresponds to a particular impact subscore for a particular region. To obtain the total impact score for a particular region, the z-scores are averaged.

2.4 Visualization

The results of the model are presented via an online interactive map[3][4]. The web application we used to build the map is designed by Esri (an international supplier of geographic information system software, web GIS and geodatabase management applications). To create the online interactive map, we collected necessary base layer data for both countries including population density, transmission lines, road networks, and locations of power stations. We used zonal statistics to calculate population density for each region.

We then uploaded all the base layers, along with the impact scores, for each region in Myanmar and Nepal. Filter widgets from the online web application builder provide Users with the option to select specific regions of interest.

3. Results

3.1 Myanmar

The following variables in Table 9 are included in the regression models for each subsequent impact subscore (excluding the M_IS4, which is not calculated using a regression model).

Table 9: Variables used in Myanmar impact score regression models.

Regression Reference	Survey Reference	Category
M_A	**A03_02A**	Number of household members who have ever attended school
M_B	**A_05_c02**	Total minutes per day household spends on income generating activities outside the house
M_C	**A_05_c03**	Total minutes per day household spends on income generating activities inside the house
M_D	**A03_06**	Average daily at-home study time per student before sunset (mins)
M_E	**A03_07**	Average daily at-home study time per student after sunset (mins)
M_F	**A05_b06**	Daily time household spends on cooking (min)
M_G	**C1_501**	Total number of radios owned by household
M_H	**C1_804**	Total number of smartphones/tablets owned by household

[3] Map for Myanmar:
https://dukeuniv.maps.arcgis.com/apps/webappviewer/index.html?id=52c8cd6b7a614d05827f19726e0a3db5

[4] Map for Nepal:
https://dukeuniv.maps.arcgis.com/apps/webappviewer/index.html?id=0035adbfe33544d09fc5b6d9f5f972fb

M_I	**I02_07**	Monthly transportation costs (2018 USD)
M_J	**I03_A**	Total non-food expenditures in the past 12 months (2018 USD)
M_K	**E01_02_day**	Days per month household uses candles for lighting
M_L	**I03_B**	Average weekly expenditures (2018 USD)
M_M	**NA**	Household electrification status (0 = non-electrified, 1 = electrified)
M_N	**A04_02b**	Number of employed household members
M_O	**A04_06**	Monthly income of highest-paid household member (2018 USD)
M_P	**A01_05**	Total number of household members
M_Q	**A05_b04**	Time household spends collecting fuel per day
M_R	**A05_b_05**	Total minutes per day household spends on preparing fuel/energy sources

For each of the subsequent regression equations, an asterisk (*) indicates a significant variable at the $\alpha = 0.05$ level.

3.1.1 M_IS1: School Attendance Subscore

The following regression was obtained with respect to the increase in the total number of household members who ever attend school as a result of electrification.

$$(M\_A) \sim 0.0157(M\_B)^* + 0.0219(M\_C)^* + 0.0059(M\_D) + 0.0096(M\_E)^* + 0.0131(M\_F)^* + 2.822(M\_G)^* + 1.2589(M\_H)^* + 0.0008(M\_I) + 0.0043(M\_J) + 0.0955(M\_K)^* + 0.0008(M\_L)^* + 0.0989(M\_M) - 3.0964$$

This model has an R^2 value of **0.888.** Using this regression equation, and plugging in regional averages for each abovementioned variable, we calculate that the average estimated per-household increase in the number of individuals who ever attend school is **1.75 individuals**, with a standard deviation of **1.18 individuals**. The estimated average per-household increase in the number of individuals who ever attend school, with the corresponding z-score, is displayed in Table 10.

Table 10: Estimated per-household increase in the number of individuals who have ever attended school (after electrification)

Region	Increase in no. individuals who ever attend school	Z-score
Kachin	1.61	-0.112
Kayin	3.60	1.576
Mandalay	2.16	0.355
Chin	2.08	0.288
Sagaing	2.33	0.494
Tanintharyi	2.20	0.389
Bago	0.41	-1.139
Magway	1.81	0.053
Mon	-0.51	-1.923
Rakhine	3.95	1.875
Yangon	1.30	-0.383
Shan	1.50	-0.209
Ayeyawady	1.53	-0.185
Naypyitaw	0.48	-1.078

High z-score values indicate regions expected to see greatest increase in the number of individuals that ever attend school per household.

3.1.2 M_IS2: Employment Subscore

The following regression was obtained with respect to the increase in the total number of employed members per household as a result of electrification:

$$(M\_N) \sim 0.0090(M\_B)^* - 0.0009(M\_C) + 0.0058(M\_D)^* + 0.7530(M\_G)^* + 0.0606(M\_H)^* + 0.0049(M\_I)^* - 0.0003\ (M\_J) + 0.0004(M\_L)^* + 0.0269(M\_K) + 0.0029(M\_D) + 0.0881(M\_M) - 0.3760$$

This model has an R^2 value of **0.682**. Using this regression equation, and plugging in regional averages for each abovementioned variable, we calculate that the average estimated increase in the number of employed individuals per household is **2.57 individuals**, with a standard deviation of **0.84 individuals**. The estimated average increase in the number of employed individuals per household for each region, with the corresponding z-score, is displayed in Table 11.

Table 11: Estimated per-household increase in the number of employed individuals after electrification.

Region	Increase in no. of employed individuals	Z-score
Kachin	2.96	0.464
Kayin	3.33	0.897
Mandalay	2.70	0.155
Chin	2.84	0.320
Sagaing	2.73	0.192
Tanintharyi	3.40	0.981
Bago	2.01	-0.656
Magway	2.36	-0.244
Mon	1.46	-1.306
Rakhine	4.47	2.251
Yangon	2.33	-0.287
Shan	1.50	-1.267
Ayeyawady	2.46	-0.126
Naypyitaw	1.41	-1.375

High z-score values indicate regions expected to see greatest increase in the number of employed individuals per household.

3.1.3 M_IS3: Expenditures Subscore

The following regression equation was obtained with respect to the estimated per-household increase in annual non-food expenditures as a result of electrification (in 2018 USD):

$$(M\_J) \sim 2.4620(M\_B)^* - 0.1668(M\_D) - 0.0972(M\_E) - 0.8141(M\_O)^* + 0.8669(M\_I) + 7.7847(M\_K)^* + 39.0658(M\_P)^* + 0.0562(M\_Q) + 4.2962(M\_R) + 38.5300(M\_M) - 50.7218$$

This model has an R^2 value of **0.498**. Using this regression equation, and plugging in regional averages for each abovementioned variable, we calculate that the average estimated per-household increase in annual non-food across regions is **$590 (2018 USD)**, with a standard deviation of **$302 (2018 USD)**. The estimated increase per region, with its corresponding z-score, is displayed in Table 12.

Table 12: Estimated per-household increase in annual non-food expenditures after electrification

Region	Increase in annual non-food expenditures (2018 USD)	Z-score
Kachin	24.62	-1.873
Kayin	832.73	0.801
Mandalay	861.80	0.897
Chin	580.19	-0.034
Sagaing	852.18	0.865
Tanintharyi	480.81	-0.363
Bago	510.59	-0.265
Magway	661.06	0.233
Mon	-2.05	-1.961
Rakhine	1063.32	1.564
Yangon	787.86	0.653
Shan	589.95	-0.002
Ayeyawady	605.67	0.050
Naypyitaw	419.79	-0.565

High z-score values indicate regions expected to see greatest increase in annual non-food expenditures.

3.1.4 M_IS4: Health Subscore

Plugging in regional averages, we calculate that the average time households use solid fuels for their main cookstove is **1,100 minutes per week (MPW)**, with a standard deviation of **173 MPW**. Using this average, we calculate the z-score for each region in Table 13.

Table 13: Average minutes per week households use a solid fuel as their main cookstove fuel

Region	Number of households (HH)	No. of HH use solid fuel as main cookstove fuel	% HH use solid fuel as main cookstove fuel	Average MPW using main cookstove	Average MPW using solid fuels	Z-score
Kachin	57	53	93.0%	924	859	-1.298
Kayin	48	47	97.9%	1180	1155	0.030
Mandalay	79	78	98.7%	1024	1011	-0.614
Chin	20	20	100.0%	1426	1426	1.245

Sagaing	117	117	100.0%	1223	1223	0.334
Tanintharyi	135	110	81.5%	1158	943	-0.920
Bago	114	114	100.0%	1176	1176	0.123
Magway	80	77	96.3%	1192	1148	-0.003
Mon	73	67	91.8%	1026	942	-0.927
Rakhine	103	99	96.1%	1503	1444	1.328
Yangon	84	78	92.9%	1096	1017	-0.587
Shan	139	135	97.1%	1161	1127	-0.094
Ayeyawady	159	156	98.1%	1135	1114	-0.153
Naypyitaw	23	23	100.0%	959	959	-0.850

High z-score values indicate areas where electrification efforts have the greatest potential to decrease the average MPW households use solid fuels on their main cookstoves.

3.1.5 Total Impact Score

By averaging the z-scores for M_IS1, M_IS2, M_IS3, and M_IS4, we obtain a total impact score for each region. Based on this total impact score, we assign a prioritization indicator to denote which regions should be prioritized for renewable energy developments. This prioritization indicator is based on quantiles from the total impact score, with four regions ranking as "1" (highest priority regions), three regions ranking as "2," three regions ranking as "3," and four regions ranking as "4" (lowest priority regions).

Table 14: Total impact score and prioritization indicator for each region of Myanmar

Region	M_IS1 Subscore	M_IS2 Subscore	M_IS3 Subscore	M_IS4 Subscore	Total Impact Score	Prioritization Indicator
Kachin	-0.112	0.464	-1.873	-1.298	**-0.705**	**4**
Kayin	1.576	0.897	0.801	0.030	**0.826**	**1**
Mandalay	0.355	0.155	0.897	-0.614	**0.198**	**2**
Chin	0.288	0.320	-0.034	1.245	**0.455**	**1**
Sagaing	0.494	0.192	0.865	0.334	**0.471**	**1**
Tanintharyi	0.389	0.981	-0.363	-0.920	**0.022**	**2**
Bago	-1.139	-0.656	-0.265	0.123	**-0.484**	**4**
Magway	0.053	-0.244	0.233	-0.003	**0.010**	**2**
Mon	-1.923	-1.306	-1.961	-0.927	**-1.529**	**4**
Rakhine	1.875	2.251	1.564	1.328	**1.754**	**1**

Yangon	-0.383	-0.287	0.653	-0.587	**-0.151**	**3**
Shan	-0.209	-1.267	-0.002	-0.094	**-0.393**	**3**
Ayeyawady	-0.185	-0.126	0.050	-0.153	**-0.104**	**3**
Naypyitaw	-1.078	-1.375	-0.565	-0.850	**-0.967**	**4**

Note that the Kayah region is excluded from our analysis, as the survey data only contains one non-electrified household.

3.1.6 Visualization for Priority Ranking

Based on the prioritization indicator for each region, we produced a digital map to display priority rankings for each region of Myanmar. The map shows the regions of Sagaing, Chin, Rakhine, and Kayin as being highest priority for renewable energy developments.

Figure 9: Map showing each region of Myanmar's degree of prioritization for renewable energy developments

3.2 Nepal

The following variables are included in the regression models for each subsequent impact subscore (excluding the N_IS3, which is not calculated using a regression model):

Table 15: Variables used in Nepal impact score regression models

Regression Reference	Survey Reference	Category
N_A	**A03_03A**	Percent household members (> age 5) currently attending school
N_B	**A14B**	Number of employed (non-student) household members (> age 15)
N_C	**J37_A**	Monthly expenditures for fuel for main stove (2018 USD)
N_D	**A01_09**	Number of children (< age 18)
N_E	**MB**	Value of consumed food (that was purchased/acquired) in last 7 days
N_F	**M19**	Total weekly non-food expenditures (2018 USD)
N_G	**A14B**	Percent of employed (non-student) household members (> age 15)
N_H	**R23_A**	Total minutes per day household spends on income generating activities outside the house
N_I	**NA**	Household electrification status (0 = non-electrified, 1 = electrified)

For each of the subsequent regression equations, an asterisk (*) indicates a significant variable at the $\alpha = 0.05$ level.

3.2.1 N_IS1: School Attendance Subscore

The following regression was obtained with respect to the increase in the percentage of household members who attend school as a result of electrification:

$$(N\_A) \sim -0.0442(N\_B)^* + 0.0001(N\_C) + 0.1145(N\_D)^* + 0.0001(N\_E)^* + 0.0002(N\_F)^* + 0.0261(N\_I) + 0.1568$$

This model has an R^2 value of **0.396.** Using this regression equation, and plugging in regional averages for each abovementioned variable, we calculate that the average estimated increase in the percentage of household members who attend school is **2.68%**, with a standard deviation of **2.4%**. The estimated average per-household percentage increase, with the corresponding z-score, is displayed in Table 16.

Table 16: Estimated percentage increase in household members attending school after electrification in Nepal.

Region	Increase in % household members who attend school	Z-score
Bagmati	-1.62%	-1.793
Bheri	2.08%	-0.247
Dhaulagiri	3.47%	0.331
Gandaki	1.30%	-0.576
Jankpur	4.00%	0.551
Karnali	8.94%	2.614
Koshi	4.08%	0.588
Lumbini	3.23%	0.230
Mahakali	2.18%	-0.209
Mechi	2.34%	-0.142
Narayani	2.38%	-0.122
Rapti	-0.14%	-1.178
Sagarmatha	1.72%	-0.400
Seti	3.52%	0.354

High z-score values indicate regions expected to see greatest increase in the percentage of household members attending school.

3.2.2 N_IS2: Employment Subscore

The following regression was obtained with respect to the increase in the percentage of employed household members (non-student and above age 15) as a result of electrification:

$$(N\_G) \sim 0.0015(N\_H)^* + 0.0001(N\_C) + 0.1117(N\_D) + 0.0014(N\_E)^* + 0.0006(N\_F) + 0.2779(N\_I)^* + 0.6582$$

This model has an R^2 value of **0.207.** Using this regression equation, and plugging in regional averages for each abovementioned variable, we calculate that the average estimated increase in the percentage of employed household members is **4.34%**, with a standard deviation of **6.94%**. The estimated average per-household percentage increase, with the corresponding z-score, is displayed in Table 17.

Table 17: Estimated percentage increase in employed household members after electrification in Nepal

Region	Increase in % employed household members	Z-score
Bagmati	5.82%	0.214
Bheri	2.72%	-0.234
Dhaulagiri	15.13%	1.555
Gandaki	11.38%	1.015
Jankpur	8.43%	0.590
Karnali	6.12%	0.256
Koshi	1.24%	-0.447
Lumbini	9.76%	0.780
Mahakali	-7.42%	-1.696
Mechi	11.03%	0.964
Narayani	4.67%	0.047
Rapti	-4.66%	-1.297
Sagarmatha	3.68%	-0.096
Seti	-7.13%	-1.652

High z-score values indicate regions expected to see greatest increase in the percentage of employed household members.

3.2.3 N_IS3: Health Subscore

Plugging in regional averages, we calculate that the average time households use solid fuels for their main cookstove is **1,042 minutes per week (MPW)**, with a standard deviation of **588 MPW**. Using this average, we calculate the z-score for each region in the table below:

Table 18: Average minutes per week Nepal households use a solid fuel as their main cookstove fuel

Region	Number of households (HH)	No. of HH use solid fuel as main cookstove fuel	% HH use solid fuel as main cookstove fuel	Average MPW using main cookstove	Average MPW using solid fuels	Z-score
Bagmati	285	178	62.5%	1594	996	-0.078
Bheri	379	180	47.5%	1615	767	-0.467
Dhaulagiri	213	170	79.8%	1541	1230	0.320
Gandaki	364	273	75.0%	1333	1000	-0.071

Jankpur	892	231	25.9%	1258	326	-1.217
Karnali	93	90	96.8%	2502	2421	2.347
Koshi	79	72	91.1%	1774	1617	0.979
Lumbini	27	27	100.0%	1670	1670	1.068
Mahakali	173	90	52.0%	1241	645	-0.674
Mechi	127	53	41.7%	1097	458	-0.993
Narayani	75	57	76.0%	1379	1048	0.011
Rapti	284	91	32.0%	1000	320	-1.226
Sagarmatha	102	91	89.2%	1540	1374	0.566
Seti	183	106	57.9%	1226	710	-0.564

High z-score values indicate areas where electrification efforts have the greatest potential to decrease the average MPW households use solid fuels on their main cookstoves.

3.2.4 Total Impact Score

By averaging the z-scores for N_IS1, N_IS2, and N_IS3, we obtain a total impact score for each region. Based on this total impact score, we assign a prioritization indicator to denote which regions should be prioritized for renewable energy developments. This prioritization indicator is based on quantiles from the total impact score, with four regions ranking as "1" (highest priority regions), three regions ranking as "2," three regions ranking as "3," and four regions ranking as "4" (lowest priority regions).

Table 19: Total impact score and prioritization indicator for each region of Nepal

Region	N_IS1 Subscore	N_IS2 Subscore	N_IS3 Subscore	Total Impact Score	Prioritization Score
Bagmati	-1.793	0.214	-0.078	**-0.552**	**4**
Bheri	-0.247	-0.234	-0.467	**-0.316**	**3**
Dhaulagiri	0.331	1.555	0.32	**0.735**	**1**
Gandaki	-0.576	1.015	-0.071	**0.123**	**2**
Jankpur	0.551	0.59	-1.217	**-0.025**	**3**
Karnali	2.614	0.256	2.347	**1.739**	**1**
Koshi	0.588	-0.447	0.979	**0.373**	**1**
Lumbini	0.23	0.78	1.068	**0.693**	**1**
Mahakali	-0.209	-1.696	-0.674	**-0.860**	**4**
Mechi	-0.142	0.964	-0.993	**-0.057**	**3**
Narayani	-0.122	0.047	0.011	**-0.021**	**2**

Rapti	-1.178	-1.297	-1.226	**-1.234**	**4**
Sagarmatha	-0.4	-0.096	0.566	**0.023**	**2**
Seti	0.354	-1.652	-0.564	**-0.621**	**4**

3.2.5 Visualization for Priority Ranking

Based on the prioritization indicator for each region, we produced a digital map to display priority rankings for each region of Nepal. The map shows the regions Karnali, Dhaualagiri, Lumbini, and Koshi as being highest priority for renewable energy development.

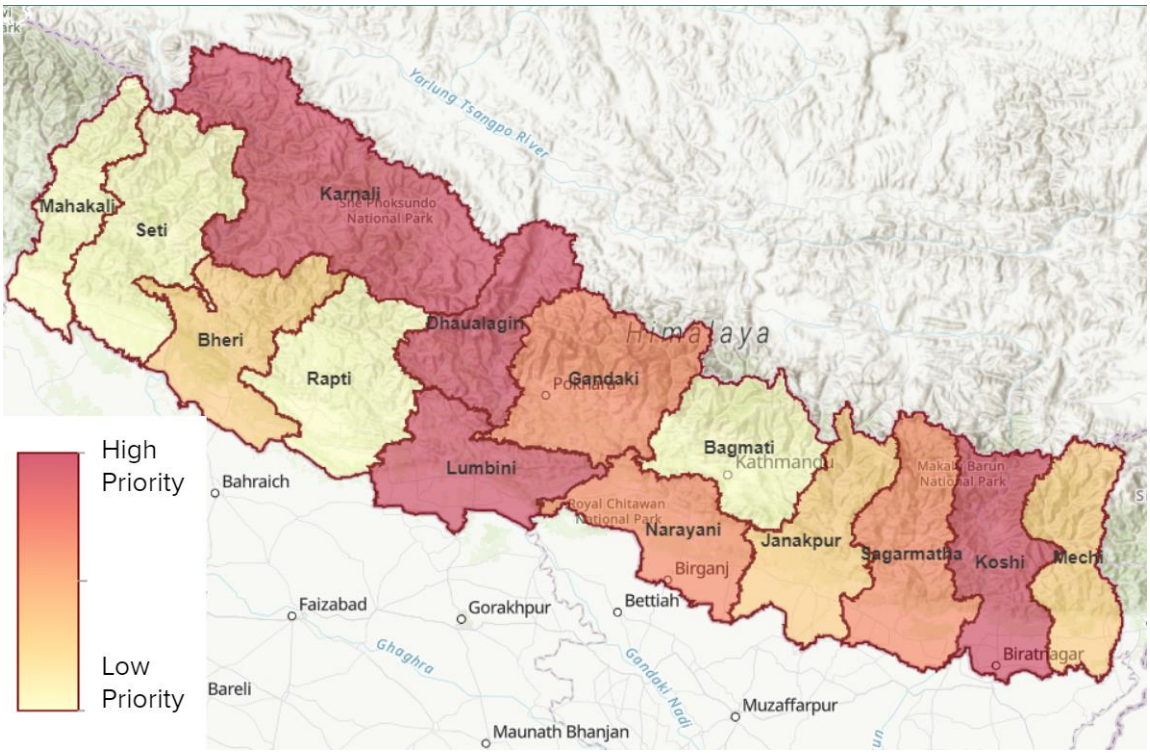

Figure 10: Map showing each region of Nepal's degree of prioritization for renewable energy developments

4. Discussion

4.1 Myanmar Impact Scores

Myanmar is comprised of 15 administrative regions. Due to data availability in Myanmar's MTF survey, however, we have calculated the total impact score for 14 regions (excluding the region of Kayah). Regions Kayin, Ching, Sagaing, and Rakhine yield the highest total impact scores, and are thus deemed the highest priority regions in terms of renewable

energy developments. According to the 2018 Multidimensional Welfare in Myanmar report, there are significant variations in the types and magnitudes of disadvantages among the regions of Myanmar. To understand why the aforementioned regions yielded high impact scores relative to other regions, one must investigate these regions' specific features.

Figure 11: Administrative regions of Myanmar

The region of Rakhine has the highest total impact score out of the 14 administrative regions analyzed in this study. Rakhine – a remote coastal region in Myanmar and the center of Myanmar's Rohingyan crisis – is considered one of the country's least-developed regions. Furthermore, it has the highest unemployment rate and lowest labor force participation. As of 2017, the state had a recorded poverty rate of 41.6%, making it the 2nd poorest region in the country. The large majority of the region's inhabitants (~83%) resides in rural areas (Department of Population Ministry of Immigration and Population, 2015). According to the 2018 Multidimensional Welfare in Myanmar Report, Rakhine has the highest Multidimensional Disadvantage Index (MDI) compared to other regions (The World Bank, 2018).

Out of 3,742 villages in Rakhine, only 1,893 villages are electrified, making the region's current electrification rate 21% (Myanmar News Agency, 2019). A number of electrification infrastructure projects are well underway to meet the state's target electrification rate of 75% by 2025 (Htwe, 2019). The state is currently working aggressively towards infrastructure development, including roads and bridges to help lift the state out of poverty. These statistics suggest that a combination of Rakhine's remote location, lack of infrastructure, past political conflict, and poor productivity are potential drivers of how electrification can generate the most impact in Rakhine compared to other regions. Renewable energy projects that are aligned with the state's infrastructure development projects, both in terms of timeline and geographical location, can help amplify potential impacts. Off-grid renewable energy projects can be seen as potential solutions that can target remote communities located far from the existing national grid.

The other regions classified as high priority are Kayin, Chin, and Sagaing. Kayin, a mountainous state home to 4,092 villages, has the second highest total impact score. Kayin has a high unemployment rate of 7.5% (Department of Population Ministry of Immigration and Population, 2015), making it the region with the second highest unemployment rate. Chin, a mountainous state in Western Myanmar has an unemployment rate of 5.3%, which makes it the 4th highest in the country. Sagaing, Myanmar's second largest state after Shan, however, has a relatively lower unemployment rate of 3.6% which ranks it 10th in terms of unemployment.

According to the 2017 Myanmar Living Conditions Survey, the number of impoverished people in rural areas is 6.7 times higher than in urban areas. The distribution of the population in urban and rural areas in Kayin is quite stark, shown by 78% of the population living in rural areas and 22% of the population living in urban areas. The State of Chin also has an approximately similar urban-rural divide of 79% of the population living in rural areas and the remaining 21% of the population living in urban areas. The region of Sagaing shares a similar urban-rural divide with 83% of the population living in rural areas. Kayin's urban-rural divide is approximately close to that of Rakhine. Kayin, however, has a lower poverty rate of 24.2%. Sagaing, has the third highest number of impoverished inhabitants. Chin has the highest poverty rate in Myanmar (at a rate of 58% as of 2017) and the lowest per adult equivalent daily consumption (The World Bank, 2019).

Regional variations in indicators such as unemployment rate, poverty rate, and remoteness drive the different levels of total impact scores. Regions in the hills and mountainous zones (Kayin and Chin) are faced with the challenge of remoteness and a terrain that significantly hinders development of infrastructure and accessibility. It is also notable that the urban-rural divide is aligned with disparities in welfare. The 2017 Myanmar Living Conditions Survey reports that poverty is high and concentrated in rural areas. Rural development is a top priority for the nation's government, which is also reflected in one of its key points in its National Electrification Plan: pre-electrification in rural areas prior to the arrival of the national grid and permanent mini-grid and off-grid connections in remote areas.

Although the model provides directional guidance on which region yields the highest impact, there is no divide between the impacts on urban and rural households. However, given supplemental information on other welfare indicators provided by other surveys and the township-level Multidimensional Disadvantage Index, the User can combine this information to arrive at a more granular decision on where to invest in renewable energy projects. The User can also benefit from information on the occupational sector of households and land ownership. Households that are still working in the agricultural sector and have no land ownership are in the highest poverty rate level of 48.5% (The World Bank, 2019). In addition, these households are sensitive to shocks such as climate-related floods, which can affect the productivity of crops and lower prices of agricultural products. The addition of this information to the impact score estimation model can better reflect the real impact that electrification can bring to improve the socio-economic development of these communities.

Observation of statistically significant predictors in each regression occasion also sheds light on what drives the impact of electrification. In the employment subscore, time spent on income-generating activities, ownership of radios and smartphones, expenditures associated with transportation, average weekly expenditures, and usage of candles are significant predictors. In the school attendance subscore, the aforementioned predictors are also statistically significant. These predictors are indicators of the welfare of the household. As for the expenditures subscore, the independent variables candle usage, the treatment (electrification), household size, and monthly income of highest paid individual in the household are statistically significant. Expenditures is chosen to be a proxy of economic welfare of the household. This is the only subscore in which the treatment (electrification) is statistically significant.

4.2 Nepal Impact Scores

Currently, Nepal is officially divided into seven federal provinces. In order to obtain more granular results, the study divides the country geographically into 14 zones, which was the earlier system Nepal used for administrative boundaries. Due to the diverse nature of Nepal in several socioeconomic and geographic aspects, the distribution of total impact scores does not show any obvious trend. The total impact scores indicate that Karnali, Dhaualagiri, Koshi, and Lumbini should be the zones prioritized for renewable energy investment.

Figure 12: Former administrative zones in Nepal

Karnali has exceedingly high impact subscores, especially for education impacts and health impacts. Though Nepal has a fairly diverse geography, the northern part of the country, generally speaking, is more mountainous – and therefore has a lower population density – than the southern part. Karnali, being situated in northwest Nepal, is fairly remote, and is considered one of the poorest regions of Nepal. The most recent available data (from 2011) suggests that about 79% of the region lives under the poverty line (Department for International Development, 2011).

Due to its remoteness and geographic setting, Karnali critically lacks transportation infrastructure. The resulting degree of inaccessibility has largely prevented the deployment

of renewable energy developments requiring high up-front construction costs. Distributed energy resources with higher flexibility in terms of installment, however, could be a good choice for remote regions like Karnali. An impact study of solar tuki (small solar home systems) in the Karnali zone in 2007 indicates improvement in home life, respiratory and optical health, and sanitation for most participants (AEPC, 2014). Furthermore, participants showed retroactive interest in solar systems with even greater capacities.

Currently, according to Nepal Electricity Authority, there are still five districts within the Karnali region that completely lack any degree of electricity access. Before they are able to connect to the national grid (which will take *at least* two years), distributed renewable energy is going to be the most feasible and beneficial path towards electricity access. Dhaualagiri, which also possesses a high total impact score, shows similar characteristics to Karnali: it, too, is characterized by a remote geography and a high poverty rate.

In analyzing and deciding on placement of renewable energy developments, Users might have additional considerations apart from our model's impact score estimates. One of these considerations is the role of tourism, which is one of the largest industries in Nepal, contributing 7.9% of the country's total GDP (WTTC 2019).

There are some zones, like Lumbini, in which tourism could be a barrier to grid construction and, consequentially, electrification. Lumbini is home to several ancient temples which are widely considered the birthplace of the historical Buddha. Consequentially, the build-out of renewable energy developments may be met with significantly social, cultural and/or political challenges. Even though its relatively low HDI score of 0.519 indicates potential for largescale improvement following electrification, the User might need to use caution in the site selection process in order to avoid damage to archeological and/or tourist sites (Human Development Report, 2019).

4.3 Comparing the Impact of Renewable Energy Developments Between Countries

Ideally, our model would be completely flexible, producing results for any given area (independent of geographical location). In constructing our model, however, we understand this is not feasible for two reasons.

The first reason centers on the fact that MTF surveys differ from country to country. Although MTF surveys are *mostly* similar for all countries, there are important differences which, ultimately, drive changes in the formation of our regression equations. For example, the Myanmar MTF survey asks participants to report the income levels for each household member. This parameter was then used in calculating M_IS1 and M_IS3 (and was significant at the $\alpha = 0.05$ level). The MTF survey in Nepal, however, does *not* ask participants to report income levels. This parameter is therefore absent from our regression equations and, consequently, our impact subscore calculations.

The second reason involves key differences in the *results* of the MTF surveys between countries (such as Myanmar and Nepal); The social, political, geographic, and cultural differences between countries have important implications on the magnitude of impact from electrification. This is evident in the differences in predictive variables in each subscore regression model: for example, M_IS2 and N_IS2 both estimate the impacts of electrification on employment. Both corresponding regression equations include similar predictive parameters such time spent on income-generating activities and household expenditures. The regression for N_IS2 also includes the number of children in the household, while the regression for M_IS2 does not. This highlights the fact that some unidentified, underlying difference between the two countries is driving a difference in the estimation of electrification's impact.

Considering these findings, it is only possible to conduct a comparison of regions *within a specific country.* In other words, we are unable to compare a region of Myanmar with a region of Nepal and determine which region would see greater benefits from a renewable energy development. Again, this is due to differences in the MTF survey questions, and the significant predictive variables that arise from the MTF survey data.

4.4 Implications of Defining "Electrified" and "Non-electrified" Households

Another noteworthy implication of our analysis rests on our selected definitions of "electrified" and "non-electrified" households.

Although our definition of "electrified" households mirrors the MTF definition of Tier 5 (highest level) energy access, our definition of "non-electrified" households is arbitrary in nature. It is possible that our chosen criteria for a "non-electrified" household does not

entirely capture a true non-electrified status, as many of these households do, in fact, have *some* level of access to electricity.

On the other hand, our definition of "electrified" requires households to have reliable and near-constant access to electricity. While we feel this was necessary to capture the *true* impacts of energy access and minimize potentially-confounding factors, this also eliminated many households that were represented in the MTF survey from our ultimate regression analysis. In Nepal, for example, our rigid definition of an "electrified" household left us with approximately 200 electrified households for forming our regression equations. This ultimately decreased the robustness of our regressions for Nepal.

5. Conclusions and Future Work

5.1 Conclusions

Using Multi-Tier Framework data for Myanmar and Nepal, we have estimated the region-level impact score of a renewable energy development, which comprises social, economic, and health impact subscores on the methodological basis of statistical analysis. Given the variations of the MTF survey structure for Myanmar and Nepal, our set of criteria to distinguish electrified and non-electrified households is essential to measuring the impacts of electrification in each region of both countries.

Given the data-driven nature of this project, as well as the available survey data for both countries, we were able to construct an estimation model using a regression-based approach, supplemented by propensity score matching and a non-regression-based approach. The estimation of the total impact scores on a regional level has enabled us to classify regions using a prioritization indicator on a scale of 1 to 4; 1 being "highest priority regions" and 4 being "lowest priority regions." The impact score estimation model has achieved its objective in providing directional guidance regarding optimal placement of renewable energy developments within Myanmar and Nepal to maximize social and economic benefits to local communities.

5.2 Future Work

Future work can focus on the following aspects:

- Deeper Regional Background Research
    - In order to acquire a deeper understanding of the drivers behind the impact scores, it would be beneficial to conduct preliminary background research on each region. For instance, because the formerly-used administrative boundaries were abandoned in 2015, there is currently limited information on each specific zone of Nepal. Consequently, it is difficult to meaningfully discuss the results in the context of each specific zone.
- Improve Model Performance
    - Future studies could break down electrification status into several tiers to improve data balance and model performance. Incorporating electrification status as a binary variable has potentially weakened our results. For instance, in the case of Nepal, there are 1,200 households that are defined as "non-electrified," while only 200 households are defined as "electrified". As such, only 200 sample pairs are available if we conduct 1-to-1 matching during propensity score matching.
    - For several outcome variables considered for both countries, the associated R^2 values are relatively low. Only a few outcome variables' associated equations were statistically significant enough to be incorporated in our total impact scores. As a result, the total impact score is most likely over-simplified.
    - Data collection and aggregation is another important step towards a more precise model. There are several important aspects to electrification – including distance to the closest grid – that our model does not consider.
- Extend the model to other countries / regions
    - As mentioned, one of the goals of this project is to provide a sound method for estimating and quantifying the socioeconomic benefits from renewable energy developments for future similar studies. With sufficient country-level data, our method could be applied to other countries with different social, economic, and cultural settings than Myanmar and Nepal.
- Improve flexibility of the model
    - Due to the limitation of outcome variables, the model is designed to produce only one total impact score for each region. To provide a more user-friendly impact model, we suggest breaking down the socioeconomic impact score into one social impact score, and one economic impact score. In this way, the User could choose (or weigh) the impact scores according to their own preferences.

Acknowledgements

This undertaking would simply not be possible without the guidance and support of various Duke faculty members, Duke students and alumni, and energy sector experts.

We would like to extend thanks first and foremost to our advisor, Dr. Luana Marangon Lima, for her technical guidance, expert advice, and moral support throughout this endeavor. Our sincerest thanks also goes out to Lina Khan, whose excellent research laid the foundation for this study. Thank you to Dr. Dalia Patino-Echeverri for taking the time to provide us with key information and insights regarding the quantification of benefits from renewable energy.

We'd also like to acknowledge Jonathan Phillips – Director of Duke's Energy Access Project – and Frederick Freeman, whose knowledge and guidance ultimately drove the direction of our project. Our thanks also go out to Alicia Oberholzer, who introduced us to Multi-Tier Framework (MTF) data. We would like to thank Sumin Wang for providing us with technical support on our online web application. We would also like to recognize Pradygdha Kumayan Jati of IBEKA, who provided insights regarding renewable energy projects in emerging energy markets. Thank you also to Mathew Tiedemann, who advised our research on energy markets in Myanmar. Lastly, we'd like to extend our thanks to Marc Jeuland for teaching us the econometric technique which ultimately led us to our results.

We appreciate all your support and guidance immensely.

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