Causal Effects of Renewable and Fossil Fuel Energy Sectors

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ABSTRACT

In this work we explore causality with real-world data from the United Nations, International Labor Organization, and a few others. Specifically we look at the effects of the energy sector on the economy by disentangling the sources, from which energy is derived, into renewables and fossil fuels (combustibles). We run a case study on the United States, looking at the change in energy production and consumption to find causality with labor statistics and GDP. We find correlations between renewable energy production and both employment in utilities and GDP, while combustible based energy has no direct link. We also have preliminary results on causality for accessibility of electricity, where we determine that renewable energy output is positively correlated with accessibility in a subset of the world's nations. We also run Granger tests to explore the time series component of our data, looking for causality among the variables.

1 INTRODUCTION

We focus on the seventh goal of the United Nations Sustainable Development Goals[1] (UN SDGs). The SDGs are 17 goals to improve the quality of life of people, focusing on problems that need to be addressed before 2050. The seventh goal is called "Affordable and Clean Energy" and aims to "ensure access to affordable, reliable, sustainable and modern energy for all".

The relationships between segments of the economy and the energy sector are complex. It is obvious that one depends on the other, but details about how to quantify the effects of the energy sector based on the source where energy is derived are not so clear. The benefits of relying on renewable energy over combustible based sources are based mostly on the fact that the combustibles have a serious environmental impact, many of which are yet to be observed. On the other hand, few discuss the other benefits of renewable energy. For example, the International Renewable Energy Agency[2] illustrates the lesser well-known benefits, such as a significantly growing number of jobs, the increase in accessibility through the reliability of the technology, and the resilience of the technology to failures. In our work we focus on the first two. We hope to provide some evidence of the lesser well-known benefits by exploring causality through data from various sources. In Section 7, we discuss the shortcomings of our approach and potential future directions.

2 RELATED WORK

Finding causal relationships in the energy sector is something that has been explored already. Jaforullah et al. [6] describe the effects of the renewable energy on CO_2 emissions through a negative relationship and find no evidence of a relationship between the development of nuclear energy and reduced CO_2 emissions, but Al-mulali [7] shows the opposite. Chang et al. [4] indicate that there is evidence that, in G7 countries except for Italy (that does not use nuclear power since the '80s), the economic growth causes nuclear energy consumption, but not vice versa. Al-mulali [7] highlights a negative causal relationship between fossil fuel and nuclear energy consumption, and that both of them have a positive relationship with GDP growth. Many papers reach different conclusions [6], so here we try to answer more general causal questions using mainly the UNdata, that is the dataset that includes the higher number of countries and indicators with the higher quality that we are aware of, and we discuss the main limitations of this approach.

3 GRANGER CAUSALITY

We begin by considering the formulation from [3] for Granger Causality (GC) [5] and the *feature causal network*. We have a set of N features (i.e., indicators) $\{x_i\}_{i=1}^N$, where each x_i is a sequence of T observations. We wish to model their causal relationships and characterize the *causal feature network* that is assumed to exist. When there is a causal relationship, the edge between them is paired with a weight called the *lag*. Where the lag is defined as the time delay for causal influence. More concretely, if the variable x_i is a cause of x_j with a lag of k then there is a directed edge $x_i^{T-k} \rightarrow x_j^T$ where we superscript a feature to represent its position in the time sequence. The graph models the distribution over the next set of elements in the sequence conditioned on the lag variables, $P(\{x_i^T\}|\{x_i^t\}_{i=1,..,N,t=0,..,T-1})$. The distribution can be defined in many ways and in many cases they are linear Gaussian models.

As mentioned previously, the Granger test is the key to finding GC. If variable X improves the accuracy of predicting Y better than just previous time steps of Y then we can say X Granger causes Y. This is formalized by considering the following two equations when have linear Gaussian models:

$$\begin{aligned} r_Y(t) &= Y^t - \textstyle\sum_{i=1}^T \alpha_i Y^{t-i} \\ r_{YX}(t) &= Y^t - \textstyle\sum_{i=1}^T \left[\alpha_i Y^{t-i} + \beta_i X^{t-i}\right] \end{aligned} \tag{1}$$

where α and β are the optimal coefficients from regressing on Y. We can compare the performance of these two models in numerous ways like the F-test or Bayesian Information Criterion (BIC) [2, 1]. If the difference in performance, when including X produces a statistically significant improvement (reduction in variance), then we say that X Granger causes Y. Therefore, a naive approach to discovering the graph structure is to run an exhaustive Granger test on all pairs of variables.

4 INITIAL SOLUTIONS

In order to obtain the results that we discuss in Section 6 we initially used the data from the UN. We started by downloading in a CSV format each dataset with the indicator that we wanted to study and we ran some exploratory data analysis (EDA) on the datasets. Based on all the available data, we built our hypothetical causal graph. In this way we selected a subset of all available indicators and we focused on those. As we discuss in Section 5, we integrated

[1] https://www.un.org/sustainabledevelopment/
[2] https://www.irena.org/benefits

datasets from three other sources with what we previously had to increase the quality of the results. We used R and Python for the EDA and the Granger tests.

5 DATA DESCRIPTION AND CLEANING

We collected our data from various locations, mostly from UNdata[3], but there are some other sources. There are four major variables we are measuring: the electrical production per country based on how the power was generated, the labor demographics per country which are categorized based on the type of work, GDP per country, and finally access to electricity which is measured as a percentage. Below we discuss the details of each relevant dataset along with how we process and aggregate them. Data of this kind is valuable. Usually the motive for organizations like the UN and the ILO to collect the data is influencing public policy, in particular to provide the necessary statistics to make informed decisions.

When looking at the structure of the data as a whole, a general pattern emerges. We have a set of features for each country/year pair. An option for structuring was to have a wide dataset where each country is an entry/row in the table, but this would mean that we would need a column for every feature in every year. This has a few problems, particularly with handling the data sparsity in the columns that would arise. It is much more efficient, memory-wise, to have the former strategy of country/year pairs because we will only have entries for years that have data. The data, in its raw form, is also in a long format so it was easier to maintain this structure than to perform a full transformation.

All of the data we collected is measuring real-world processes, specifically we have observations on the national scale. We will demonstrate in later sections that data of this nature is very noisy and subject to many latent factors. They are either infeasible to measure adequately, even if organizations like the UN and ILO wanted to do so, or are simply missed because of an incomplete understanding of factors that contribute to economic prosperity or availability of labor on the national scale. That being said, when we do discover interesting trends we attempt to use our own experience by introducing discrete variables that could make causality identifiable in some cases. We then try to support the usage of the discrete variables by making country-wise comparisons.

UN Data on Energy

The source is the Energy Statistics Database, which provides statistics on numerous aspects of the production, consumption, import, and export of energy. All measurements are in the millions of kilowatt-hours (kWh). There are numerous ways in which a country can derive its power to meet demand locally, or potentially export it[4]. The *combustible* fuels represent the energy sources where ignite the fuel, like coal, oil, and natural gas which represent the fossil fuels. It is worth mentioning though that there can be other sources, not fossil, but we believe those represent a small percentage of the total energy derived from combustibles so it is convenient to simply consider them all as one category and accept the small error in approximating fossil fuel usage.

[3]https://data.un.org/

[4]There are potentially many reasons for exporting, financial or complicated trade agreements with other nations for example.

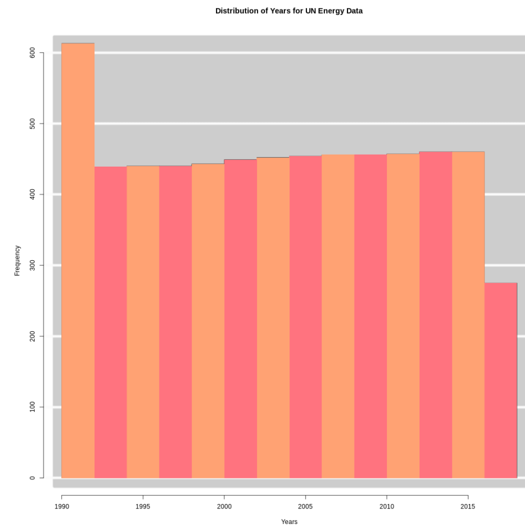

Figure 1: Counts for data entries by year for data from Energy Statistics Database.

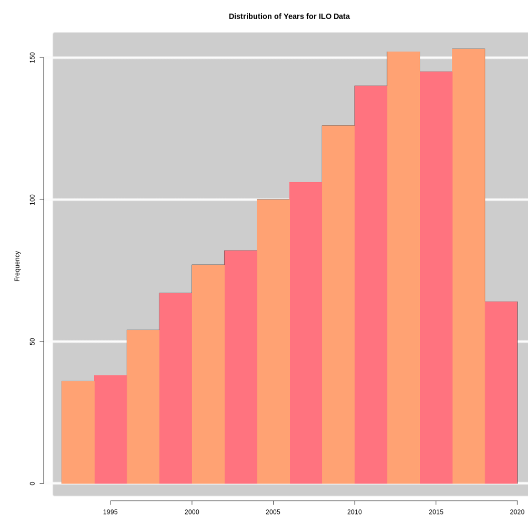

Figure 2: Counts for data entries by year for data from ILO data.

The *renewables* represent the sources that rely on processes that regenerate themselves quickly, in contrast to fossil fuels that take millions of years to form. The most well-known examples of these are energy from the sun or wind, but the most prevalent renewable source of energy is hydropower which usually consists of redirecting rivers through a dam. Geothermal energy is also a source, but in terms of total production it represents a small percentage. We choose to aggregate solar, hydro, wind, and geothermal energy as the sources of renewable energy. While nuclear power is a viable alternative to fossil fuels, particularly because of its low carbon footprint, we do not include it because uranium is not renewable.

The other categories we consider are imports, exports, and consumption. The UN reports information about how much each country consumes or how much electricity passes between borders. As we will show later, this can provide insight into what fuels are being used to meet demand or what are the motives for producing energy.

We aggregated all of these sources such that, for every year and country pair, we have all of the energy production data mentioned above. We include a histogram of the data in Figure 1 to show the distribution of entries by year, where each bin corresponds to approximately two years. In total there are 243 countries, the data is almost uniformly distributed and indicates that every year will have data for around 200 or so countries.

Among the countries, 56 have an energy production from combustible sources greater or equal to 90% of total energy consumption. 25 countries have an energy production from renewable sources higher than the 90% of total energy consumption, while 15 have a renewable energy production higher than the 90% of total energy production. 4 countries have a production of energy from nuclear sources greater than 90% of total consumption, but the only country currently existing is France (the other 3 are countries that do not longer exist)[5].

BEA Data on Energy

Since the more is the available data the more accurate are the results, we decided to extend the UNdata information with another dataset. While the UNdata has data about many indicators on an annual basis, the dataset we used, aggregated from DataHub[6] with the data coming from the Bureau of Economic Analysis[7], has an observation for each quarter of a year from April 1st 1947 to April 1st 2017 (280 observations). The problem with this dataset is that we only have U.S. data on a subset of the indicators that we can find on UNdata. The indicators are CO_2 emissions, fossil fuel consumption, nuclear consumption, primary consumption, renewable consumption, fossil fuel production, nuclear production, primary production, renewable production, and GDP chained.

ILO Data on Labor Statistics

The International Labor Organization (ILO) conducts surveys on countries with the goal of collecting demographic information about the workforce. A major challenge to collecting useful and insightful data is defining an appropriate classification for the types of work. The ILO has changed the way they classify over the years, but the current scheme is called the International Standard Industrial Classification of All Economic Activities (ISIC) Revision 4. The data we have contains both Revision 3 and Revision 4, so we merged the data as best as we could by mapping both revisions to one combined space. The ISIC tries to classify according to activity to remain culturally agnostic, and we chose to aggregate a subset of the categories that we thought was expressive enough for our task: Agriculture, Mining and Quarry, Manufacturing, Utilities (including Electricity, Heating, and Sewage), Construction, Retail and Trade, and Education.

[5]The information about the specific countries is available in our GitHub repository.
[6]https://datahub.io/
[7]https://www.bea.gov/

Variables	Coeff	StdErr	p	Adj R^2
LCD ← TR	8.08E-4	1.55E-4	8.17E-5	0.633
LCD ← Comb	-3.63E-4	2.09E-4	0.10	0.11
LCD ← Comb (2007)	-2.44	1.32E-4	0.12	0.26
GDP ← LCD	51.33	13	0.001	0.47
GDP ← TR	6.66E-2	7.33E-3	1.73E-7	0.84

Table 1: All Regression Results. Comb stands for combustible based energy, 2007 is the subset of data from range 2000-2007. Adj R^2 is the adjusted R^2.

Following the same format as the electrical data, we aggregated so that each entry is for a unique country-year pair. We plot the distribution of entries by year in Figure 2 using the same format from the electrical data. We can observe that the data we have is not as complete as the UN data. In this case there are only approximately 127 unique countries in the data, and the histogram indicates that the data is still sparse and skewed towards later years.

Access to Electricity and GDP

An interesting statistic, percentage of the population with access to electricity, comes from the World Bank[8]. It is a joint work with the International Energy Agency and the Energy Sector Management Assistance Program. This is a more relevant statistic for developing nations, as most of the developed world has had complete access to electricity since the ‘90s. For the developing world, certain countries may be unable to access the necessary resources to meet electrical demand because of financial or geographical reasons. The infrastructure required to power some regions using combustibles might be too difficult, therefore it is worth investigating if renewable sources have greater potential to power such regions. We omit the figure for access, but can confirm that the distribution is much more uniform and closer to the UN data.

Finally we have Gross Domestic Product (GPD) per capita, which our source is the UN, and is a measurement of the total value of goods and services produced by a country in a certain time period. In our case, the time frame is one year. We have multiple years, similar to the other datasets, and entries for approximately 243 countries.

6 EXPERIMENTAL RESULTS

6.1 Case Study: USA

Here we will propose a Structural Causal Model (SCM) of the relationships between labor, energy production, and GDP. The United States is what we will call a true *combustible-based* nation, which simply means that the demand for energy is satisfied primarily by combustible fuels. While the United States does produce large amounts of energy with renewables, in terms of absolute output it can be greater than the entire energy production of whole countries, it can be observed in Figure 3 that there is no connection with total consumption. For combustibles, there is a strong connection. This can also be seen by regressing one on the other, which we present a summary of all of the analysis done here in Table 1. All statistical

[8]https://data.worldbank.org/indicator/EG.ELC.ACCS.ZS

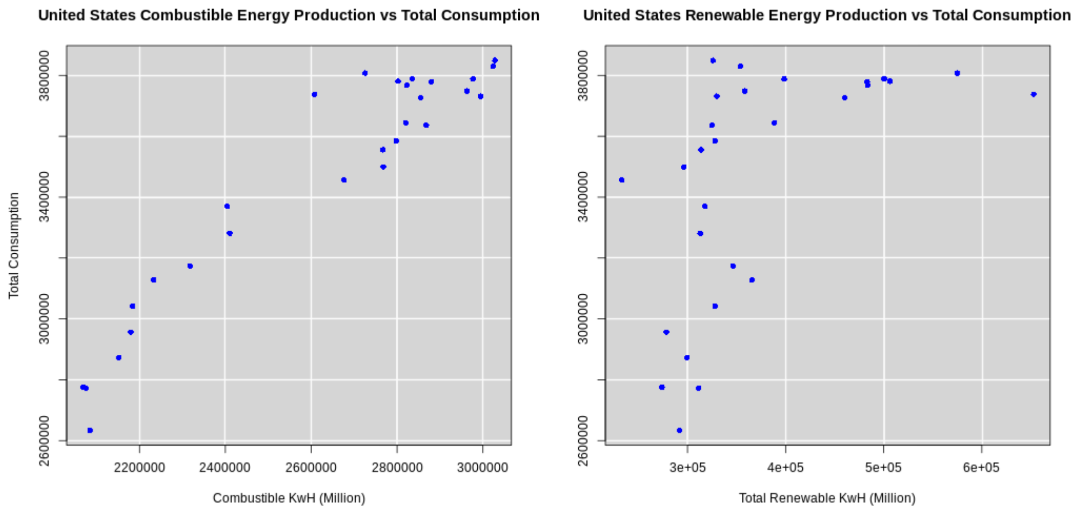

Figure 3: An illustration of how certain fuel sources align with consumption. It is clear that combustible fuels are being used to meet demand in the United States.

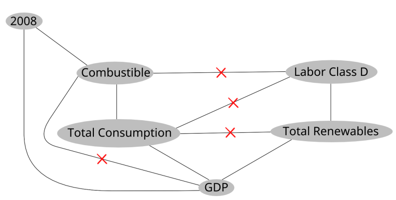

Figure 4: SCM for Case Study of USA

tests are done with the F-Test. We choose to use the regression models as a proxy for observing the plots because they are a compact way to deduce a correlation.

We begin our investigation by considering the effect of energy production on employment figures. As mentioned above, our data comes from the ILO and we specifically use Labor Class D (LCD) for our analysis. LCD represents utilities, which includes electricity, so it could be reasonable to assume that this class is affected by the total output of energy. We disentangle the production of energy into combustible and Total Renewable components and run regression for each on LCD respectively, using the data from 2000 to 2016[9].

The results for regressing the renewables on LCD show a significant ($p < 0.05$) coefficient of $8.078E - 4$ while regressing with combustibles shows no significant correlation. This would indicate that there was an observable connection between renewables but it is unclear the direction of causality and does not rule out the possibility of confounding. On the other hand, we could find no observable influence of combustible energy production on LCD which definitely not a realistic assumption to make in general. We can postulate that the lack of direct influence is only present within the time frame we are considering, in other words the production of combustible energy has no significant influence on LCD within the last two decades.

At this point it is worth discussing the state of combustible energy in this time frame. We present Figure 5 which illustrates that the total production has no clear positive trend after 2007. So we could consider another variable between combustible production and LCD that controls influence based on the unknown event that occurs at this time[10]. Our hypothesis is that if such a factor were to exist, it would be an influence on combustibles only instead of a confounder because the trend in combustible production is not in the LCD data when you look at it over time. We then regress again using combustible production on LCD but use only the time frame from 2000 - 2007, and we find that there is no significant correlation. So what we can conclude is that even when we condition on the time before the 2008 event, there is no significant influence.

As a final note on the state of combustible energy, we acknowledge that there are probably other factors that are worth investigating which could explain the lack of influence on LCD. For example, the scale of production between Total Renewables and Combustibles are vastly different. The United States produces roughly 6 times more combustible energy than total renewable energy, in total about 3 trillion kWh. We use energy production as an incomplete proxy for the sector. It could be the case that a *saturation* effect occurs, where once a certain level of energy production as a percentage of total consumption has been reached it is no longer a good proxy for the sector when used to measure the effect on labor figures. At the saturation point it could be the case that other, unmeasured, factors of the sector have more influence.

The next experiments we run are related to GDP, which represents an aggregate of total value produced in a nation. We present Figure 5 to show its trajectory and we can observe that for the

[9]This is because we are limited in years by the ILO figures.

[10]We guess that this was the financial crisis of 2008.

most part the trend is positive over time. We would expect that the factors we have studied, energy production and labor, would influence GDP in some way. So we begin by running similar regression analysis, applying our knowledge of the relationship between LCD and renewable energy production. We ran regression with each variable separately on GDP, first we observe that renewable energy production has the strongest correlation with GDP. It achieves a significant ($p < 0.05$) positive coefficient of $6.657e-2$ with an adjusted R^2 of 0.84. On the other hand, LCD also achieves a significant coefficient of 51.33 but an adjusted R^2 of 0.47 which indicates that it does a poor job of modeling the variance in GDP. What this could mean is that LCD indirectly affects GDP through renewable energy production. To further support this hypothesis, we regress one more time but we use both variables. The coefficient for renewable energy production is only significant. We find that the resulting model achieves a worse adjusted $R^2 = 0.829$ than just regressing on renewable energy production, which means that LCD contributes no useful information beyond what is already provided from production measurements.

As a final experiment we run some basic Granger Tests to see if we can detect causality from previous time steps. Since the relationship between renewable energy production and GDP was strong we decided to test for Granger Causality (GC) and compare it with combustibles. We found that GC exists between GDP and TR ($p < 0.05$) with lag $l = 2$. We also observe no statistically significant GC for Combustible based energy. We attempted to run the same Granger test for combustibles but conditioning on before the 2008 event but the results were inconclusive[11].

Putting all the results together, we construct a Structural Causal Model that reflects our understanding of the effects of energy production on labor and GDP in Figure 4. We illustrate all of the causal links that were investigated here, some of which were not described here but we used a similar process of deduction.

6.2 Granger tests on U.S. data

As mentioned in Section 5, we used a dataset from BEA to extend our analysis with more detailed data for U.S. specifically. Here we show that this led to different results.

With the BEA dataset we ran a Granger test on each couple of variables using the Python `statsmodels` library[12]. We found out that, for almost each one of the variables, we can reject the hypothesis that one variable does not cause the other with a p value of at most 0.01. This is reasonable since 8 out of 10 variables are energy consumption or production. Among the other two variables we find the CO_2 emissions, that both Granger causes and is Granger caused by every energy source. This is straightforward both for fossil fuel production and for renewable production, since the more energy is produced by renewable sources, the less is the CO_2 emitted, as shown in Figure 6.

Almost all the variables Granger cause and are Granger caused by each other variable. The exceptions are reported in Table 2. We can notice that the only variables that Granger cause the GDP chained are nuclear production and nuclear consumption, with a lag of more than 4 years (13 units of 4 months each).

Granger causality
$x^{t-4}_{\text{GDP chained}} \rightarrow x^{t}_{\text{CO}_2}$
$x^{t-4}_{\text{GDP chained}} \rightarrow x^{t}_{\text{fossil fuel consumption}}$
$x^{t-1}_{\text{GDP chained}} \rightarrow x^{t}_{\text{primary consumption}}$
$x^{t-1}_{\text{GDP chained}} \rightarrow x^{t}_{\text{renewable consumption}}$
$x^{t-2}_{\text{GDP chained}} \rightarrow x^{t}_{\text{fossil fuel production}}$
$x^{t-2}_{\text{GDP chained}} \rightarrow x^{t}_{\text{primary production}}$
$x^{t-1}_{\text{GDP chained}} \rightarrow x^{t}_{\text{renewable production}}$
$x^{t-4}_{\text{nuclear consumption}} \rightarrow x^{t}_{\text{primary production}}$
$x^{t-4}_{\text{nuclear production}} \rightarrow x^{t}_{\text{primary production}}$
$x^{t-3}_{\text{fossil fuel production}} \rightarrow x^{t}_{\text{primary production}}$

Table 2: Every couple of variables has a relations through Granger causality. While almost all couples have a two-way relationship (A Granger causes B and vice versa), the relations reported in this table are the exceptions, since one variable causes another but not vice versa. A unit of time is 3 months.

6.3 Accessibility of Electricity

We ran a small preliminary set of data exploration experiments with the goal of finding the effects of renewable energy on accessibility. As mentioned above, some nations might have had an easier time electrifying by investing in renewables over the traditional combustible infrastructure. While most of the world has access to electricity, there are still some nations who struggle with this issue. Our experiments build upon our knowledge from the previous experiment by conditioning on variables that are known to have causal effects on each other. We hypothesize that the most important variable to consider, outside of the usual energy production, is GDP. A wealthier nation will have an easier time electrifying than one of modest means. This is because wealthier nations will have more available capital for investment, for example on infrastructure projects.

These experiments are only useful for a specific subset of countries where there is a noticeable change in the accessibility of electricity. Therefore our threshold for deciding whether or not a country should be considered is based on if there is at least a 20% positive difference in the percentage of the population with electricity starting from the first year in the data. This subset represents 58 countries. We then took a subset of this population such that renewable energy makes up at least one quarter of the total energy produced by a nation, and these countries would represent the nations who have made significant accessibility gains while not solely depending on combustible fuel. We regress on the accessibility variable, using renewable/combustible based energy production and GDP as predictors.

While it is worth exploring the causal effects of energy production, for this preliminary experiment we only look at the significance of the estimated coefficients. From this information we

[11] We used R `grangertest` from `lmtest` library. It failed the waldtest and reported aliased coefficients.
[12] https://www.statsmodels.org/

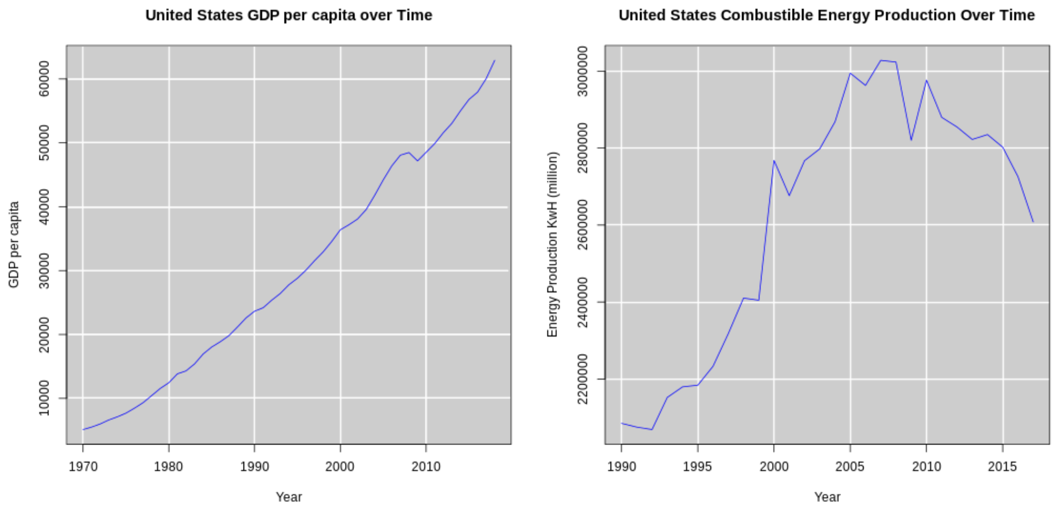

Figure 5: GDP and combustible energy production over time. Note that 2008 combustibles begin to stagnate, and GDP experiences a small dip.

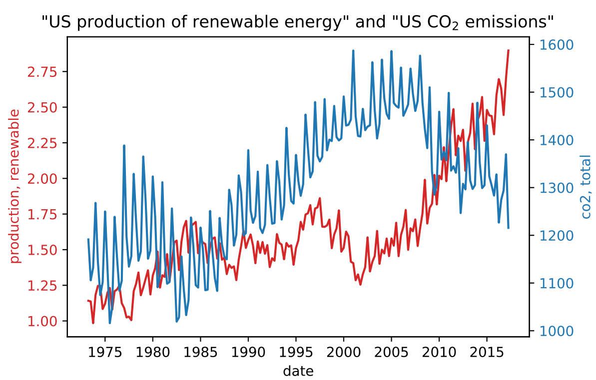

Figure 6: US production of renewable energy vs. US CO_2 emissions by quarter of year.

hope to get a sense of the true distribution of accessibility based on the variables recorded in the UN data. Firstly we report that $P(R) = 0.57$, where R represents the presence of a significant coefficient for renewable energy production, and 100% of the nations who had $R = True$, had a positive slope. While the base rate is a little low, this indicates that the energy produced by the renewable sector has some positive correlation with accessibility. We also observe that $P(G) = 0.63$, where G represents the presence of a significant coefficient for GDP. This confirms that GDP is correlated with accessibility because it was a useful predictor in over half of the country in our subset. We record these results, along with a few others, in Figure 7.

7 FUTURE WORK

A major challenge with the UNdata was the data quality. Every country has its own data collection methods and it is obvious that the same value in different countries may lead to different results. The UN has tried to merge, for each indicator, all the data coming from different countries to make it available under one single format, but this does not mean that data has been collected in the same way in every country. For this reason, we ran some more in-depth tests for U.S. in particular since more data was available. Future work may be focused not on every country of the world but on a specific subset with high-quality data, in order to run the same experiments and obtain results with a high confidence level.

If many countries do not have data for a certain indicator, the UN (that is interested in publishing data for almost all the countries in the world) may avoid publishing data about that indicator at all. We may consider finding (or building) a dataset with the indicators that are available for some countries in order to extend our study.

For the accessibility experiments, one issue that has not been addressed is about backdoor paths and latent confounders. We used multiple linear regression, conditioning on GDP which is a variable that has many influences that are definitely unobserved in our model. A future direction could be to build a more complete picture so minimize the influence of these latent factors. Since our results were preliminary the next step is to measure the causal effect of renewable energy on accessibility. In general the data we collected was much more comprehensive than the experiments we collected, because we only ran experiments on the USA for the most part. There is still a lot of potential for experimenting with data from other countries and generalizing our SCM to multiple countries. We also aggregated data on imports and exports of energy, but these factors were not studied here. We see a natural next step as building models that align with country *profiles*, like for example the USA being a *combustible-based* nation, instead of just building a model for each country. As a final note, we point out that our main proxy for the energy sector is the production of energy in kilowatt-hour and labor. While we believe this is reasonable, we acknowledge

Distribution	Measurement
P(G)	0.63
P(R)	0.58
P(G|R)	0.58
P(T|G)	0.53
$P(G\|\bar{R})$	0.69
$P(R\|\bar{G})$	0.64

Figure 7: The distribution of slope significance within a subset of nations, as it is related to accessibility. G is the indicator variable for a significant slope on GDP, and R is the indicator for a significant slope on Total Renewable Energy Production. A bar indicates the negative of the indicator.

that it is an incomplete estimate. There could be other factors that are relevant, for example if the sector is receiving subsidies.

CODE

The code and the dataset used in this work are publicly available on GitHub at https://github.com/LucaDiba/renewable-causal-effects.

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