Article

Do Wealthy States in the USA Have a Disproportionate Advantage in Generating Renewable Energy?

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Abstract
This paper tries to establish some causal connection between per capita income and the percentage of renewable energy generated by a state in the US, through the course of 2000-2018. The literature on relations between different macroeconomic factors and renewable energy indicate reverse causality. Moreover, there is not much consensus on whether wealthier states and countries truly have an edge over other countries other than financial and investment ability. Hence, this paper tries to establish a relation between per capita income and renewable energy generation in the context of the USA. Granger Causality was used to establish causal links between the per capita income and the percentage of energy generated by different states that is derived from renewable sources. For states without bidirectional causality, fixed effects regression indicated a statistically significant positive relation between Per Capita Income and renewable energy – a $100 increase in per capita income was associated with a 0.04% increase in the percentage of total energy of a state derived from renewable sources. This points at potential disparities between wealthy and poorer states and adds to the argument of providing more regulatory, financial, and technological aid to poorer states in order to reduce their reliance on non-renewables.

Keywords: Renewable energy, Fixed-Effects Regression, Time-series, Macroeconomics, Sustainability

1. Introduction

With the appointment of Brian Deese as the Director of the National Economic Council and President Joe Biden setting a goal of getting America to net-zero carbon emissions by 2050, the USA is moving rapidly towards a greener future and confronting the climate crisis with ambitious solutions. Currently, over 40% of carbon emissions are generated through power plants using fossil fuels (DOE, 2021). Therefore, electricity generation is a very big part of the push to a greener economy.

However, there is a lot of capital required to build the infrastructure to generate renewable energy – whether it's solar panels, massive wind farms, or geothermal plants – and also R&D to develop better, more efficient technology. Over the past few decades, the efficiency of such technology has improved and capital required has decreased, but it's interesting to ask whether over the past 20 odd years, richer states have been able to adopt renewable energy at a higher rate than poorer states.

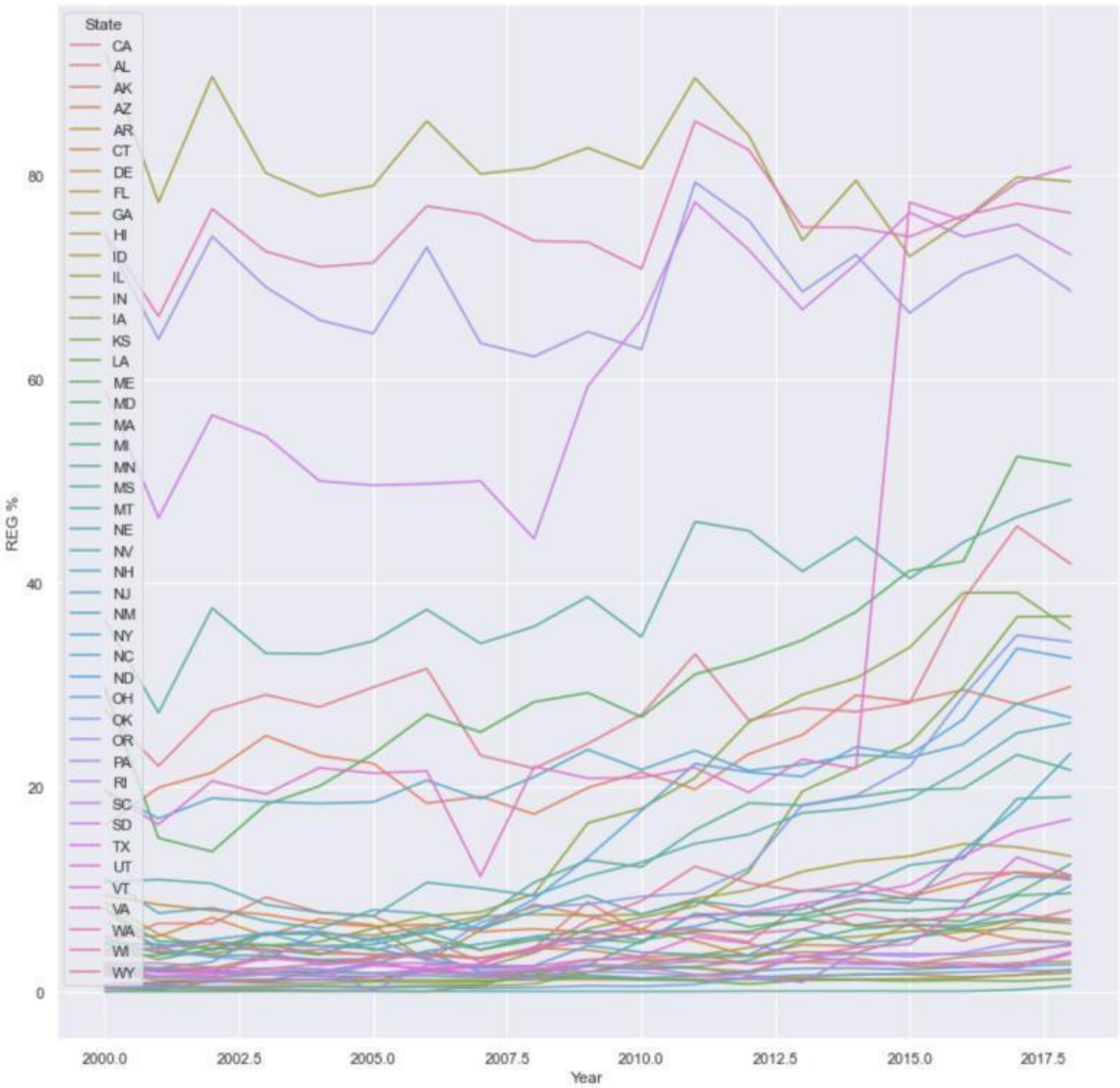

Figure 1: REG% time series for each state

In Figure 1, REG% refers to the total percentage of energy generated in each state from renewable sources. As seen in this chart, over the course of 18 years, clearly some states have consistently maintained a high share of their total energy generation from renewable sources. The top states include Idaho, Washington, Oregon, South Dakota, and Montana. If we look closely, we can almost cluster these lines into a few states with high REG%, a

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few between 20-40 REG% and a lot of states under the 20 REG% mark. The four states mentioned above are not the richest states in terms of per capita income, but there definitely seem to be certain factors that allow certain states to consistently outperform others.

This paper tries to build on Uzar (2020) to identify whether per capita income has had any significant causal effect on REG% for US states from 2000-2018. As such, this paper is divided into four main sections:

- Literature Review: developing some background on the literature behind this study and what other scholars believe to be the connection between macroeconomic factors and renewable energy generation
- Data and Methodology: discussing details about the data, the time series analysis, the regression equation, model, fixed-effects methodology, and robustness checks that are conducted for heteroskedasticity and fixed effects
- Results: describing the results of the regression, and the empirical implications
- Discussion: a brief discussion of next steps, pitfalls, and potential policy implications

2. Literature Review

The electric energy industry has high costs of capital. As such, the switch to a greener economy requires substantial amounts of capital for investment. However, there are a lot of other factors that also contribute to renewable energy. A rich country that has limited land and is surrounded by water might find it difficult to tap into solar power or wind power. On the other hand, a country with vast swathes of open land and sunshine might be cash-strapped. Hence, there is not a lot of consensus on whether richer countries actually have a disproportionate advantage in tapping into green energy. In order to understand the relationship between macroeconomic factors like wealth and the ability to generate renewable energy, I decided to conduct an investigation in the context of the United States of America, examining whether richer states have found it easier to generate more renewable energy.

There is some literature discussing renewable energy consumption and generation in OECD countries like Apergis and Payne (2009). This study examines the relationship between renewable energy consumption and economic growth for a panel of twenty OECD countries over the period 1985–2005 within a multivariate framework. Given the relatively short span of the time series data, a panel cointegration and error correction model is employed to infer the causal relationship. The results for the heterogeneous panel cointegration test reveal there is a long-run equilibrium relationship between real GDP, renewable energy consumption, real gross fixed capital formation, and the labor force. This long-run relationship indicates that a 1 percent increase in renewable energy consumption increases real GDP by 0.76 percent. This long-run relationship also suggests that there might also exist some sort of reverse causality. Economies that are growing may find it easier to invest in renewable energy. Other papers like Sinha (2017) use various measures like Thiel's inequality index to demonstrate that although inequality in renewable energy generation exists within OECD countries, it is gradually diminishing.
Another similar paper is by Chien and Hu (2006). Because economies signing the Kyoto Protocol are CO2-emission conscious, many of them will increase their renewable energy intensity. It is thus quite important to confirm if the increasing usage of renewable energy improves energy efficiency, i.e., the amount of energy required to perform a certain task.

According to the paper, the share of renewable energy in the total energy supply is higher in nonOECD (developing) economies than in OECD (developed) economies. OECD economies with lower renewable energy shares have higher technical efficiency (higher effectiveness of converting resources into goods and services), and thus renewable energy has a negative effect on technical efficiency. This paper indicated the need to include some measures of not only technical efficiency but also technical limitations and innovation that might affect the ability of a state in the US to generate renewable energy.

Most of the regression variables in this paper are based on Uzar (2020). As far as is known, the study is the first attempt to discover the relationship between income inequality and renewable energy consumption. The impact of income inequality on renewable energy consumption is examined theoretically and empirically in 43 developed

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and developing countries for 2000-2015. The results demonstrate that the decline in income inequality will enhance renewable energy consumption. In other words, policymakers have the opportunity to reduce income inequality and environmental degradation at the same time.

The time-series analysis done in this paper to deduce causality is a framework I have tried to imitate. Moreover, the premise of finding causal links between macroeconomic factors and renewable energy is what made this paper important to my research.

Energy cost is an important aspect that can also impact the ability of a state to generate renewable energy and invest in this technology. A paper discussing a similar concept is Schilling and Esmundo (2009). Plotting the performance of a technology against the money or effort invested in it most often yields an S-shaped curve: slow initial improvement, then accelerated improvement, then diminishing improvement. Analyzing renewable energies using S-curves can show us the payoff for investment in these technologies. The paper suggests that government R&D investments in fossil fuels are still excessive. Secondly, results suggest that renewable energy sources (particularly wind and geothermal) have been significantly under-funded relative to their potential payoffs. Thirdly, the strategic commitments firms have to fossil fuels may still make this more profitable. This prompted me to include cost and institutional factors in my regression model. Institutional factors might indicate strategic commitments to fossil fuel suppliers, and due to the high costs of renewable energy, we should observe the higher generation of renewable energy from richer, larger states.

Mourmouras (1991) is another paper relevant to this study that shows the impact of conservationist government policies on intergenerational equity based on renewable resources. The overlapping generations model is a very fundamental framework that also can be loosely employed in the time series data. Moreover, I also introduce similar variables that indicate the political affiliation of the governor of a state in order to factor in any governmental aspects that also affect policies and incentives given to the renewables sector.

An important tool used in this paper's analysis is Granger causality. The theory behind Granger causality is based on Shojaie and Fox (2021). According to this paper, Granger causality finds whether one time series is predictive of another time series. A time series X is deemed to be 'causal' of another time series Y if utilizing the history of series X reduces the variance of the prediction of series Y. X is then said to 'Granger cause' Y. The way it has been applied in this paper is loosely based on Uzar (2020) and Dumitrescu and Hurlin's (2012) panel causality test. In the next few sections, we will essentially demonstrate how per capita income and renewable energy generation can have bidirectional causality, and then use Granger causality to isolate only those states in the US where only a unidirectional relationship exists, i.e., per capita income Granger causing renewable energy generation and not vice versa.

Finally, a range of papers and review papers, including Toman (1994), Grubb et al. (2015), Pezzey and Toman (2002), and Howell (2007) give a great overview of the field of sustainability economics and the role of energy in making our economy greener. These papers helped me understand the concept of sustainability, the ongoing issues in the field, and the way economic analysis can help shed light on important environmental conundrums.

3. Data and Methodology

3.1. Main Idea & Hypotheses

The main hypothesis I intend to test is whether Per Capita Income (PCI) has any causal effect on the percentage of total energy in a state derived from renewable sources (REG). Therefore, the null and alternative hypotheses are:

- ***H_0: PCI has no effect on REG***
- ***H_A: PCI has a statistically significant effect on REG***

This paper investigates whether wealthier states in the USA over 2000-2018 have had a higher percentage of their total energy generated through renewable sources. I chose to leave out 2019 and 2020. 2019 had incomplete data and the COVID-19 pandemic in 2020 induced an aberrant shock that can skew the analysis in this paper. I

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have represented the per capita income of a state through PCI, and the dependent variable is Percent of Renewable Energy generated through renewables (REG), along with other controls as discussed below.

3.2. Empirical Strategy

The general equation to be estimated is:

$$REG_{it} = \beta_0 + \beta_1 GDP_{it} + \beta_2 Growth_{it} + \beta_3 PerCapitaIncome_{it} + \beta_4 CO2\_Emissions_{it} + \beta_6 Nameplate\_Capacity_{it} + \beta_7 AvgEnergyPrice_{it} + \beta_8 Energy\_Revenue_{it} + \beta_9 Governor\_Party_{it} + \beta_{10} Crude\_Oil_{it} + \alpha_i + \gamma_t + \varepsilon_{it}$$

Where:

- *REG:* Renewable energy as a percent of total energy generated by the state
- *GDP:* Gross Domestic Product of the state (Millions of chained 2012 dollars)
- *PerCapitaIncome:* Per capita personal income of the state (Dollars)
- *CO2_Emissions:* Carbon Dioxide emissions of the state (Metric Tons)
- *Nameplate_Capacity:* Total energy generating capacity of the state (Megawatts)
- *AvgEnergyPrice:* Price of energy as Dollars/Megawatthour
- *Energy_revenue:* Total electric industry revenue from sales to ultimate customers (Thousand dollars)
- *Governor_Party:* Binary variable which is 1 if the Governor of the state is Democrat, 0 when Republican
- *Crude_oil:* Crude oil production (Thousand Barrels)
- α: State dummies for fixed effect
- γ: Year dummies for fixed effect
- ε: Error terms

The general empirical strategy is to control for all these factors and confounding variables and use fixed effects regression to isolate any causal effect of PCI on REG. However, a simple fixed effect regression like this may potentially have endogeneity issues. PCI may have an effect on REG, but Renewable energy sources, consumption, and generation may also effect welfare and wealth of a region according to Makešová and Valentová (2021).

Such reverse causalities are depicted by double-sided arrows in Figure 2.

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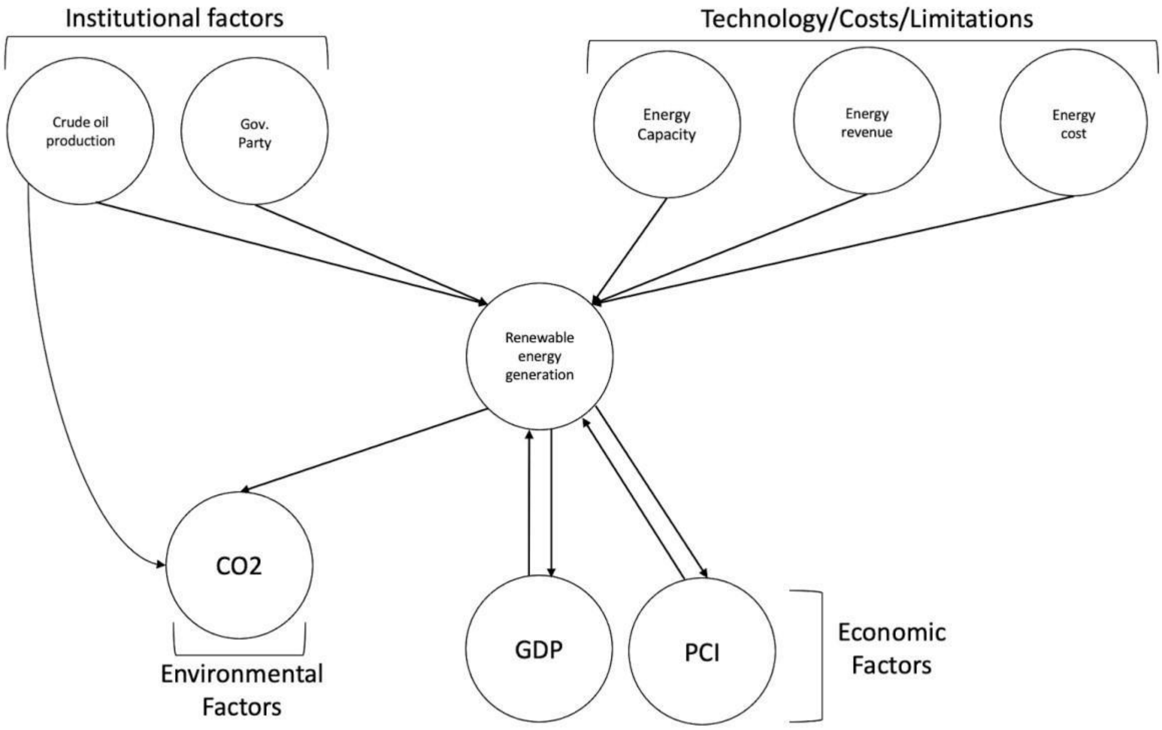

Figure 2: Causal Graph

Therefore, the general framework I use is as follows:

1. Use the Augmented Dickey-Fuller (ADF) Test to see if the time series for each variable is stationary
2. Use Vector Auto Regression (VAR) to find the maximum lag order based on the smallest Akaike Information Criterion (AIC)
3. Use the Granger causality test to map causal links between all variables
4. Check for heteroskedasticity
5. Use step (3) to filter out states that have a unidirectional causal relation between PCI and REG
6. For these states, use fixed effects regression to find the potential causal impact of PCI on REG

3.3. Data

In order to understand renewable energy generation, there are four main factors to consider – institutional, technology, economic, and environmental – as seen in Figure 2. This is loosely based on Uzar (2020).

Institutional factors like the government, regulation, subsidies, and tax breaks can directly affect REG in a state. While it was difficult to compile data on all such factors, I decided to include a dummy variable that is 1 when the governor of the state at a point in time was Democrat and 0 when Republican. This data on governors has been taken from the open ICPSR database and the National Conference of State Legislatures dataset. I also included a variable for crude oil production since some states may have long-term contractual obligations regarding fossil fuels that may prohibit increased funding of renewable fuels, so I hope to represent that using this variable. This data has been taken from the US Energy Information Administration (EIA) website.

The Technology variables are other confounding factors that affect the REG of a state. The total energy generation capacity, the cost to generate a megawatt-hour, and the revenue collected from electricity generation affect how much percentage of the state's energy comes from renewable sources and how much money the state may have to invest into this technology. If a state's energy generation costs a lot of money with not much revenue pulled in, then it is likely the state might not use expensive renewable energy technology and might resort to more polluting fuels. Hence, I included these factors. All these variables have been compiled from the US EIA database.

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The main Economic factors included are the GDP of the state and the Per capita income (PCI). These variables have been compiled from the St. Louis Federal Reserve database for each of the 50 states.

The environmental factors included are CO_2 emissions. Now, although I have included CO_2 emissions in one of the fixed effects regression, the causal graph shows that crude oil production might potentially have an effect on CO_2 emissions as well. This makes the CO_2 emissions variable a possible ‘collider variable’ and including it in the regression procedure might induce bias and make causal relations more difficult to interpret. Hence, I will do two regressions, one with and one without CO_2 emissions. This data has also been taken from the US EIA online database.

Finally, REG represents the percentage of total energy generated that was derived from renewable sources. This is the dependent variable. The data has been taken from the US EIA as well.

The final regression will have dummies for 47 states (leaving the states of Arkansas, Maine, and Georgia out because of insufficient data).

3.4. Robustness Checks

Two main robustness checks have been conducted to check for heteroskedasticity and stationarity of the panel data.

3.4.1. Heteroskedasticity

There are two main robustness checks I did – the Hausman test for Fixed and Random Effects and a graphical test for heteroskedasticity.

The p-value in the Hausman test was very small (around 0.009), so we can reject the null hypothesis and Fixed effects seems like the most suitable framework.

I then performed a simple Pooled OLS regression and graphed the fitted values and residuals.

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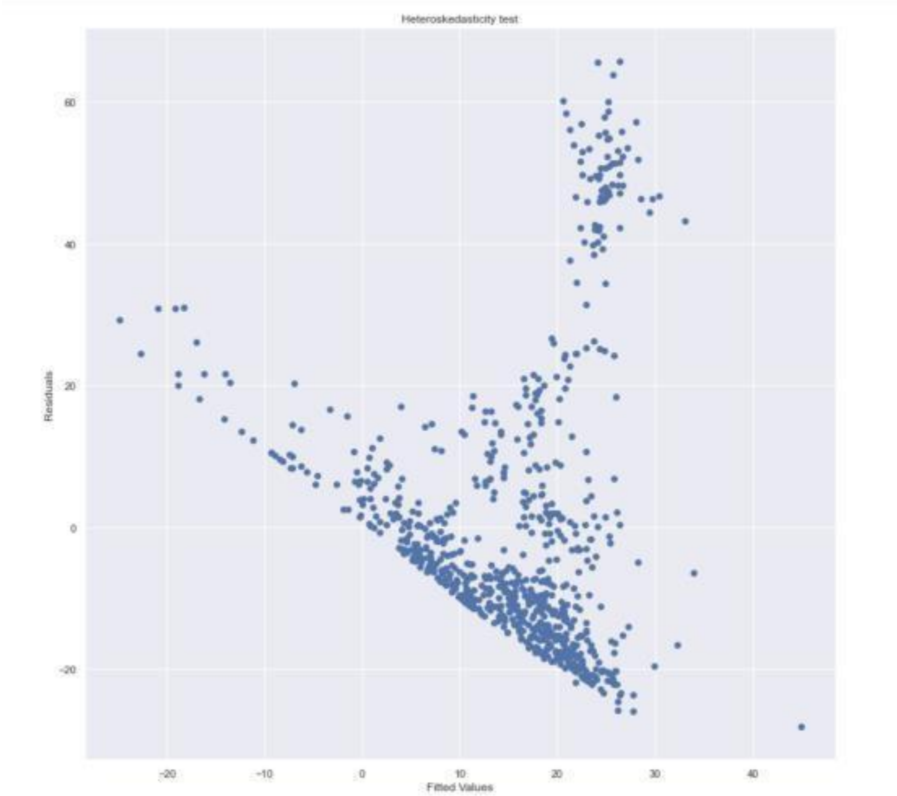

Figure 3: Fitted Values vs Residuals

It can be clearly seen that the errors are heteroskedastic, and so we will adjust for heteroskedasticity in our fixed effects regression model.

3.4.2. Augmented Dickey-Fuller Test

The ADF test was conducted in order to check if each variable was stationary. Stationarity is important for the subsequent VAR model and Granger causality analysis. The results for this test are shown in Table 1.

Variables	ADF Statistic	P-value
GDP	-5.117798	0.000013***
PCI	-6.200680	0.000000***
Capacity(Megawatts)	-4.863828	0.000041***
Cost($/Megawatts)	-5.549901	0.000002***
Total Revenue	-5.064636	0.000017***
Governor Party	-7.480971	0.000000***
Crude Oil	-5.159224	0.000011***

*** shows statistical significance at the 1% level

Table 1: ADF Test results

As seen in Table 1, all the values prove to be stationary according to this test. Hence, we can proceed with the next steps without imposing stationarity by taking first differences.

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4. Empirical Findings

As described above, the empirical findings are based on the idea of isolating states, which exhibit a unidirectional Granger causality between PCI and REG, and then performing Fixed Effects Regression. However, we will discuss the differences of a general fixed effects regression bypassing the Granger causality step (using and not using CO2 emissions) and then see if there is any difference in the relation between PCI and REG for states that do exhibit this unidirectional relation.

4.1. Granger Causality

The VAR model's results for each of the different lag orders tried are shown in the following table.

Lag Order	AIC
1	108.52030855000051
2	108.53460269859967
3	108.54648025368468
4	108.53285247862898
5	108.56448431444772
6	108.59517963174751
7	108.58395479398328
8	108.58620547821113
9	108.56173546993985
10	108.57793337952569
11	108.57347193659378
12	108.63151357477724
13	108.65786965128076
14	108.71383205731456
15	108.71206323638484

Table 2: Lag Order and AIC

Lag orders for the Granger causality are generally chosen in an empirical fashion, but it is advised that the lag order with the smallest AIC value is chosen. As seen in Table 2, the lag order with the smallest AIC is 1. Hence, this will be chosen as the 'max lag' parameter in the Granger causality model.

Next, the Granger causality model is fitted to the whole compiled dataset for every state.

Note that Table 2 does not contain CO2 per capita since it is potentially a collider variable.

	GDP_x	PCI_x	Nameplate Capacity (Megawatts)_x	$/Megawatthour_x	Total Revenue_x	Gov_Party_Dummy_x	Crude Oil_x	REG_x
GDP_y	1.0000	0.0239	0.5393	0.7466	0.6236	0.3875	0.2225	0.4059
PCI_y	0.9949	1.0000	0.3965	0.1106	0.7991	0.5529	0.2499	0.2067
Nameplate Capacity (Megawatts)_y	0.6215	0.0080	1.0000	0.4681	0.4554	0.7278	0.0005	0.2729
$/Megawatthour_y	0.7392	0.0000	0.3905	1.0000	0.5782	0.4813	0.4083	0.0474
Total Revenue_y	0.7029	0.0006	0.1827	0.3389	1.0000	0.5987	0.0512	0.7159
Gov_Party_Dummy_y	0.1771	0.7203	0.8036	0.5570	0.5461	1.0000	0.1340	0.5910
Crude Oil_y	0.2357	0.7086	0.0057	0.6734	0.0634	0.1840	1.0000	0.8997
REG_y	0.2957	0.0992	0.4548	0.5980	0.4077	0.4388	0.7890	1.0000

Table 3: Granger causality for each time series

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In Table 3, the rows can be considered the response variables (y) and the columns are predictors (x). If the value in the corresponding cell is below the 0.05 p-value threshold, then we reject the null hypothesis and can conclude that column_x Granger causes row_y. However, here we see that the value for PCI causing REG is 0.0992 and the value for REG causing PCI is 0.2067. This implies that neither variable Granger causes each other.

However, it is important to consider the limitations of this model:

1. The data on which the Granger causality model is fitted contains data for each state in each column. Checking Granger causality between time series values like GDP and dummy variables like Gov_Party_Dummy calculates a p-value that is difficult to interpret and may skew results.
2. The lag order chosen through the VAR model is an assumption based on the AIC values, so it might not be the ideal lag order to calculate Granger causality. As such, I decided to fit the Granger causality model for the data of each state, as this will give us a better understanding of each time series. On doing this, contrary to Table 4, most states individually exhibited statistical causality between PCI and REG. However, it was found that there are only 23 states where PCI Granger causes REG, but not vice versa. For most other states, there exists bidirectional causality. Hence, it is important to acknowledge that the endogeneity issue of reverse causality is true and may be a hindrance in trying to figure out a one-way causal relationship between PCI and REG.

Based on these results, the following states exhibit a one-way Granger causal link:

State	PCI causing REG	REG causing PCI
AZ	0.0164	0.1526
CO	0.0385	0.2682
CT	0.0006	0.9674
FL	0.0000	0.4880
HI	0.0000	0.3912
IN	0.0264	0.0982
IA	0.0006	0.5485
KS	0.0074	0.9266
MD	0.0010	0.6338
MA	0.0000	0.4329
MI	0.0019	0.3316
MN	0.0202	0.6837
MT	0.0000	0.4566
NE	0.0179	0.9773
NV	0.0196	0.0940
NH	0.0000	0.3357
NJ	0.0000	0.4007
NY	0.0000	0.3794
OH	0.0086	0.8563
RI	0.0175	0.8374
SD	0.0075	0.5708
UT	0.0144	0.1102
VT	0.0294	0.7615

Table 4: P-values for unidirectional Granger causality

I decided to filter the main dataset to contain only these 23 states and then conduct a fixed effects regression. It is difficult to provide an economic reason behind why some states portray this unidirectional relationship and some do not, as this result was derived merely by checking time series metrics like p-values and AIC. However, one reason may be that some states have had a lot more funding provided by state governments for renewable energy generation according to Geier (2021). States like North Carolina and California have provided billions in funding to develop the renewable energy sector, which may have in turn resulted in economic growth, resulting in renewable energy generation actually having some causal impact on per capita income growth. On the other hand,

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some states that have had lesser government incentives to develop this sector might have to rely more on consumers choosing to use renewable energy, thus resulting in a different direction of causation. This disparity in government support will also be discussed in more detail in the final Policy

Implications section. Hence, we filter for the latter case, making our framework more robust in trying to estimate how much per capita income impacts renewable energy generation. However, I also conducted fixed effects regression for the entire dataset to see if there was any marked difference in the coefficient for PCI relative to REG.

4.2. Fixed Effects Regression Results

There are three main fixed effects models computed. The first two can be seen in Table 5, computed on the entire dataset without filtering for the 23 states. Regression (A) contains CO2 per capita but Regression (B) does not.

Variables		
	(A)	(B)
GDP	-1.434e-05***	-1.409e-05***
	(6.99e-06)	(7e-06)
PCI	0.0005***	0.0005***
	(8.12e-05)	(8.01e-05)
Capacity(Megawatts)	0.0006***	0.0006***
	(0.000)	(0.000)
Cost($/Megawatthour)	0.0199***	0.0187
	(0.010)	(0.009)
Total_Revenue	-6.909e-07***	-6.913e-07***
	(1.88e-07)	(1.87e-07)
Governor Party	-1.0627***	-1.0272***
	(0.491)	(0.491)
Crude Oil	4.304e-06	4.38e-06
	(2.9e-06)	(2.89e-06)
CO2 Per Capita	0.0728	
	(0.085)	
State Fixed Effect	Yes	Yes
Year Fixed Effect	Yes	Yes
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Number of observations	792	792
R^2	0.947	0.947

Note: Arkansas, Maine, and Georgia have been left out of this because their GDP data before 2005 was missing.

Table 5: Fixed Effect Regression – whole dataset

Here, we can see that in regression (A), all the coefficients other than those for Crude Oil and CO2 emissions per capita are statistically significant. In regression (B), except for the Cost and Crude Oil coefficients, others are significant.

When using normal pooled regression, the GDP coefficient was positive, but using fixed effects the GDP coefficient becomes negative. This shows that a $1 million increase in Real GDP correlates strongly with a 0.000014% decrease in REG (the percent of the total energy of a state derived from renewable sources). However, a $100 increase in PCI correlates with a 0.05% increase in REG. This indicates that over 20002018, really rich states might have relied more on non-renewables but states with high amounts of individual wealth have had higher REG. Income inequality perhaps also plays an important role in this as seen in Uzar (2020).

The Governor Party coefficient shows that if the Governor is a Democrat, there is a nearly 1% decrease in the total energy of the state derived from renewables. This is an interesting result as we would generally tend to

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believe that Democrats lean more towards environmental action and favour the renewables industry. We must take into account the fact that this result may be because of some sort of bias, endogeneity, or there might be some lagged effects of previous Republican governors that cause this negative coefficient. In order to try and remedy the problem of bidirectionality, the following fixed effect regression table is only for the 23 states that have a unidirectional Granger causal relation between PCI and REG.

As seen in Table 6, the coefficient for PCI is still statistically significant. However, it seems to have changed slightly. In this regression, a $100 increase in PCI is associated with a 0.04% increase in REG. However, taking into account Granger causality, this estimate can be considered to have lesser endogeneity than the regression in Table 5. Moreover, some variables like Cost, and Governor's Party lose their statistical significance in this regression model.

Variables	Coefficient
GDP	-3.9e-05**
	(1.16e-05)
PCI	0.0004***
	(0.000)
Capacity(Megawatts)	0.0009***
	(0.000)
Cost($/Megawatthour)	0.0019
	(0.011)
Total Revenue	-1.144e-06**
	(2.38e-07)
Governor Party	-1.3325
	(0.741)
Crude Oil	3.217e-05**
	(1.46e-05)
State Fixed Effect	Yes
Year Fixed Effect	Yes
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Number of observations	437
R^2	0.878

** indicates statistical significance

Table 6: Fixed Effect Regression – Granger filtered

5. Conclusion and Policy Implications

Based on the Granger causality and Fixed Effects Regression, there is definitely a strong relationship between PCI and REG, which is most likely a positive one. As found in the regressions, a $100 increase in PCI possibly causes a 0.04% - 0.05% increase in the total percentage of energy derived from renewable sources in a state in the US. However, it is important to be cognizant of the problem of bidirectional causality as shown in the Granger tests.

There are a few limitations to this analysis. Obviously, endogeneity and reverse causality is one of them as explained above. However, there may be other variables that I have included that may be colliders, or there might be some important variables that I have left out that may be confounders. Aspects like land area, natural resources already possessed by a certain region, the amount of money devoted to investment in renewable energy technology, and the number of policies and incentives offered by a state over the years might be important confounders that have been left out due to lack of readily available data. In addition, per capita income may not

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be the best indicator of ‘wealth’ differences between states. Using other indicators of wealth might yield more holistic results.

There are definitely many ways to improve upon this research in the future. One of the most fundamental aspects to improve is randomization. By finding a programme, event, shock, or policy, it may be possible to employ a more robust method like Difference-in-Difference or Regression Discontinuity to find stronger causal links between wealth and renewable energy generation. Also, using time-series techniques other than Granger causality can exploit the nature of the data and illuminate more endogeneity biases. Finally, conducting a similar study in the context of other countries or multiple countries at once may expose more interesting relationships.

Although this research was conducted only in the context of the US, this perhaps sheds light on a similar relation between PCI and REG for other regions of the world too. With countries announcing ambitious net-zero carbon emission goals and concentrating on more sustainable methods, illuminating such macroeconomic relations can have important policy implications. For example, there is definitely a need for more regulatory policies and incentives to help poorer states invest more and develop renewables.

Currently, there is a large difference in the number of policies and incentives some states offer for renewable energy growth. According to the Database of State Incentives for Renewables and Efficiency (DSIRE), California (169), Texas (123), Minnesota (140), and New York (115) are a few of the top states with the greatest number of policies and incentives directed towards renewables development and energy sustainability. There are many countries with a lesser number and magnitude of policies directed towards renewable energy generation. Hence, we need more such policies.

However, bidirectional causality implies both wealth and renewable energy probably impact each other in a cycle that can be exploited for sustainability and green growth. Policies (in the US and other countries) that help improve wealth, income inequality, and economic differences in groups of people can also help boost demand and consumption of renewable energy, which will increase renewable energy generation.

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