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Daniel Perez. On Sovacool's et al. study on the differences in carbon emissions reduction between countries pursuing renewable electricity versus nuclear power. 2021. hal-03170325v1

**HAL Id: hal-03170325**

**<https://hal.science/hal-03170325v1>**

Preprint submitted on 16 Mar 2021 (v1), last revised 26 Jun 2022 (v2)

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# On Sovacool’s *et al.* study on the differences in carbon emissions reduction between countries pursuing renewable electricity versus nuclear power

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March 16, 2021

## Abstract

In this paper, we attempt to reproduce the results obtained by Sovacool *et al.* in their recent paper that focuses on the differences in carbon emissions reduction between countries pursuing renewable electricity versus nuclear power. We have found several flaws in the models and the statistical analysis performed therein, notably the correlations performed between the fractions of renewable power and of nuclear power and greenhouse gas emissions per capita and the lack of consideration for natural bias between the variables examined.

## 1 Introduction

Lowering Greenhouse Gases (GHG) emissions, foremost amongst which are carbon dioxide emissions, has been established as a priority in order to mitigate the effects of anthropogenic climate change. While it is clear that abandoning fossil fuels is imperative, there is still some debate about the details of the transition to decarbonized sources of energy. As it was reported in Chapter 2 of the 2018 IPCC report [14], the role of nuclear energy increases along most pathways to decarbonation, although the variance in the share of nuclear energy is quite large across the spectrum of the different models and paths considered in the literature [11, 13]. For instance, there are scenarios of 100% renewable energy which have been considered by some authors [6, 10], although the validity of the assumptions of these high-renewable models have been contested [5]. By contrast, there are also examples where the role of nuclear power is greatly increased, such as in [3, 4, 9, 17].

In the context of this debate, Sovacool *et al.* performed a study concluding that “the implication for electricity planning is that diverse renewables are generally proving in the real world to be significantly more effective than nuclear power at reducing climate disruption” [16]. Fell *et al.* have since published a response [7], criticizing the methodology and other aspects of their paper. This paper provides supplementary criticism for the validity of the conclusions of [16].

Sovacool *et al.*’s paper relies on the statistical analysis of historical data available for different variables across a variety of countries. In particular, it relies on establishing correlations amongst the the share of nuclear energy (henceforth denoted  $N$ ) versus renewable energy (henceforth denoted  $R$ ) as a fraction of the electrical mix and CO<sub>2</sub>eq emissions per capita, while taking Gross Domestic Product (GDP) per capita as a confounding variable.

After attempting to reproduce the results of Sovacool *et al.* [16], we have found that the analysis performed is considerably flawed both because there were mistakes in the statistical analysis, but also because there were inconsistencies in the logic of the authors, in particular concerning

- the “crowding out” hypothesis, *i.e.* that renewables and nuclear power are structurally incompatible, so there is an anticorrelation between them;

- the rejection of the “climate mitigation” hypothesis, which states that “the relative scale of national attachments to nuclear electricity production will vary negatively with carbon emissions,”

both which involved regressions of non-carbonated sources of electricity with GHG emissions, despite the fact that decarbonated energy sources are not good predictors of GHG emissions. The rest of this paper is separated as follows. First, we will give a more detailed account of each of the arguments above. Then, we will give some complementary technical details regarding the data set and our analysis of the complementary data provided by the authors.

## 2 Criticism

### 2.1 Fossil fuels as the real predictor and the “crowding out” hypothesis

Both renewable and nuclear energy emit little to no GHGs, but energy stemming from fossil fuels does. With respect to the GHG emissions per capita, the only relevant variable is the fraction of fossil fuels in the electricity production of each country (which we will denote  $F$ ). It follows that the fraction of nuclear energy or renewables in the electrical mix is not a good predictor of GHG emissions, independent of statistical treatment of the data. As shown by our in depth analysis in the appendix, the rejection of the authors of the “climate mitigation” hypothesis arises from an inadequate statistical analysis (*cf.* section 2.2) and from the following fact.

The fraction of electricity produced with renewable, nuclear and fossil fuels satisfies the tautological relation :

$$R + N + F = 1. \tag{2.1}$$

This relation implies that these three variables are necessarily correlated with one another. In light of this reasoning, no matter the statistical treatment of the data the predictive power of  $R$  or  $N$  for the GHG emissions can only stem from that of  $F$  (*cf.* proposition A.1 and section A.3). In particular, the analysis of the authors of [16] on the effect of renewables and nuclear energy as well as their rejection of the “climate mitigation” hypothesis reflects nothing other than relation 2.1.

Moreover, the reasoning behind the “crowding out” hypothesis is flawed. Indeed, the authors of [16] motivate the proposal of the “crowding out” hypothesis as follows. Intermittent renewables require a decentralized electrical infrastructure as soon as they occupy a significant fraction of the electricity produced. By contrast, the optimal electrical infrastructure of non-intermittent power sources, such as fossil fuels, hydroelectricity and nuclear power is centralized [2]. The authors then suggest that, for these reasons, there should be an anticorrelation between  $R$  and  $N$ , which is the statement of the so-called “crowding out” hypothesis. They back this statement by verifying that  $R$  and  $N$  are indeed anticorrelated and use this to justify their statements.

However, this explanation is inconsistent with the data studied, since most of the electric production considered to be “renewable” from 1990 to 2015 was hydroelectricity – with intermittent power sources such as wind and solar contributing only negligible amounts to the statistic according to the BP Statistical Review of World Energy (2019) [1]. Furthermore, given any three positive random variables satisfying relation 2.1, one can always find at least two pairs of variables that are negatively correlated (*cf.* proposition A.1). It is thus little to no surprise to find that  $R$  and  $N$  are negatively correlated, but this has nothing to do with the causality relation of the “crowding out” hypothesis suggested by Sovacool *et al.* It is simply the consequence of the simple mathematical relation between the variables studied. This statement is backed by our in-depth analysis in the appendix of this paper.

### 2.2 Flaws in the statistical analysis and the rejection of the “climate mitigation” hypothesis

Sovacool *et al.* propose two timeframes (1990-2004 and 2000-2014) along which the data is split and averaged and justify this by claiming this is “an optimal use of the data”, because “renewable energy figures were only recorded since the nineties.” However, from a statistical standpoint, this treatment is incorrect and disregards any potential time series complications which may arise, such as non-stationarity [8, 15], which we expect over this time frame. This questions the integrity of the

averaged data used by the authors to perform their analysis, and by extension, the entire analysis itself.

Even ignoring the time series complications which might arise from studying the complete data set, there are also inconsistencies and flaws in the statistical analysis performed in [16]. These will be treated in more detail in the appendix, but a non-exhaustive list includes:

- The forward selection performed is inadequate (*cf.* section A.3). The ultimate goal of Sovacool *et al.*'s study is to assess the validity of a causal model. In this context, a more appropriate approach would be to consider bidirectional selection, as it also excludes independent variables which do not play a significant role in the predictive power of the model [12].
- The poor study of the data set before the start of the regression analysis (for instance, there was no check for heteroskedasticity), which inevitably led to a suboptimal model, *i.e.* one with too many variables (or inappropriate ones) – some of which turn out not to be significant – without an increase in goodness of fit, or predictive power (*cf.* section A.3);
- The failure to take into account concentration along the fraction of nuclear power axis of the data set (most countries have no nuclear power, hence most of the data set lies exactly at zero with respect to this variable, which is a huge bias of the statistics regarding this variable), which biases the regressions performed (*cf.* section A.2).

### 3 Conclusion

The analysis of Sovacool *et al.* does not back their concluding statements. As demonstrated in this paper and its appendix, all the conclusions of their paper do not follow from the data or from proper statistical treatment of it. In particular, the failure to recognize that the predictive power of their model came from the fraction of fossil fuels in the electrical mix, and to take into account the basic relation between the fraction of renewables and nuclear in the electrical mix is fatal to their conclusions. Additionally, there are many mistakes in the regression analysis performed and important considerations were not addressed in [16], thus also undermining the validity of their results.

## A Statistical analysis

### A.1 Correlation of fractions of the same whole are inherently biased

Let  $R$ ,  $N$  and  $F$  be positive random variables (which can be interpreted as fractions), such that the following relation holds:

$$R + N + F = 1. \tag{A.2}$$

Linear regression consists in minimizing

$$\mathbb{E}[(aN + b - R)^2]. \tag{A.3}$$

which amounts to an orthogonal projection in  $\mathbb{R}^n$ , as a result the slope parameter of the regression is nothing other than the projection coefficient of the vector  $N$  onto the line generated by  $R$ :

$$a = \frac{\text{Cov}(N, R)}{\text{Var}(N)} \tag{A.4}$$

However, the relation between the three variables above immediately implies the following proposition.

*Proposition A.1.* Suppose that  $N$ ,  $R$  and  $F$  are three random variables on  $[0, 1]$  such that  $N + R + F = 1$ . Then at least two out of the three off-diagonal entries of the covariance matrix are negative, *i.e.* at least two out of  $\text{Cov}(N, R)$ ,  $\text{Cov}(N, F)$  and  $\text{Cov}(F, R)$  are negative. Furthermore, the condition to have  $\text{Cov}(N, R) > 0$  is that  $\text{Var}(F) > \text{Var}(N) + \text{Var}(R)$ .

*Proof.* Suppose otherwise that  $\text{Cov}(N, R) > 0$ . Take the relation and take  $\text{Cov}(-, -)$  of both sides thereby obtaining:

$$\text{Cov}(N, R) + \text{Cov}(N, F) = -\text{Var}(N) \quad (\text{A.5})$$

$$\text{Cov}(R, N) + \text{Cov}(R, F) = -\text{Var}(R) \quad (\text{A.6})$$

$$\text{Cov}(F, N) + \text{Cov}(F, R) = -\text{Var}(F) \quad (\text{A.7})$$

By the positivity of the variance, as soon as one of the covariances is positive, the other two are immediately negative. Inverting the above relation, one can write:

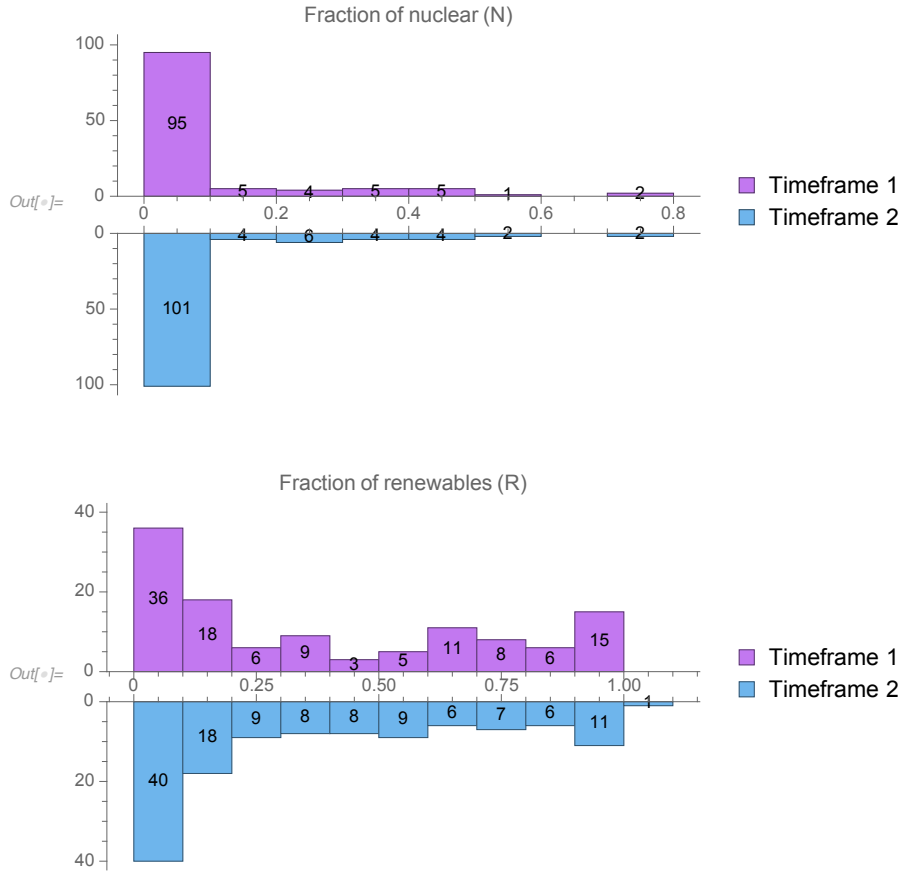
$$\text{Cov}(N, R) = \frac{1}{2}(\text{Var}(F) - \text{Var}(N) - \text{Var}(R)) \quad (\text{A.8})$$

which is positive if the condition of the proposition is satisfied. Note also that this implies the relationship  $\text{Var}(R + N) = \text{Var}(F)$ .  $\square$

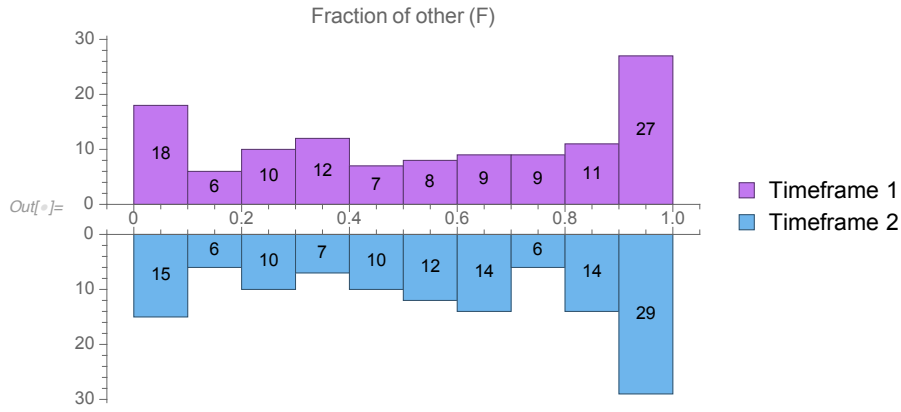
This means that, given any situation, one can expect to find negative correlation of fractions of the same whole more than two thirds of the time.

## A.2 Covariances and correlations of $N$ , $R$ and $F$

If we now let  $N$ ,  $R$  and  $F$  denote the fraction of nuclear, renewable and other sources of the electrical production, proposition A.1 applies. Taking a look at the data from the study, we find the following distributions for each of these variables (the fractions are along the  $x$  axis and the  $y$  axis is the count of the histogram). Note that  $F$  is dominated by fossil fuel contributions.



Upon examining the distribution of  $F$ , one sees that it is approximately uniform, which should set its variance to be close to  $\frac{1}{12}$ . By contrast, nuclear power tends to play a small role in the electrical mix of most countries, which tells us that  $\text{Var}(N)$  should be negligible with respect to  $\text{Var}(R)$  and  $\text{Var}(F)$ , as the observed values of  $N$  concentrate around 0. In particular, this immediately implies



Timeframe 1	$N$	$R$	$F$
$N$	0.0252887	-0.0161068	-0.00918191
$R$		0.122027	-0.10592
$F$			0.115102

Table 1: Covariances between different variables of timeframe 1 for renewable countries (nuclear countries included).

that  $\text{Cov}(R, F)$  is relatively large in absolute value and negative (independent of interpretation). This is of capital importance when we examine stepwise selection models, which will yield significance for  $R$ , but which we will see actually stem from the greater predictive power of the variable  $F$  of GHG emissions per capita. In particular, the conclusions of Sovacool *et al.* about the efficacy of renewables to decarbonate do not follow from any statistical analysis, as this covariance is only large and negative because  $\text{Var}(N)$  is negligible.

Finally, we must compare  $\text{Var}(F)$  with  $\text{Var}(R)$ . Here,  $\text{Var}(R) > \text{Var}(F)$ , and so we have the negative correlation between  $N$  and  $R$  mentioned in the paper. Looking at the distributions of  $R$  and  $F$ , one finds that this is due to the fact that most countries seem to either focus on renewables (mainly hydroelectric power in the timeframes considered) or not have any at all, whereas the distribution of other (fossil) sources is more or less uniform. This negative covariance between  $N$  and  $R$  is thus explained solely by the latter and the mathematical relation linking the three variables.

The exact values of these covariances can be found in tables 1 and 2 for timeframe 1 and timeframe 2 respectively.

### A.3 Stepwise selection

“Hierarchical regression” is more commonly known as stepwise selection in statistics. Stepwise selection can be done in two different directions: forwards or backwards. In forwards stepwise selection, one starts with the null model and progressively adds variables while evaluating the significance of each addition. And so, at step  $n$ , if the variable  $X_n$  does not yield a significant improvement in the predictions of the model, this variable is discarded. In backwards stepwise selection, the opposite is done. That is, we start with a family of variables, and taking out variables by examining which

Timeframe 2	$N$	$R$	$F$
$N$	0.0252823	-0.0128735	-0.0124088
$R$		0.107508	-0.0946345
$F$			0.107043

Table 2: Covariances between different variables of timeframe 2 for renewable countries (nuclear countries included).

loss gives the most statistical insignificant deterioration of the model fit. Finally, one can do both steps simultaneously, that is, go backwards and forwards to provide an extra check that the choice of variables is optimal.

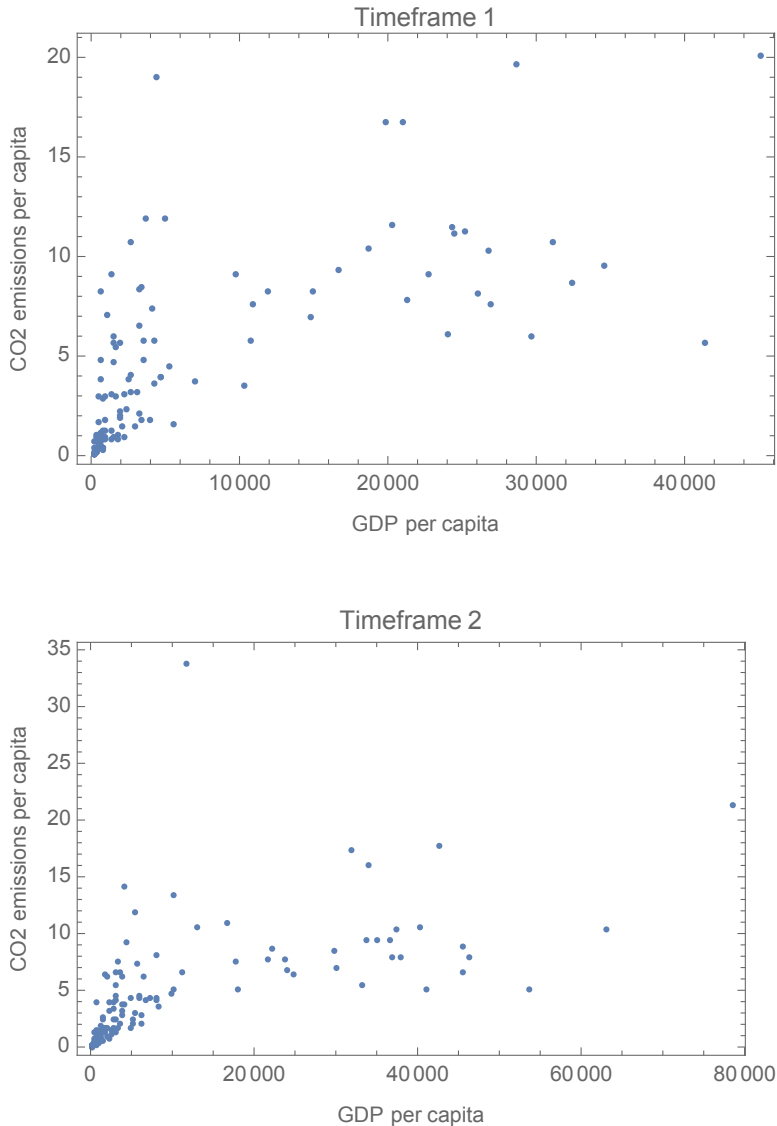
Beyond this choice of approach, trying to maximize predictive power via improvement of the goodness of fit ( $R^2$ ) while intending to study causation is wrong. Relying on  $R^2$  alone can induce into error for two main reasons:

- $R^2$  increases monotonously in the number of parameters added into the model.
- The data spans multiple orders of magnitude. This renders small relative variations of the points at large scales to have a considerable effect on the significance of the increase in  $R^2$ , despite there being no real meaning behind this significance.

Adapted statistical tools should have been used, such as the adjusted  $R^2$  of the fit which takes into account the number of parameters in the model. As for the second point it is more delicate to address so we will do it stepwise, by attempting to reproduce and correct at each step the steps taken in [16]. The data set studied will be that of timeframe 1.

### A.3.1 GDP and GHG emissions per capita

Plotting the GDP per capita and the  $CO_2$ eq emissions per capita (henceforth denoted  $GDP$  and  $CO_2$  respectively, for simplicity) for the countries considered in [16] yields the results in the figures below.



Following Sovacool *et al.* the regression model looks like:

$$CO_2 = \beta_0 + \beta_1 GDP \quad (A.9)$$

However, after performing a regression analysis in this model, we notice that  $\beta_0$  is not significant (although we do retrieve their result an  $R^2$  of 0.48 for this model). Applying the principles of bidirectional selection, we exclude  $\beta_0$  and examine instead:

$$CO_2 = \beta_0 GDP \quad (A.10)$$

For timeframe 1, the estimates for the parameters of the model given by the regression are:

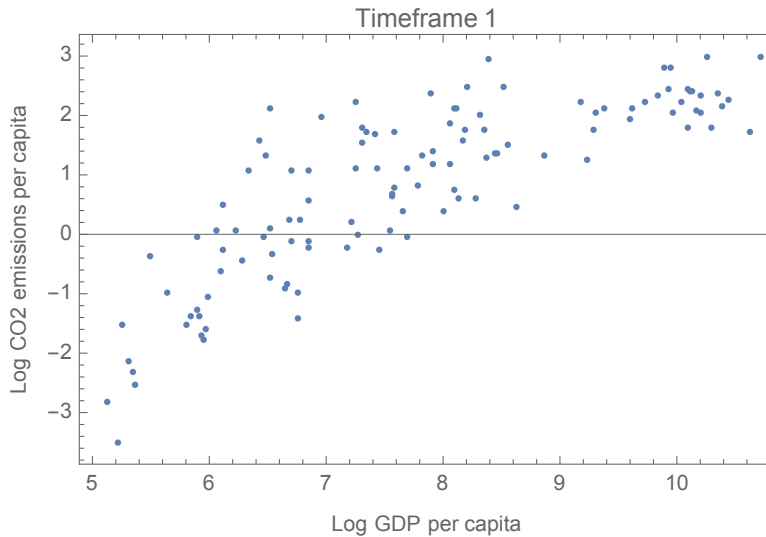
	Estimate	Standard Error	$t$ -Statistic	$P$ -Value
$\beta_0$	0.0000931758	$8.90 \times 10^{-6}$	10.4719	$1.99 \times 10^{-18}$

and an adjusted  $R^2$  of 0.64, a result which already rivals the (non-adjusted)  $R^2$  they obtain at the end of their forwards selection (0.66).

*Remark A.1.* The reported  $P$ -values are grossly underestimated, since the underlying distribution of the residuals is not exactly normal as shown by the Kolmogorov-Smirnov test. A more reliable statistic in this setting is the  $t$ -statistic and the standard error. We report nonetheless the  $P$ -value for the sake of completeness.

However, this data set can spans multiple orders of magnitude and is very clearly heteroskedastic in both timeframes, which means that the typical assumptions behind linear regression are not at all satisfied. Failing to take this into account in a linear regression – and particularly one where the data covers such large magnitudes – is catastrophic, as one can have significant increases in  $R^2$  without this reflecting anything other than a couple of points with high GDP getting closer to the regression plane.

Clearly, we should be looking at this plot in log-scale. In so doing, the simplest model we can



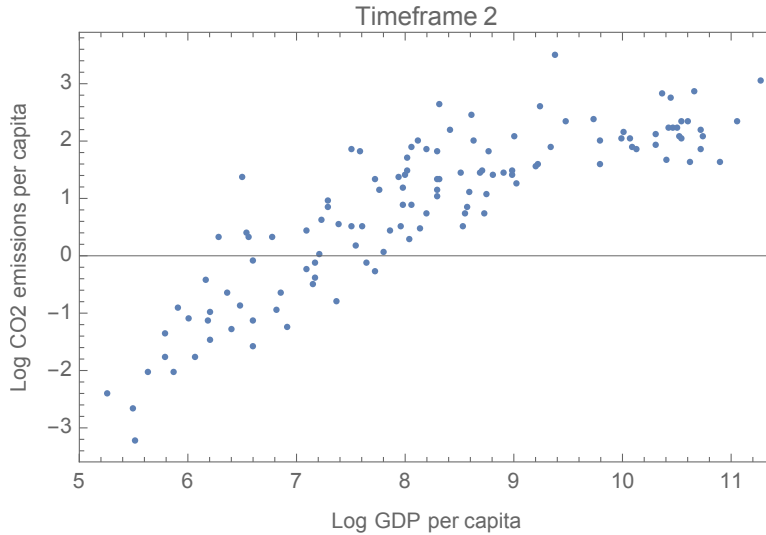
postulate that GHG emissions are a power law of GDP per capita.

$$\log CO_2 = \beta_0 + \beta_1 \log GDP \quad (A.11)$$

This simple model has an adjusted  $R^2$  of roughly 0.69 and the following regression table for timeframe 1.

	Estimate	Standard Error	$t$ -Statistic	$P$ -Value
$\beta_0$	-5.2705	0.389961	-13.5154	$1.99 \times 10^{-25}$
$\beta_1$	0.781987	0.0493198	15.8554	$1.31 \times 10^{-30}$

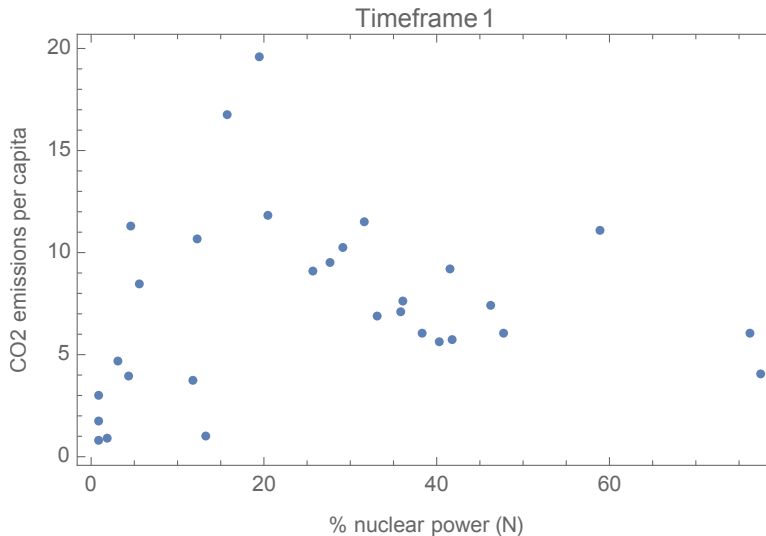




This shows that poor *a priori* inspection of the data from the part of the authors of [16] ultimately led to a suboptimal model. In particular, we notice that this adjusted  $R^2$  is already higher than any of the  $R^2$  values obtained by the authors at the end of their forwards selection (0.66), despite being penalized for taking into account the number of variables in the model and only having two predictors.

Since the goal of this paper is an attempt to reproduce the results of Sovacool *et al.* we will keep model of equation A.10 in what will follow, despite the fact that going forwards we should consider accounting for the confounding variable with a power law and not just a linear model.

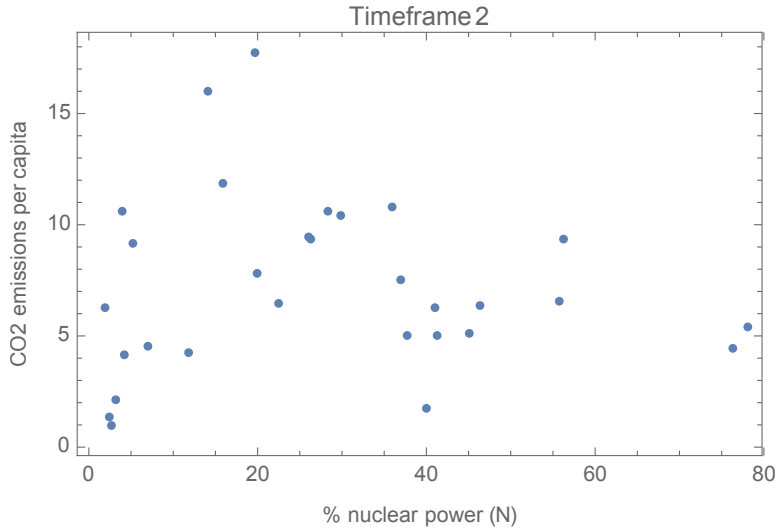
### A.3.2 Nuclear, Renewables, GDP and CO<sub>2</sub>eq emissions



We discard the  $N$  variable after performing bidirectional selection, as the variable doesn't prove to be significant or to provide considerable improvement to the adjusted  $R^2$ . Other than the obvious reason that nuclear power emits little to no GHGs, there are other explanations of why this is not a significant explanatory variable in our model. The addition of  $N$  as a variable only affects 30 of the data points, many of which lie close to 0% nuclear energy, which doesn't add much information to the model (around half of them are below the 20% mark). On timeframe 2, one can speculate that there are two trendlines, one before the 30% mark, which is increasing, and the other afterwards, which decreases. Of course, this may purely be an artifact of the data given the low sampling.

Still following Sovacool *et al.*, let us now look at what happens when we add the variable  $R$  into the model of equation A.10, which becomes:

$$CO_2 = \beta_0 GDP + \beta_1 R \tag{A.12}$$



We can look at the regression analysis of this model:

	Estimate	Standard Error	t-Statistic	P-Value
$\beta_0$	0.000414812	0.0000307419	13.4934	$2.24 \times 10^{-25}$
$\beta_1$	0.00635995	0.00720374	0.882869	0.379165

The adjusted  $R^2$  value for this iteration of the model is 0.64, which does not improve the previous model. Furthermore,  $\beta_1$  is not deemed significantly different from 0, meaning that  $R$  plays no role in predicting the GHG emissions per capita. This is of course, obvious from the fact that renewable energy emits little to no GHGs.

By contrast,  $F$  mostly carries information about the fraction of fossil fuels in the electrical mix, since other sources of energy are negligible once we have excluded fossil fuels, renewables and nuclear power. It follows that a more reasonable model is simply

$$CO_2 = \beta_0 + \beta_1 GDP + \beta_2 F, \quad (\text{A.13})$$

As before, the parameter  $\beta_0$  was found to be non-significant. Following the principles of bidirectional selection, we exclude  $\beta_0$ , and instead consider:

$$CO_2 = \beta_1 GDP + \beta_2 F, \quad (\text{A.14})$$

which has the following regression table:

	Estimate	Standard Error	t-Statistic	P-Value
$\beta_1$	0.000314618	0.000025023	12.5731	$2.84 \times 10^{-23}$
$\beta_2$	0.0447815	0.00485628	9.22136	$1.81 \times 10^{-15}$

Both variables are significant predictors and the adjusted  $R^2$  of this model is 0.80, and the standard error of the predictors decreased.

Finally, let us show that the predictive power of  $R$  in Sovacool *et al.*'s suboptimal model came from  $F$ . To do this, we compare their model

$$CO_2 = \beta_0 + \beta_1 GDP + \beta_2 R, \quad (\text{A.15})$$

to the following (also suboptimal) model

$$CO_2 = \beta_0 + \beta_1 GDP + \beta_2 F. \quad (\text{A.16})$$

These models have the following respective regression tables

Model <b>A.15</b>	Estimate	Standard Error	$t$ -Statistic	$P$ -Value
$\beta_0$	4.41294	0.47065	9.37627	$8.47 \times 10^{-16}$
$\beta_1$	0.000288171	0.0000268078	10.7495	$5.43 \times 10^{-19}$
$\beta_2$	-0.0468907	0.00785489	-5.96962	$2.80 \times 10^{-8}$

Model <b>A.16</b>	Estimate	Standard Error	$t$ -Statistic	$P$ -Value
$\beta_0$	-0.083787	0.546209	-0.153397	0.878359
$\beta_1$	0.000316026	0.0000267566	11.8112	$1.87 \times 10^{-21}$
$\beta_2$	0.0457721	0.00809241	5.65617	$1.18 \times 10^{-7}$

There a couple of things to note. First, the suboptimality of Model **A.16** is reflected by the fact that  $\beta_0$  is evidently not significant. More importantly,  $\beta_2$  is almost exactly the same in absolute value as it was in the previous model. This, in conjunction with the large anti-correlation between  $F$  and  $R$  allows us to conclude that the predictive power of  $R$  in Model **A.15** was in fact inherited from that of  $F$ . Of course, there is a tautological causal link behind this correlation given that  $F$  mostly consists of the fraction of fossil fuels in the electrical mix.

## References

- [1] BP Statistical Review of World Energy. Technical report, BP, 2019.
- [2] Conditions and requirements for the technical feasibility of a power system with a high share of renewables in france towards 2050. Technical report, IEA, Paris, 2021.
- [3] A. Berger, T. Blees, F. M. Breon, B. W. Brook, M. Deffrennes, B. Durand, P. Hansen, E. Huffer, R. B. Grover, C. Guet, W. Liu, F. Livet, H. Nifenecker, M. Petit, G. Pierre, H. Prévot, S. Richet, H. Safa, M. Salvatores, M. Schneeberger, B. Wornan, and S. Zhou. Nuclear energy and bio energy carbon capture and storage, keys for obtaining 1.5°C mean surface temperature limit. *International Journal of Global Energy Issues*, 40(3/4):240, 2017.
- [4] A. Berger, T. Blees, F. M. Bréon, B. W. Brook, P. Hansen, R. B. Grover, C. Guet, W. Liu, F. Livet, H. Nifenecker, M. Petit, G. Pierre, H. Prévot, S. Richet, H. Safa, M. Salvatores, M. Schneeberger, and S. Zhou. How much can nuclear energy do about global warming? *International Journal of Global Energy Issues*, 40(1/2):43, 2017.
- [5] C. Clack, S. Qvist, J. Apt, M. Bazilian, A. Brandt, K. Caldeira, S. Davis, V. Diakov, M. Handschy, P. Hines, P. Jaramillo, D. Kammen, J. Long, M. Morgan, A. Reed, V. Sivaram, J. Sweeney, G. Tynan, D. Victor, J. Weyant, and J. Whitacre. Evaluation of a proposal for reliable low-cost grid power with 100wind, water, and solar. *PNAS; Proceedings of the National Academy of Sciences*, 114(26):6722–6727, 2017.
- [6] F. Creutzig, P. Agoston, J. C. Goldschmidt, G. Luderer, G. Nemet, and R. C. Pietzcker. The underestimated potential of solar energy to mitigate climate change. *Nature Energy*, 2(9), aug 2017.
- [7] H. Fell, A. Gilbert, J. Jenkins, and M. Mildenerger. Reply to 'differences in carbon emissions reduction between countries pursuing renewable electricity versus nuclear power,' by sovacool et al. (2020). *SSRN Electronic Journal*, 2021.
- [8] J. Hamilton. *Time Series Analysis*. Princeton University Press, 1994.
- [9] S. Hong, C. J. Bradshaw, and B. W. Brook. Global zero-carbon energy pathways using viable mixes of nuclear and renewables. *Applied Energy*, 143:451 – 459, 2015.
- [10] M. Z. Jacobson, M. A. Delucchi, Z. A. Bauer, S. C. Goodman, W. E. Chapman, M. A. Cameron, C. Bozonnat, L. Chobadi, H. A. Clonts, P. Enevoldsen, J. R. Erwin, S. N. Fobi, O. K. Goldstrom,

- E. M. Hennessy, J. Liu, J. Lo, C. B. Meyer, S. B. Morris, K. R. Moy, P. L. O'Neill, I. Petkov, S. Redfern, R. Schucker, M. A. Sontag, J. Wang, E. Weiner, and A. S. Yachanin. 100% clean and renewable wind, water, and sunlight all-sector energy roadmaps for 139 countries of the world. *Joule*, 1(1):108–121, sep 2017.
- [11] S. H. Kim, K. Wada, A. Kurosawa, and M. Roberts. Nuclear energy response in the EMF27 study. *Climatic Change*, 123(3-4):443–460, mar 2014.
- [12] I. Pardoe. *Multiple Linear Regression*. John Wiley & Sons, Ltd, 07 2012.
- [13] J. Rogelj, A. Popp, K. V. Calvin, G. Luderer, J. Emmerling, D. Gernaat, S. Fujimori, J. Strefler, T. Hasegawa, G. Marangoni, V. Krey, E. Kriegler, K. Riahi, D. P. van Vuuren, J. Doelman, L. Drouet, J. Edmonds, O. Fricko, M. Harmsen, P. Havlík, F. Humpenöder, E. Stehfest, and M. Tavoni. Scenarios towards limiting global mean temperature increase below 1.5°C. *Nature Climate Change*, 8(4):325–332, mar 2018.
- [14] J. Rogelj, D. Shindell, S. F. K. Jiang, P. Forster, V. Ginzburg, C. Handa, H. Kheshgi, S. Kobayashi, E. Kriegler, L. Mundaca, R. Séférian, and M. Vilariño. Mitigation pathways compatible with 1.5°C in the context of sustainable development. *Global Warming of 1.5°C. An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty*, 2018.
- [15] R. H. Shumway. *Applied statistical time series analysis*. Prentice Hall, Englewood Cliffs, NJ, 1988.
- [16] B. K. Sovacool, P. Schmid, A. Stirling, G. Walter, and G. MacKerron. Differences in carbon emissions reduction between countries pursuing renewable electricity versus nuclear power. *Nature Energy*, oct 2020.
- [17] X.-J. Xiao and K.-J. Jiang. China’s nuclear power under the global 1.5°C target: Preliminary feasibility study and prospects. *Advances in Climate Change Research*, 9(2):138 – 143, 2018. Including special topic on mitigation for 1.5°C: Scenarios and options.