First in, First out: Econometric Modelling of UK Annual CO_2 Emissions, 1860–2017

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Abstract

The United Kingdom was the first country into the Industrial Revolution in the mid-18th Century. 250 years later, real income levels in the UK are about **7-10 fold** higher per capita, even greater elsewhere, many killer diseases have been tamed, and longevity has approximately doubled. However, such beneficial developments have led to a global explosion in anthropogenic emissions of greenhouse gases. Following the Climate Change Act of 2008, the UK is now one of the first countries out, with annual CO_2 emissions per capita below **1860**'s levels. We develop an econometric model of its highly non-stationary emissions process over the last 150 years, confirming the key roles of reduced coal use and of the capital stock, which embodies the vintage of technology at its construction. Major shifts and outliers must be handled to develop a viable model, and the advantages of doing so are detecting the impacts of important policies and improved forecasts. Large reductions in all CO_2 sources will be required to meet the 2050 target of an 80% reduction from 1970 levels, and their near elimination for a net-zero level.

JEL classifications: C51, Q54.
KEYWORDS: UK CO2 Emissions; Model Selection; Saturation Estimation; *Autometrics*; Climate Change Act; Climate Policy Implications.

1 Introduction

As first into the Industrial Revolution, the UK initially produced a large share of global anthropogenic CO_2 emissions, albeit that much of that was embodied in its exports of cloth production, steam engines, ships and iron products etc. Not only has its share of world CO_2 emissions shrunk to a tiny proportion following global industrialization, there has been a dramatic *drop* in its domestic emissions of CO_2, so that by 2017 they were back to 1890's levels: the country first into the Industrial Revolution is one of the

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first out. Indeed, on April 22, 2017, 'Britain has gone a full day without turning on its coal-fired power stations for the first time in more than 130 years',[1] and on May 26, 2017 generated almost 25% of its electrical energy from solar,[2] and now goes weeks without burning coal for electric energy production.

The data analyzed here are aggregate, but as the UK population has more than doubled since 1860, in 2013 the UK's CO_2 emissions in per capita terms actually dropped below the level of 1860 (see Figure 1c), and are now just 55% of their level in 1894, despite per capita real incomes being around 7-fold higher. Thus, although the UK now 'imports' substantial embodied CO_2—reversing the Industrial Revolution direction—major domestic emissions reductions have occurred but have obviously not involved substantive sacrifice: see Catherine Brinkley (2014) for an empirical analysis of decoupling growth and CO_2 emissions. Much remains to reduce CO_2 emissions towards the net zero level that will be required to stabilize temperatures, but renewable technologies offer hope of further rapid emission reductions.

The aim of this paper is to model the UK's CO_2 emissions to establish the determinants of the UK's remarkable drop accomplished with rising real incomes. We use *Autometrics* to jointly select relevant variables, their lags, possible non-linearities, outliers and location shifts in putative relationships, and also rigorously test selected equations for being well-specified representations of the data. The structure of this paper is as follows. Section 2 defines the variables and records their sources then section 3 describes the UK time-series data under analysis, using only data over 1861–2011 for estimation and selection to allow an end-of-sample parameter-constancy test to 2017.[3] Section 4 formulates the econometric model, where §4.1 consider the choice of functional forms of the regressors. Then section 5 evaluates a simple model formulation, and highlights the inadequacy of such specifications facing wide-sense non-stationary data. The four stages of model selection from an initial general model are described in section 6, then section 7 addresses selecting indicators in the general model. Section 8 describes selecting relevant regressors given the retained indicators, and implementing a cointegration reduction, where the non-integrated formulation is estimated in section 9. Section 10 conducts an encompassing test of the linear-semilog model versus a linear-linear one. Section 11 presents conditional 1-step 'forecasts' and multi-step forecasts from a VAR, then section 12 addresses the policy implications of the empirical analysis. Section 13 estimates a 'climate-environmental Kuznets curve' and section 14 concludes.

2 Data definitions and sources

The variables used in the analysis of UK CO_2 emissions are defined as follows:

E_t	$=$	CO_2 emissions in millions of tonnes (Mt)	[1], [2]
O_t	$=$	Net oil usage, millions of tonnes	[3].
C_t	$=$	Coal volumes in millions of tonnes	[4].
G_t	$=$	real GDP, £10 billions, 1985 prices	[5], [7], p.836, [8]a,b.
K_t	$=$	total capital stock, £billions, 1985 prices	[6], [7], p.864, [8]b,c.
Δx_t	$=$	$(x_t - x_{t-1})$ for any variable x_t	
$\Delta^2 x_t$	$=$	$\Delta x_t - \Delta x_{t-1}$	

[1] See https://www.ft.com/content/8f65f54a-26a7-11e7-8691-d5f7e0cd0a16.

[2] See https://www.ft.com/content/c22669de-4203-11e7-9d56-25f963e998b2.

[3] CO_2 data are available to 2018, but other series only to 2017.

Sources:
[1] World Resources Institute http://www.wri.org/our-work/project/cait-climate-data-explorer and https://www.gov.uk/government/collections/final-uk-greenhouse-gas-emissions-national-statistics;
[2] Office for National Statistics (ONS) https://www.gov.uk/government/statistics/provisional-uk-greenhouse-gas-emissions-national-statistics-2015;
[3] Crude oil and petroleum products: production, imports and exports 1890 to 2015 Department for Business, Energy and Industrial Strategy (Beis);
[4] Beis and Carbon Brief http://www.carbonbrief.org/analysis-uk-cuts-carbon-record-coal-drop;
[5] ONS https://www.ons.gov.uk/economy/nationalaccounts/uksectoraccounts#timeseries;
[6] ONS https://www.ons.gov.uk/economy/nationalaccounts/uksectoraccounts/bulletins/capitalstocks consumptionoffixedcapital/2014-11-14#capital-stocks-and-consumption-of-fixed-capital-in-detail;
[7] Brian Mitchell (1988) and Charles Feinstein (1972);
[8] Charles Bean (from (a) *Economic Trends Annual Supplements*, (b) *Annual Abstract of Statistics*, (c) *Department of Employment Gazette*, and (d) *National Income and Expenditure*).
See Hendry and Neil Ericsson (1991), and Hendry (2001, 2015) for discussions about G_t and K_t. There are undoubtedly important measurement errors in all these time series, but James Duffy and Hendry (2017) show that strong trends and large location shifts of the form prevalent in the data analyzed here help offset potential biases in the long-run relation's estimated coefficients.

3 UK CO_2 emissions and its determinants

As already noted, energy production, manufacturing, and transport each account for roughly 25% of UK CO_2 emissions, the rest coming mainly from agriculture, construction and waste in approximately equal shares. While other greenhouse gas emissions matter, CO_2 comprises about 80% of the UK total, with methane, nitrous oxide and hydrochlorofluorocarbons (HCFCs) making up almost all the rest in CO_2 equivalents. However, the various fossil fuels have different CO_2 emissions per unit of energy produced and how efficiently fuels are burnt also matters, from coal on an open fire or in a furnace, through gasoline-powered vehicles with different engine efficiencies, to a gas-fired home boiler or a power station. A standard approach to estimate country fossil fuel emissions is to use the product of the volumes of fuels produced, the proportion of each fuel that is oxidized, and each fuels' carbon content (see Greg Marland and Ralph Rotty, 1984). Table 1 records the average CO_2 emissions per million British thermal units (Btu) of energy produced for the main fossil fuels.[4]

As rough approximations for interpreting CO_2 reductions, coal has a relative weight of around 2.2, oil 1.6 and natural gas 1.1, depending on the units of measurements. Thus, switching energy production from coal to natural gas would reduce emissions by about 45%–50% for the same amount of energy. Of course, switching to renewable sources would effect a 100% reduction, and is an essential step to reach a net-zero emissions target.

[4] Variations on such data are used in David Erickson, Richard Mills, Jay Gregg and Terence Blasing *et al.* (2008), Chris Jones and Peter Cox (2005), James Randerson, Matthew Thompson, Thomas Conway and Inez Fung *et al.* (1997), and Cynthia Nevison, Natalie Mahowald, Scott Doney and Ivan Lima *et al.* (2008). Data using this methodology are available at an annual frequency in Marland, Thomas Boden, and Robert Andres (2011). CO_2 emissions from cement production are estimated to make up about 5% of global anthropogenic emissions (see Ernst Worrell, Lynn Price, Nathan Martin and Chris Hendriks *et al.*, 2001).

Coal (anthracite)	228.6
Coal (bituminous)	205.7
Coal (lignite)	215.4
Coal (sub-bituminous)	214.3
Diesel fuel & heating oil	161.3
Gasoline	157.2
Propane	139.0
Natural gas	117.0

Table 1: Pounds of CO_2 emitted per million British thermal units (Btu) of energy produced. Source: US Department of Energy https://www.eia.gov/tools/faqs/faq.php?id=73&t=11

The main data over 1860–2017 on UK CO_2 emissions, energy volumes, and the relation of CO_2 emissions to the capital stock are shown in Figure 1.

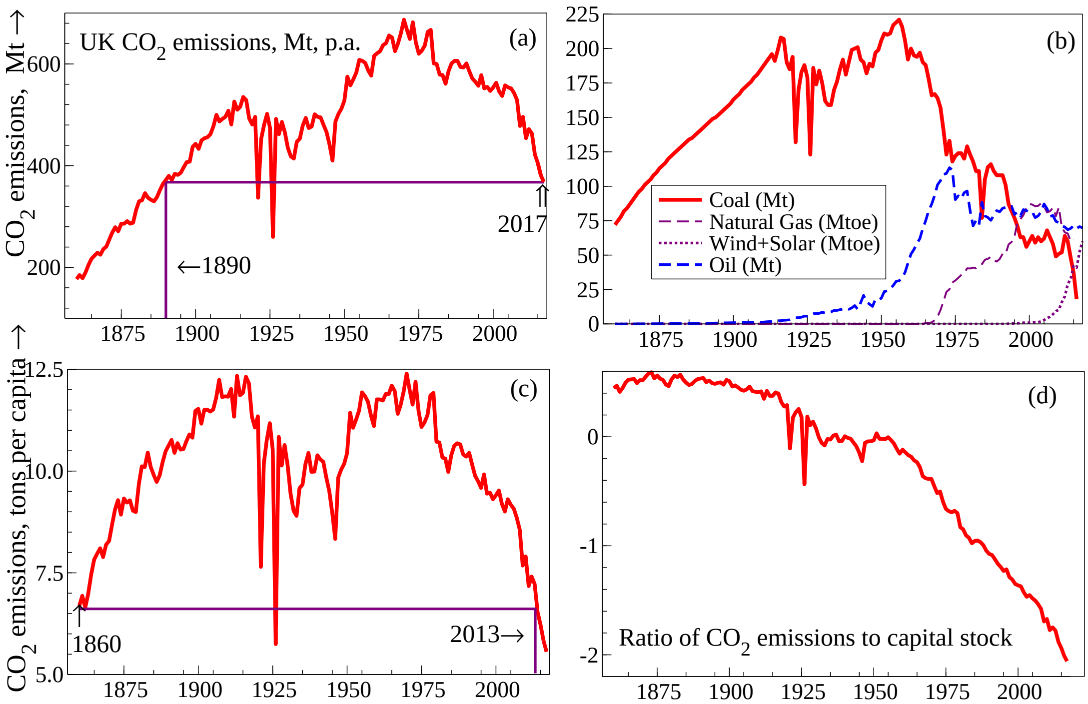

Figure 1: (a) UK CO_2 emissions in millions of tonnes (Mt); (b) UK coal (Mt), oil (Mt), natural gas (millions of tonnes of oil equivalent, Mtoe) and wind+solar (Mtoe); (c) CO_2 emissions per capita, in tons per annum; (d) ratio of CO_2 emissions to the capital stock on a log scale, all to 2017.

Panel (a) shows that UK CO_2 emissions rose strongly and quite steadily from 1860 till about 1916, oscillated relatively violently till about 1946 from the sharp depression at the end of World War I, the General Strike, Great Depression starting in 1930, and World War II, then resumed strong growth till 1970. Following another somewhat turbulent period till 1984, emissions began to fall slowly, accelerating after 2005 to the end of our time series in 2017, by which time they were below levels first reached in 1890. Panel (c) plots CO_2 emissions per capita, revealing that by 2013 they had fallen below the level at the start of our data period in 1860.

Panel (b) records the time series for coal volumes and net oil usage (imports plus domestic production less exports), natural gas and renewables. Coal volumes behave similarly to CO_2 emissions till 1956 at which point they turn down and continue falling from then onwards, dropping well below the volumes mined in 1860. The sharp dips from miners' strikes in 1921, 1926 and 1984 are clearly visible. Conversely, oil volumes are essentially zero at the start, but rise rapidly in the period of cheap oil after World War II, peak in 1973 with the first Oil Crisis, but stabilize from 1981 on, despite a doubling in vehicle travel to more than 500 billion kilometers p.a. Natural gas usage rises quickly from the late 1960s, but has recently fallen slightly, and renewables have been growing rapidly this century.

Finally Panel (d) plots the log-ratio of CO_2 emissions to the capital stock and shows that it started to decline in the 1880s, and has dropped by more than 92% over the hundred and thirty years since. As capital embodies the vintage of technology prevalent at the time of its construction, tends to be long lasting, and is a key input to production, the volumes of CO_2 produced by production are likely to be strongly affected by the capital stock: see e.g., Alexander Pfeiffer, Richard Millar, Cameron Hepburn and Eric Beinhocker (2016). Hence, 'stranded assets' could be a potential problem if legislation imposed much lower CO_2 emissions targets, as is the case for the UK.

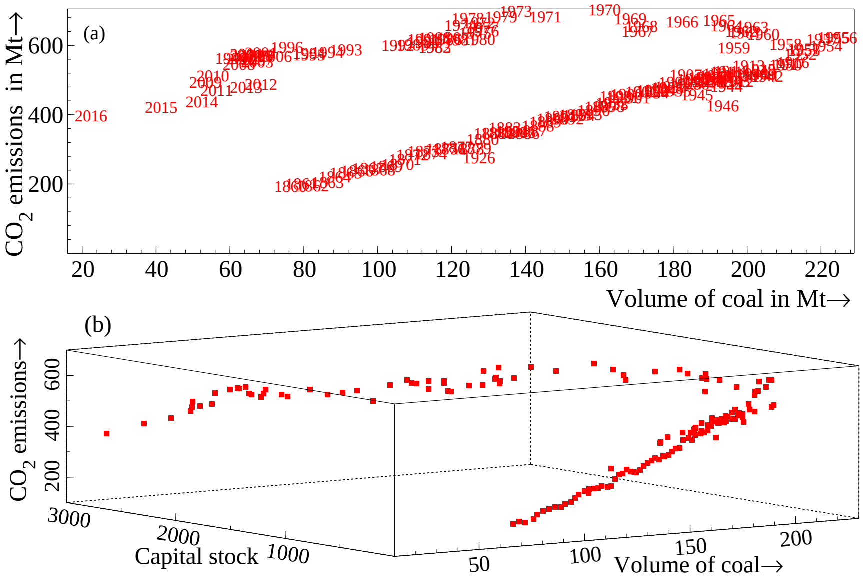

Figure 2: (a) Scatter plot of CO_2 emissions against the quantity of coal by date; (b) 3-dimensional plot of E_t against K_t and C_t.

To highlight the massive changes that have occurred in the UK, Figure 2 reports a scatter plot of CO_2 emissions against the quantity of coal, showing the dates of each pair of points, and a 3-dimensional plot of E_t against K_t and C_t. As with Figure 1(a), there is strong growth in emissions as coal output expands until the mid 1950s when coal production peaks, but emissions continue to grow till the mid 1970s despite a substantial reduction in coal volumes, and only then start to decline but fall noticeably after 2008. Referring back to Figure 1(b), the rapid rise in oil use initially offsets the fall in coal, but after the two Oil Crises of the 1970s, the fall in coal is reflected in the decline in emissions. Panel (b) shows the major role played by the capital stock in changing the link between coal and CO_2 emissions, reflecting the efficiency gains seen in Figure 1(d). Figure 3 shows the distributional shifts in CO_2 emissions that have occurred historically, using approximately 40-year sub-periods.

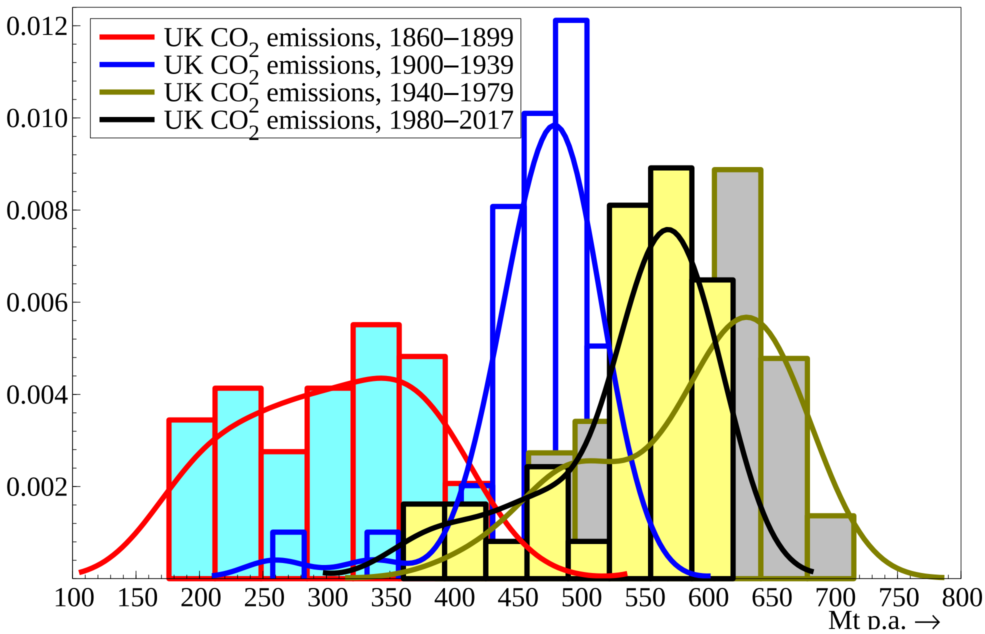

Figure 3: Sub-period distributions of UK CO_2 emissions.

All the above graphs show non-linear relationships at the bivariate level (i.e., between CO_2 emissions and coal production, say), as well as shifts in relations. An immediate implication is that simple correlations between pairs of variables change over time, so will be poor guides to what matters in a multivariable relationship, as Table 2 shows. Coal volumes have the smallest correlation with CO_2 emissions, yet were manifestly one of its main determinants.[5]

Correlations :	CO_2 emissions	Coal	Oil	real GDP	capital
CO_2 emissions	1.000	0.243	0.734	0.528	0.506
Coal		1.000	-0.424	-0.598	-0.624
Oil			1.000	0.829	0.822
real GDP				1.000	0.997

Table 2: Whole-sample correlations.

Figure 4 shows recursive estimates of the relation $E_t = \widehat{\beta}_0 + \widehat{\beta}_1 C_t + \widehat{\nu}_t$, confirming the dramatic non-constancy of that overly simple model, illustrating the problems of not modelling non-stationarity.

[5]Correlations are not well defined for non-stationary variables, as they are not constant over time.

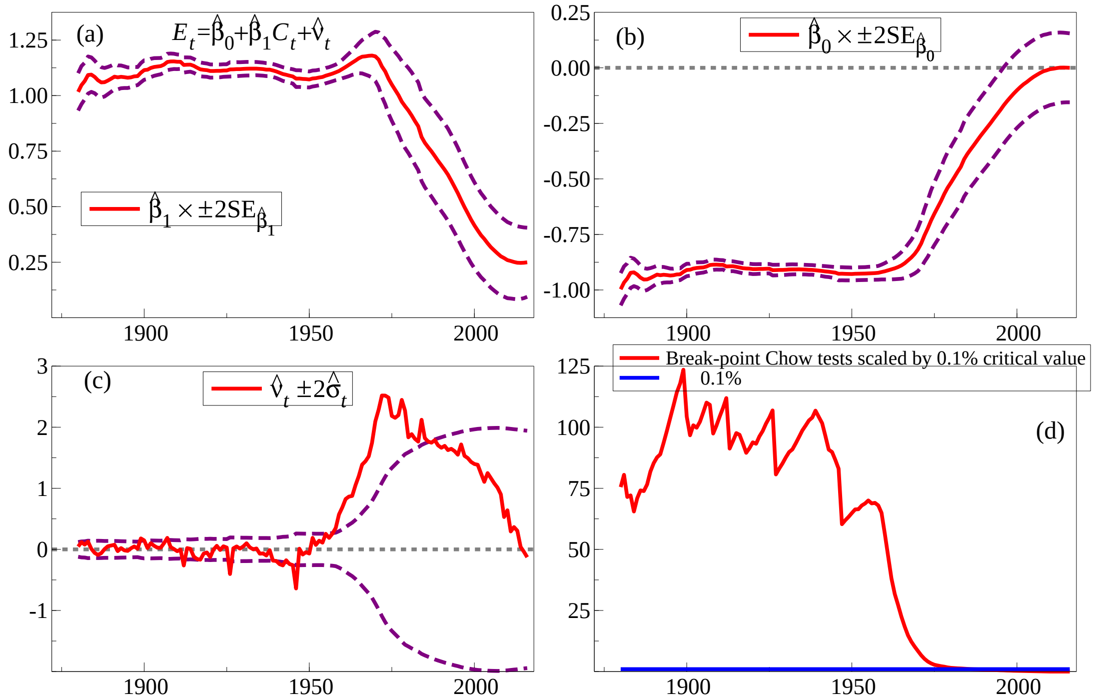

Figure 4: (a) Recursive $\widehat{\beta}_{1,t}$ with $\pm 2SE_{\widehat{\beta}_{1,t}}$; (b) Recursive $\widehat{\beta}_{0,t}$ with $\pm 2SE_{\widehat{\beta}_{0,t}}$; (c) 1-step recursive residuals $\widehat{\nu}_t$ with $\pm 2\widehat{\sigma}_t$; (d) Break-point Chow tests scaled by their 0.1% critical values.

4 Model formulation

The general model is the system characterizing the local data generating process (LDGP). We are interested in modelling UK CO_2 emissions given the volumes of coal and oil the UK used and the main representations of the scale of the economy and its productive capacity, namely GDP and the capital stock. Over most of our sample period, there would not be any contemporaneous or lagged feedbacks from CO_2 emissions to the explanatory regressors, although by the middle of the 20th century with 'Clean Air' Acts of Parliament, that is a possibility, increasingly so by the first decade of the 21st century as climate change concerns grow, but overall a conditional model seems a viable representation here.

Combining all the above information, neither of the two 'polar' approaches to modelling the UK's CO_2 emissions, namely as (a) decomposed into its sources (coal, oil, gas etc.), or (b) as a function of economic variables (capital and output) alone, seems likely to be best. On (a), not all sources have been recorded historically, especially their carbon compositions, which will have varied over time with the type of coal used, and how oil was refined to achieve which products *(inter alia)*. On (b), that changing mix will entail non-constancy in the relation between emissions and the capital stock and GDP. To capture the changing mix and its relation to the economic variables, we included the two main emitters, coal and oil, with the capital stock and GDP. The latter then explain the emissions not accounted for by the former: the solved long-run relationship in equation (5) below finds all four variables play a significant role, and the coefficients for coal and oil are also consistent with that interpretation. In turn, the additive nature of emissions suggests a linear relation with coal and oil, although that leaves open how the economic variables might enter, considered in §4.1.

A further obvious feature of Figure 1(a) is the number of very large 'outliers' occurring during the inter-war and immediate post-war periods. Consequently, the general set of variables from which the model for CO_2 emissions will be selected comprises its lagged value and current and first lagged values of coal and oil volumes, real GDP and the capital stock. These variables are all retained without selection while selecting over both impulse and step indicators at $\alpha = 0.1\%$ significance. First, however, we address the functional forms for G_t and K_t.

4.1 Functional forms of the regressors

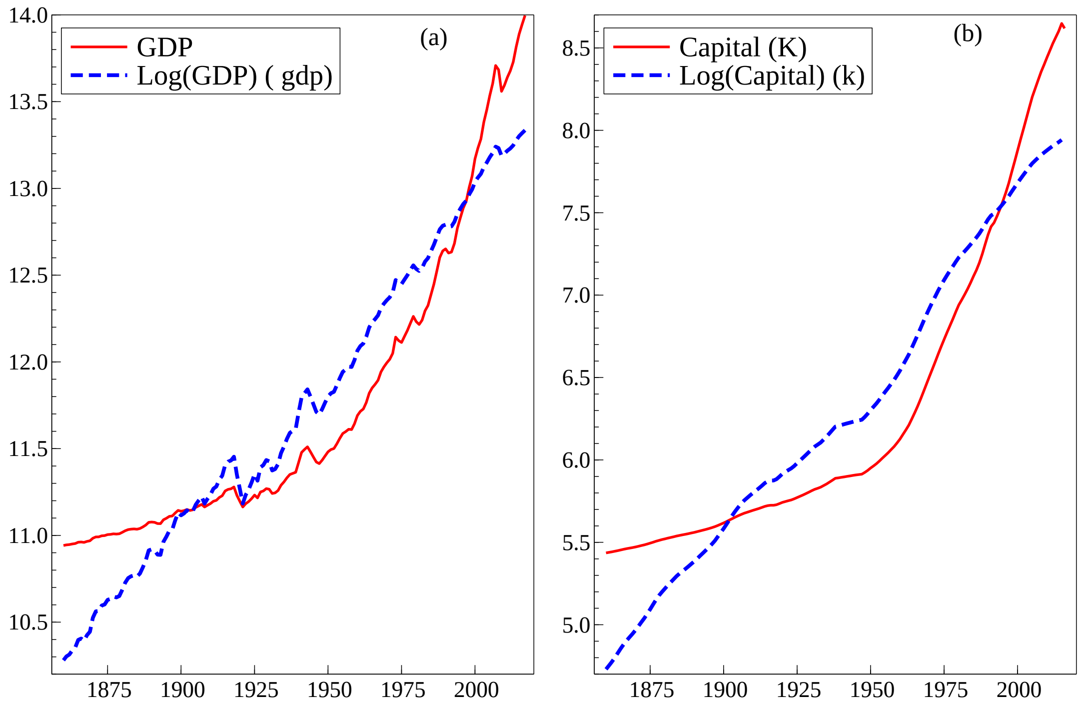

Figure 5: Graphs on a logarithmic scale matched by means and ranges of linear (capitals) and log (lower case) transforms of (a) GDP; (b) capital stock.

Castle and Hendry (2010) considered a low-dimensional representation of non-linearity, but here a more specific issue is whether to transform the various regressors to logarithms or leave as linear. CO_2 emissions depend linearly on the volumes of fossil fuels consumed with the weights shown in Table 1. Moreover, it is the volume of CO_2 emitted that has to be reduced to net zero, so we use that as the dependent variable. In turn, it is natural to include coal and oil volumes linearly as well. Nevertheless, both linear and log linear relations were investigated. As oil was used in negligible quantities in the 19th Century, early volumes were increased by unity (to ensure positive values), but the log transform still seemed to distort rather than help.

Equivalent linear and log-linear equations were formulated as:

$$\begin{aligned} E_t \;&=\; \beta_0 + \beta_1 E_{t-1} + \beta_2 C_t + \beta_3 C_{t-1} + \beta_4 O_t + \beta_5 O_{t-1} \\ &\quad + \beta_6 G_t + \beta_7 G_{t-1} + \beta_8 K_t + \beta_9 K_{t-1} + u_t \end{aligned} \tag{1}$$

the with the same form but all variables in logs. Both were estimated with impulse-indicator saturation (IIS) and step-indicator saturation (SIS), called super saturation when applied jointly, selecting indicators at a target significance level of 0.001 but retaining all the regressors in (1) without selection. The log-linear version had a residual standard deviation of 2.6%, whereas dividing the residual standard deviation of the linear form (reported in https://voxeu.org/article/driving-uks-capita-carbon-dioxide-emissions-below-1860-levels) by the mean value of E_t yielded 2.0%, so the linear representation dominated on the criterion proposed by Sargan (1964). By way of comparison, even after IIS, the formulation in (7) below had a residual standard deviation of 5.5%.

However, that leaves open the choice of log or linear just for G_t and K_t. Figure 5 graphs those variables in linear and log transforms, matched by means and ranges to highlight any relative curvature. Given the large increase in both since 1860, £100billion corresponds to very different percentage changes, illustrated by the apparently small fall in G after World War I, yet the largest drop in g, with the opposite after 2008. Consequently, we will model with the logs, denoted g and k, scaled by 100 so coefficients are between ± 10, and Δg and Δk are percentage changes. The encompassing test in section 10 checks how well the two possibilities of linear and semi-log compare. Outliers and location shifts detected by super saturation estimation may well differ between these specifications.

5 Evaluating a model without saturation estimation

Thus, the baseline relationship between emissions and its main determinants was formulated as:

$$\begin{aligned} E_t \;&=\; \beta_0 + \beta_1 E_{t-1} + \beta_2 C_t + \beta_3 C_{t-1} + \beta_4 O_t + \beta_5 O_{t-1} \\ &\quad + \beta_6 g_t + \beta_7 g_{t-1} + \beta_8 k_t + \beta_9 k_{t-1} + v_t. \end{aligned} \tag{2}$$

To demonstrate why a simple-to-general methodology is inadequate, we will first estimate and evaluate the relation in (2) over 1861–2011 with four observations retained as an end-of-sample constancy test for 2012–2017, given in (3) where estimated coefficient standard errors (SEs) are shown in parentheses below estimated coefficients with heteroskedastic and autocorrelation consistent standard errors (HACSEs) shown below those in brackets (see Whitney Newey and Kenneth West, 1987, and Donald Andrews, 1991).

$$\begin{aligned} \widehat{E}_t \;=\; & \underset{\substack{(0.054)\\ [0.070]}}{0.79}\, E_{t-1} + \underset{\substack{(0.14)\\ [0.38]}}{2.58}\, C_t - \underset{\substack{(0.18)\\ [0.40]}}{2.21}\, C_{t-1} + \underset{\substack{(0.43)\\ [0.53]}}{2.05}\, O_t - \underset{\substack{(0.43)\\ [0.53]}}{1.53}\, O_{t-1} \\ & + \underset{\substack{(0.53)\\ [0.49]}}{0.81}\, g_t - \underset{\substack{(0.53)\\ [0.57]}}{0.99}\, g_{t-1} + \underset{\substack{(2.67)\\ [2.65]}}{1.67}\, k_t - \underset{\substack{(2.62)\\ [2.57]}}{1.39}\, k_{t-1} + \underset{\substack{(133)\\ [109]}}{61} \end{aligned} \tag{3}$$

$$\widehat{\sigma} = 16.2 \ \ \mathsf{R}^2 = 0.985 \ \ \mathsf{F}_{\mathsf{AR}}(2,139) = 8.44^{**} \ \ \chi^2_{\mathsf{nd}}(2) = 64.4^{**}$$
$$\mathsf{F}_{\mathsf{ARCH}}(1,149) = 18.9^{**} \ \ \mathsf{F}_{\mathsf{Het}}(18,132) = 2.95^{**}$$
$$\mathsf{F}_{\mathsf{Reset}}(2,139) = 14.3^{**} \ \ \mathsf{F}_{\mathsf{Chow}}(6,141) = 0.96 \ \ \mathsf{t}_{\mathsf{ur}} = -3.91$$

The tests are $\chi^2_{\mathsf{nd}}(2)$ for non-Normality (see Jurgen Doornik and Henrik Hansen, 2008), F_{AR} for residual autocorrelation (see Lesley Godfrey, 1978), $\mathsf{F}_{\mathsf{ARCH}}$ tests for autoregressive conditional heteroskedasticity (see Robert Engle, 1982), $\mathsf{F}_{\mathsf{Het}}$ for residual heteroskedasticity (see Halbert White, 1980) and $\mathsf{F}_{\mathsf{Chow}}$ for parameter constancy (see Gregory Chow, 1960).

Despite the high R^2 induced by the non-stationarities in the variables, the model is completely inadequate. Every mis-specification test rejects, the key economic variables g and k are insignificant, and t_{ur} does not reject the null hypothesis of no cointegration (see Ericsson and James MacKinnon, 2002, for the appropriate critical values, which are programmed into *PcGive*) The solved long-run equation for E in Table 3 also has the 'wrong' relative coefficients of coal and oil.

	Coefficient	SE
1	289	635
C	1.77	0.17
O	2.45	0.64
g	-0.86	1.05
k	1.35	0.97

Table 3: Solved static long-run equation for E.

The HACSEs do not alter the significance or insignificance of the regressors, and given the substantive rejections on F_{AR} and $\mathsf{F}_{\mathsf{Het}}$, are surprisingly close to the conventional SEs (see the critiques of HACSEs in Castle and Hendry, 2014, and Aris Spanos and Reade, 2015), so do not alert investigators who fail to compute mis-specification tests as to the problems.

Finally, the recursively-estimated coefficients $\widehat{\beta}_{i,t}$ with $\pm 2\mathsf{SE}_{i,t}$, the residuals with $\pm 2\widehat{\sigma}_t$, and the recursive $\mathsf{F}_{\mathsf{Chow}}$ test are shown in Figure 6 revealing considerable non-constancy. The coefficient of E_{t-1} is converging towards unity, often signalling untreated location shifts (see Castle, Fawcett, and Hendry, 2010).

The dilemma confronting any investigator after fitting (3), and facing so many test rejections, is how to proceed. Mis-specification tests can reject against a number of different alternatives to those for which they were originally derived, so implementing that particular alternative is a non-sequitur. For example, residual autocorrelation need not entail error autocorrelation but may arise from incorrect dynamics, unmodelled location shifts or other parameter changes, data measurement errors and omitted variables, so adopting a recipe of the form often attributed to Guy Orcutt and Donald Cochrane (1949) can be counter-productive (see e.g. Mizon, 1995). Indeed, once there is residual heteroskedasticity and non-constancy, it is unclear what other rejections mean, except to confirm that something is wrong. The obvious alternative approach of general-to-specific is what we now explore for modelling UK CO_2 emissions.

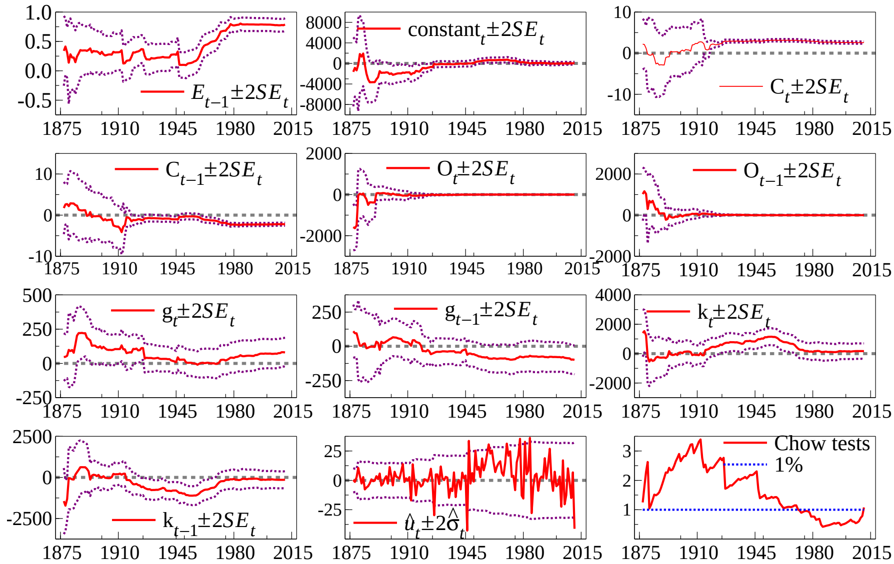

Figure 6: Graphs of $\widehat{\beta}_{i,t}, i = 0, \ldots, 9$ with $\pm 2\mathsf{SE}_{i,t}$; $\widehat{u}_t$ with $\pm 2\widehat{\sigma}_t$, and $\mathsf{F}_{\mathsf{Chow}\,t}$ over 1875–2011.

6 Four stages of single-equation model selection

In this subsection, we consider the four stages of conditional model selection from (2) extended by using super saturation (namely IIS+SIS), fitting to data over 1861–2011 to allow an end-of-sample parameter-constancy test to 2017.

First, in section 7 we select both impulse and step indicators at a tight nominal significance level α, which is the theoretical gauge, retaining all of the other regressors in (2) without selection. The studies referenced above have established that the theoretical and empirical gauges are generally close for IIS, and have derived the uncertainty around the latter, which is almost negligible for very small $\alpha_{0.001} = 0.001$. Less is known analytically about the gauge of SIS or super saturation, but the simulation studies noted earlier suggest the gauge should be set around $1/2T$. Since there are $T = 151$ observations, there will be $M \approx 300$ indicators in the candidate set (T impulse indicators and $T - 2$ step indicators), so under the null hypothesis that no indicators are needed, $\alpha_{0.001}M = 0.001 \times 300 = 0.3$ of an indicator will be significant by chance. Even doubling that, $\alpha_{0.001}2M$ can be interpreted that one indicator will be retained adventitiously approximately 3 out of every 5 times these choices are applied to new data sets with the same configuration of T, so over-fitting seems unlikely. As shown above, estimating (2) without indicator variables is unsuccessful as all mis-specification tests strongly reject. Diagnostic tests will be applied to check that the finally selected equation is well specified, with non-autocorrelated, homoskedastic and nearly Normal residuals, constant parameters, and no remaining non-linearity: (4) records that outcome.

Next, in section 8 we select over the other nine regressors at $\alpha_{0.01}$ (indicators already selected are bound to be significant at this second stage). Almost none of the 9 regressors will be retained by chance if in fact they are irrelevant.

Third, also in section 8 we solve this selected model for the cointegrating, or long-run, relation implicit in it, and reparametrize the non-deterministic variables to differences. In doing this mapping to a non-integrated specification, step indicators are included in the cointegration relation, so that they do not cumulate to trends, leaving impulse indicators and differenced step indicators unrestricted. While this may seem somewhat complicated, the reasons for doing so are explained in the survey articles by Hendry and Katarina Juselius (2000, 2001), and in Hendry and Pretis (2016). Finally, we re-estimate that non-integrated formulation in section 9.

7 Selecting indicators in the general model

Following this path, we find for $T = 1861$–2011, retaining all the regressors and selecting impulse and step indicators jointly at 0.1%, then simplifying several mixtures of impulse and step indicators, and testing constancy over 2012–2017:

$$\begin{aligned}
\widehat{E}_t \;=\; & \underset{(0.06)}{0.52}\, E_{t-1} - \underset{(13)}{47}\, 1_{\{1921\}} - \underset{(20)}{163}\, 1_{\{1926\}} - \underset{(10)}{44}\, 1_{\{1946\}} + \underset{(11)}{56}\, 1_{\{1947\}} \\
& + \underset{(9.8)}{29}\, 1_{\{1996\}} - \underset{(14)}{42}\, S_{\{1925\}} + \underset{(13)}{72}\, S_{\{1927\}} - \underset{(7.5)}{31}\, S_{\{1969\}} + \underset{(10)}{47}\, S_{\{2010\}} \\
& - \underset{(89)}{158} + \underset{(0.13)}{1.86}\, C_t - \underset{(0.18)}{0.88}\, C_{t-1} + \underset{(0.26)}{1.71}\, O_t - \underset{(0.28)}{1.07}\, O_{t-1} + \underset{(0.33)}{0.95}\, g_t \\
& - \underset{(0.33)}{1.13}\, g_{t-1} + \underset{(1.8)}{7.64}\, k_t - \underset{(1.8)}{7.02}\, k_{t-1}
\end{aligned} \tag{4}$$

$$\begin{gathered}
\widehat{\sigma} = 9.58 \;\; \mathsf{R}^2 = 0.995 \;\; \mathsf{F}_{\mathsf{AR}}(2,130) = 2.93 \;\; \chi^2_{\mathsf{nd}}(2) = 5.97 \\
\mathsf{F}_{\mathsf{ARCH}}(1,149) = 3.42 \;\; \mathsf{F}_{\mathsf{Het}}(20,123) = 0.82 \\
\mathsf{F}_{\mathsf{Reset}}(2,130) = 2.30 \;\; \mathsf{F}_{\mathsf{Chow}}(6,132) = 1.40 \;\; \mathsf{F}_{\mathsf{nl}}(27,105) = 1.04
\end{gathered}$$

where F_{nl} tests for non-linearity (see Castle and Hendry, 2010). All of these mis-specification tests are insignificant, including $\mathsf{F}_{\mathsf{Reset}}$ and F_{nl} so all of the non-linearity has been captured by (4), but the tests are applied to $\mathsf{I}(1)$ data, so correct critical values are not known: see Vanessa Berenguer-Rico and Jesus Gonzalo (2014) for a test of non-linear cointegration applied in this context.

Five impulse and four step indicators have been retained in (4) despite the very tight significance level. Combining the indicators in (4) allows some simplification by transforming $1_{\{1926\}}$ and $S_{\{1927\}}$ to $\Delta 1_{\{1926\}}$, and $1_{\{1947\}} - 1_{\{1946\}} = \Delta 1_{\{1947\}}$. This reduces the number of genuine location shifts to three, an intermediate modelling stage that was implemented before selecting over the 9 regressors. The resulting $\widehat{\sigma}$ was unaffected by these transformations.

The remaining step shifts capture major events with long-term impacts that are not otherwise captured by the variables in the model. These could reflect changes in the improving efficiency of fuel use, or the effects of omitting other sources of emissions with key technological changes, or usage shifts not taken into account in calculating emissions. Since steps in the *Autometrics* implementation of SIS terminate at the dates shown, their reported signs reflect what happened **earlier**, so a positive coefficient for $S_{\{1925\}}$ entails a higher level prior to 1926. That is the date of the 1926 Act of Parliament that created the UK's first nationwide standardized electricity distribution grid, greatly enhancing the efficiency of electricity, but also witnessed the General Strike probably captured by $\Delta 1_{\{1926\}}$. Then 1969 saw the start of the major conversion of UK gas equipment from coal gas (about 50% hydrogen) to natural gas (mainly methane) with a considerable expansion in its use. The coefficients of both these location shifts have the appropriate signs of reducing and increasing emissions respectively. Although the UK's Clean Air Act of 1956 did not need a step indicator, probably because it was captured by the resulting fall in coal use, we interpret the step shift $S_{\{2010\}}$ showing a higher level of emission of 47Mt before then as the reaction to the Climate Change Act of 2008 (see https://www.legislation.gov.uk/ukpga/2008/27/contents) and the European Union's Renewables Directive of 2009, discussed in Section 12. Thus, we doubt the explanation is the Great Recession of 2008–2012, since the previous largest GDP fall in 1921–22 did not need a step, but just had an impulse indicator for the large outlier in 1921. As coal volumes are included, indicators for miners' strikes should only be needed to capture changes in inventories, which might explain part of the large impulse indicator for 1926.

8 Selecting regressors and implementing cointegration

Secondly, selecting over the 9 regressors at 1% significance retained all of them.

Third, we solve for the long-run cointegrating relationship, justified by the Doornik and Hendry (2018) unit-root t-test value of $\mathsf{t}_{\mathsf{ur}} = -8.99^{**}$ which strongly rejects the null hypothesis of no cointegration. The resulting cointegration relation defines the equilibrium-correction trajectory $\widetilde{Q}_t = E_t - \widetilde{E}_{LR,t}$ (adjusting to a mean of zero in-sample). Step indicators need to be **led** by one period as $\widetilde{Q}_{t-1}$ will be entered in the transformed model.

However, being at the end of the initial sample up to 2011 from the definition of step indicators here, $1 - S_{\{2010\}}$ only has 2 observations in sample. Consequently, it was decided to extend the estimation sample by two observations to 2013 since the current full sample now ended in 2017, to enable the cointegrating relation to include $S_{\{2010\}}$. This led to closely similar estimates to (4) with $\mathsf{t}_{\mathsf{ur}} = -9.34^{**}$ and:

$$\begin{aligned}\widetilde{E}_{LR} \;=\; & \underset{(0.06)}{2.0}\ C + \underset{(0.18)}{1.4}\ O + \underset{(0.27)}{1.18}\ k - \underset{(0.28)}{0.27}\ g + \underset{(6)}{63}\ S_{\{1924\}} \\ & - \underset{(14)}{64.0}\ S_{\{1968\}} + \underset{(13)}{70}\ S_{\{2009\}} - \underset{(165)}{328} \end{aligned} \tag{5}$$

All variables are significant at 1% other than g. The coefficient of coal is close to the current standard estimate of ≈ 2.1–2.3, as is that of oil to its estimate, though somewhat lower than the 1.6 in Table 1.

Because the units in which the different variables in (5) are measured are not directly comparable, their relative importance as determinants of the level of E_t is hard to judge. However, Figure 2(b) provided a 3-dimensional plot of E_t against K_t and C_t to show that while the rise then fall of coal usage in Figure 2(a) explains much of the behavior of CO_2 emissions, the increases in the capital stock track the shift in the mid 20th Century to higher emissions for the same volumes of coal as in the 19th (a similar picture emerges when plotting E_t against C_t and O_t, but with a more erratic spread). Moreover, in the relatively similar long-run solution in a log-linear formulation, where coefficients are elasticities, the two dominant influences were 0.42 from coal and 0.40 from capital stock, with much smaller effects from GDP and oil. These effects match prior anticipations as discussed above. Indeed, in the linear and log-linear models, the long-run effect of GDP is also negative, possibly reflecting the move from manufacturing to a service-based economy, although it is insignificant in the semi-log form (5).

Figure 7(a) shows how closely the long-run derived relation $\widetilde{E}_{LR,t}$ in (5) tracks E_t (previously, there was a substantial departure at the end of the sample when omitting $S_{\{2010\}}$). Panel (b) records the resulting time series for $\widetilde{Q}_t$ centered on a mean of zero. While $\widetilde{Q}_t$ is not stationary from a changing variance—unsurprising given the huge variation in E_t—a unit root is rejected.

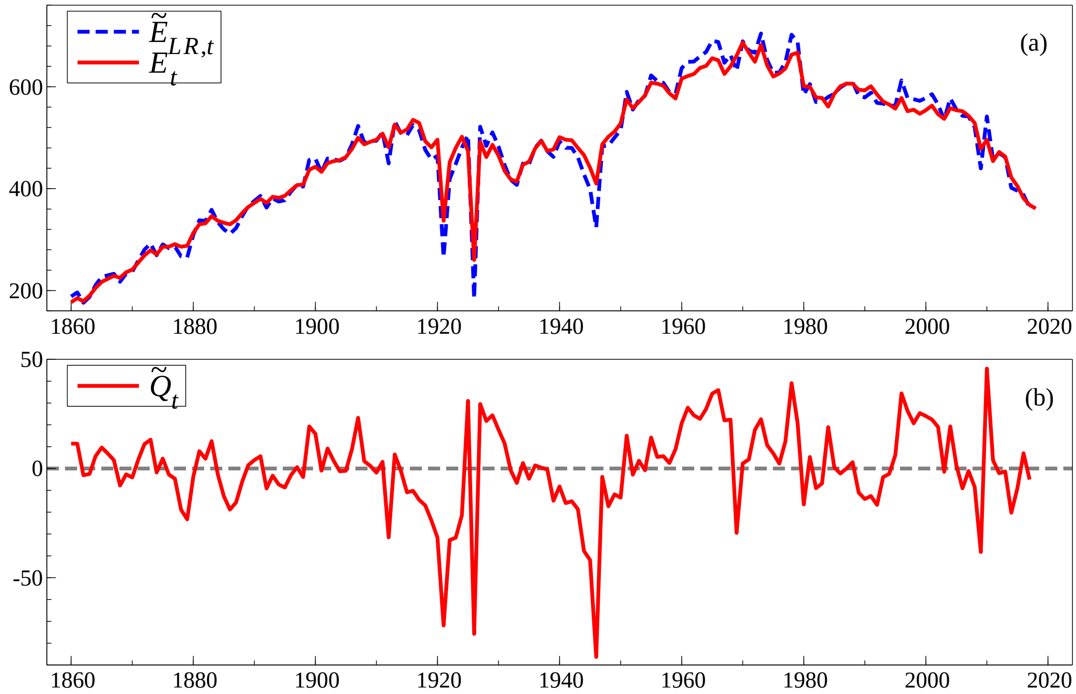

Figure 7: (a) E_t and $\widetilde{E}_{LR,t}$; (b) $\widetilde{Q}_t = E_t - \widetilde{E}_{LR,t}$ centered on a mean of zero.

9 Estimating the cointegrated formulation

Fourth, transforming to a model in differences and the lagged cointegration relation from (5) then re-estimating revealed a couple of additional outliers, and adding indicators for those (significant at 1% but not the original 0.1%) yielded (6) for 1861–2013, testing constancy over 2014–2017. Increases in oil, coal, k and g all lead to increases in emissions, which then equilibrate back to the long-run relation in (5). There are very large perturbations from this relationship, involving step shifts, impulses and blips.

$$
\begin{aligned}
\widehat{\Delta E}_t = &\underset{(0.10)}{1.88}\ \Delta C_t + \underset{(0.21)}{1.71}\ \Delta O_t + \underset{(1.09)}{7.15}\ \Delta k_t + \underset{(0.28)}{0.89}\ \Delta g_t - \underset{(0.05)}{0.50}\ \widetilde{Q}_{t-1} \\
&- \underset{(2.4)}{15.2} - \underset{(8.8)}{79.4}\ \Delta 1_{\{1926\}} + \underset{(6.4)}{50.2}\ \Delta 1_{\{1947\}} - \underset{(11.1)}{45.8}\ 1_{\{1921\}} - \underset{(8.9)}{27.5}\ 1_{\{1912\}} \\
&+ \underset{(8.9)}{26.8}\ 1_{\{1978\}} + \underset{(8.9)}{28.4}\ 1_{\{1996\}}
\end{aligned} \tag{6}
$$

$$
\widehat{\sigma} = 8.87 \ \ \mathsf{R}^2 = 0.94 \ \ \mathsf{F}_{\mathsf{AR}}(2,139) = 0.49 \ \ \chi^2_{\mathsf{nd}}(2) = 1.67 \ \ \mathsf{F}_{\mathsf{ARCH}}(1,151) = 0.53
$$
$$
\mathsf{F}_{\mathsf{Het}}(14,134) = 1.03 \ \ \mathsf{F}_{\mathsf{Reset}}(2,139) = 1.50 \ \ \mathsf{F}_{\mathsf{nl}}(15,126) = 1.35 \ \ \mathsf{F}_{\mathsf{Chow}}(4,141) = 1.75
$$

Archival research revealed that 1912 saw the first **national** strike by coal miners in Britain causing considerable disruption to train and shipping schedules, although nothing obvious was noted for 1978.

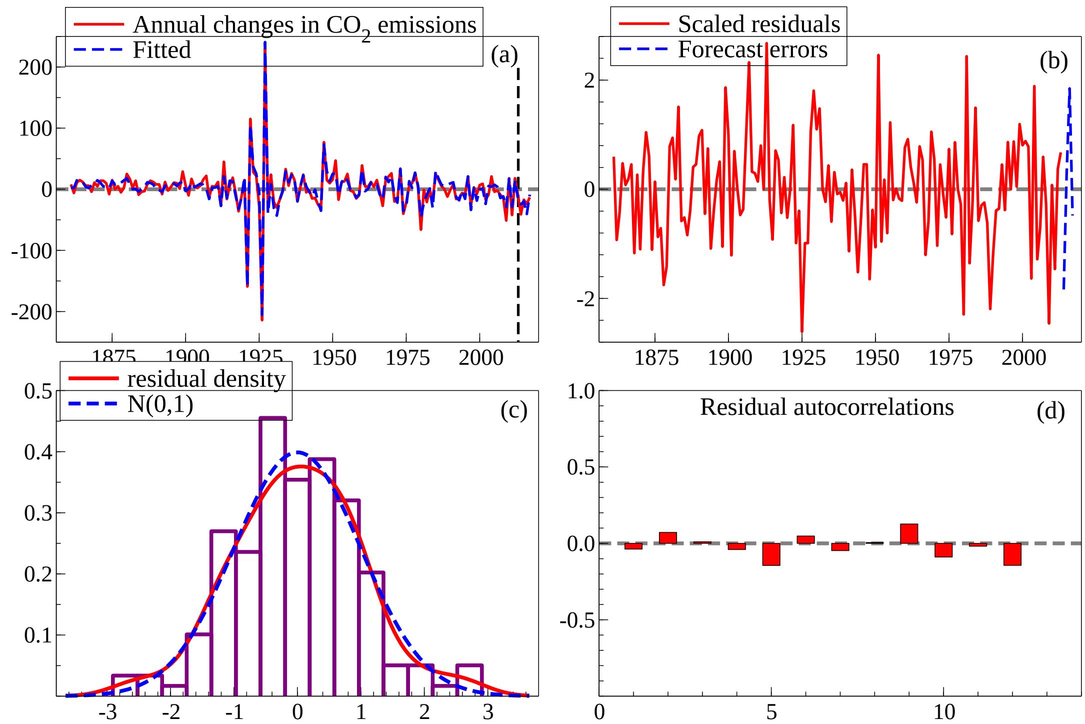

Figure 8: (a) Actual and fitted values for ΔE_t from (6); (b) residuals scaled by $\widehat{\sigma}$; (c) residual density and histogram with a Normal density for comparison; (d) residual autocorrelation.

The turbulent periods create such large changes it is difficult to ascertain how well the model describes the data from Figure 8, so Figure 9 records the implied levels' fitted values and outcomes. The match is extremely close, although the sudden lurches are only 'modelled' by indicator variables, as are several of the step shifts. Possible explanations for the need for impulse indicators, some discussed above, include the role of gas, changes in stocks of coal and oil leading to divergences from measured output (so having different effects on emissions), the changing efficiency of production and usage (e.g., replacing electric fires by central heating), and general changes such as better insulation. All of the diagnostic statistics remain insignificant.

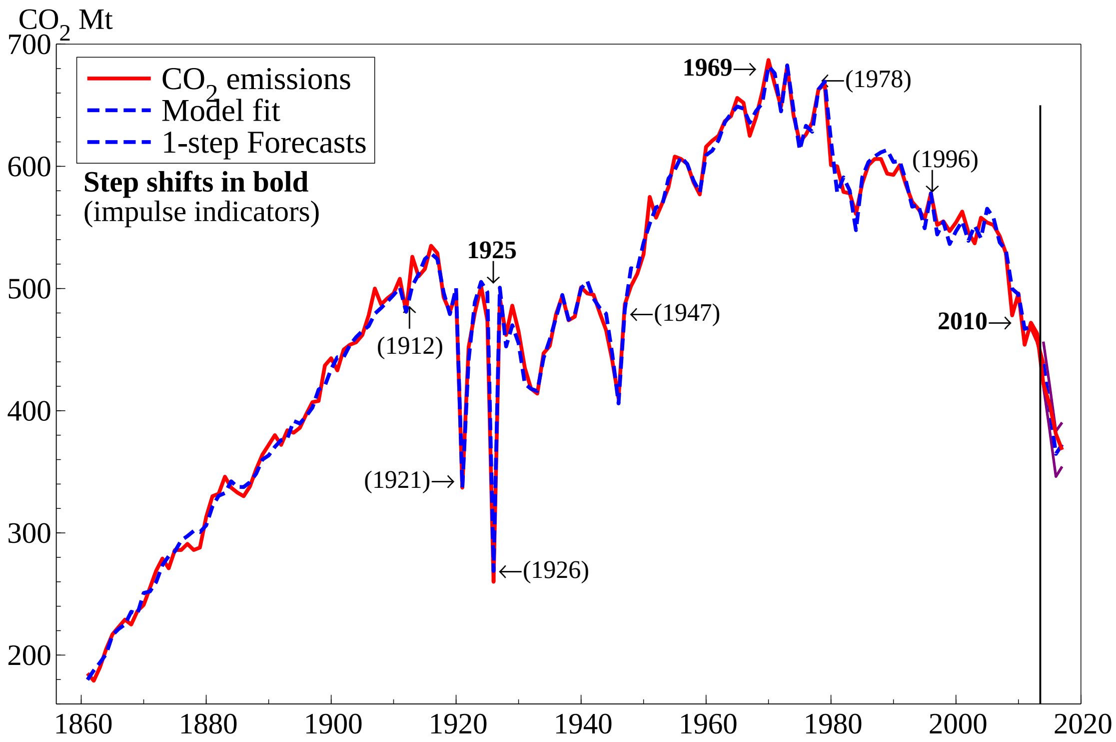

Figure 9: Actual and fitted values for UK CO_2 emissions with indicator dates.

10 Encompassing of linear-semilog versus linear-linear

Encompassing tests can be applied to discriminate between the linear-semilog model in (6) denoted M_1 against the earlier linear-linear model reported in https://voxeu.org/users/davidfhendry0 denoted M_2. The instruments are the combined regressors of the two models. Table 4 records the outcome.

Test	Form	M_1 vs. M_2	Form	M_2 vs. M_1
Cox (1962)	N[0,1]	-3.74^{**}	N[0,1]	-5.40^{**}
Ericsson (1983) IV	N[0,1]	3.26^{**}	N[0,1]	4.53^{**}
Sargan (1964)	$\chi^2(4)$	10.0^{*}	$\chi^2(4)$	17.9^{**}
Joint model	F(4,134)	2.62^{*}	F(4,134)	5.00^{**}

Table 4: Encompassing test statistics where M_1 is (6) with $\sigma_{\mathsf{M}_1} = 8.89$, M_2 is the linear model with $\sigma_{\mathsf{M}_2} = 9.18$ and $\sigma_{\mathsf{Joint}} = 8.69$.

The instruments used were $S_{\{2010\}}$, Δg_t, Δk_t, Constant, $\Delta 1_{\{1947\}}$, $\widetilde{Q}_{t-1}$, ΔC_t, ΔO_t, $1_{\{1912\}}$,

$1_{\{1921\}}$, $1_{\{1978\}}$, $1_{\{1996\}}$, ΔK_t, $1_{\{1970\}}$, $\Delta S_{\{1983\}}$, $\Delta 1_{\{1926\}}$, and $\widetilde{Q}_{GK,t-1}$, where $\widetilde{Q}_{t-1}$ and $\widetilde{Q}_{GK,t-1}$ denote the equilibrium correction terms of the versions with log and linear GNP and Capital respectively. Although M_1 is rejected against M_2, the $\mathsf{F}(4,134)$ parsimonious encompassing test against the joint model is equivalent to adding the four variables from the linear model, and is not significant at the 1% level used for selection, nor are any of those variables individually significant at 1%. Conversely, $\widetilde{Q}_{t-1}$, Δg_t, Δk_t, and $1_{\{1921\}}$ are highly significant at less than 0.1% if added to M_2.

11 Conditional 1-step 'forecasts' and system forecasts

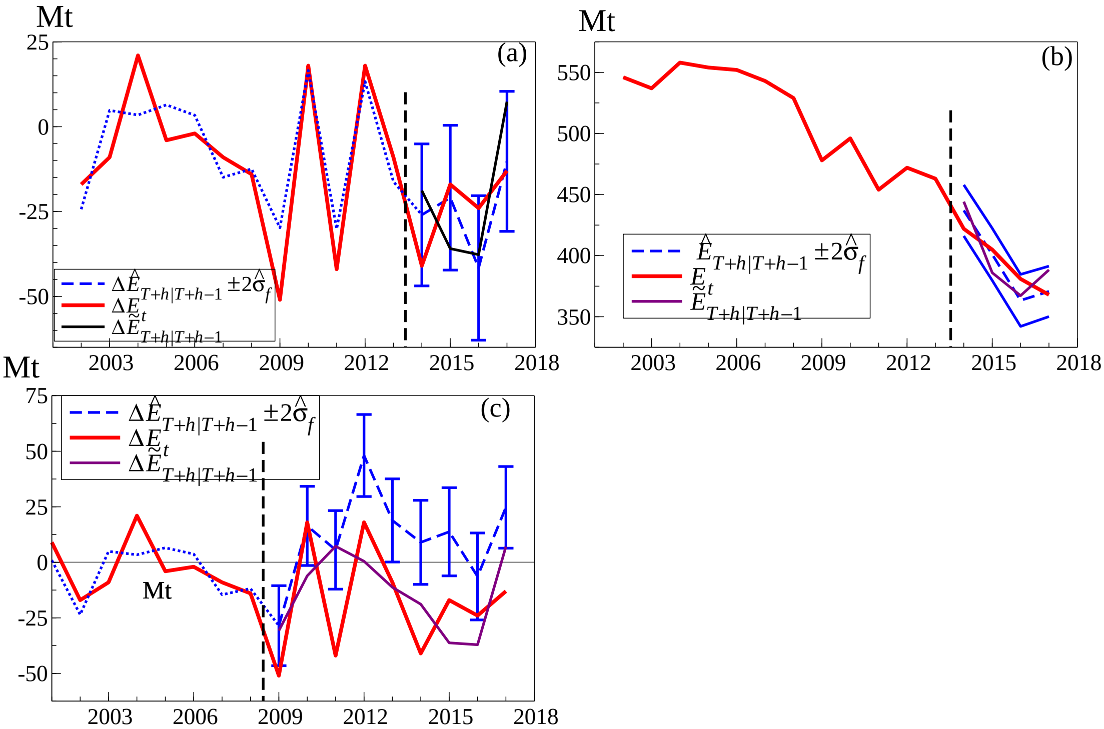

Figure 10: (a) Outcomes ΔE_t, fitted values, and 1-step conditional 'forecasts' $\widehat{\Delta E}_{T+h|T+h-1}$ with $\pm 2\widehat{\sigma}_f$ shown as bars, and robust 'forecasts' $\widetilde{\Delta E}_{T+h|T+h-1}$; (b) implied $\widehat{E}_{T+h|T+h-1}$ from (a) with $\pm 2\widehat{\sigma}_f$, and corresponding robust 'forecasts' $\widetilde{E}_{T+h|T+h-1}$, both from 2013; (c) ΔE_t, fitted values, and 1-step conditional 'forecasts' $\widehat{\Delta E}_{T+h|T+h-1}$ with $\pm 2\widehat{\sigma}_f$ shown as bars, and robust 'forecasts' $\widetilde{\Delta E}_{T+h|T+h-1}$ commencing in 2008.

To check the constancy of the model after 2013, Figure 10 (a) records the four 1-step ahead 'forecasts' $\widehat{\Delta E}_{T+h|T+h-1}$ for ΔE_{T+h} from (6), from $T = 2013$ with $h = 1 \dots 4$, conditional on the realized values for the regressors, where $\widehat{\sigma}_f$ denotes the forecast standard error. We also report 'forecasts' from a robust device denoted $\widetilde{\Delta E}_{T+h|T+h-1}$ (see Hendry, 2006). The derived 'forecasts' $\widehat{E}_{T+h|T+h-1}$ for the levels E_{T+h} are also shown in Panel (b). The robust devices have slightly larger root mean square forecast errors (RMSFEs) of 14.9, as against $\widehat{\Delta E}_{T+h|T+h-1}$ of 13.7, so the conditional 'forecasts' suggest no substantive shift in the relationship, despite describing the lowest levels of CO_2 emissions seen since the 19th century. However, Panel (c) shows the importance of the step-indicator for 2010 as the forecasts resulting when it is absent are systematically too high.

Re-estimating the CO_2 model up to 2017 shows little change in $\widehat{\sigma}$ to 8.99, consistent with constancy. However, dropping S_{2010} then re-estimating to 2017 leads to a jump in $\widehat{\sigma}$ to 10.7 and rejection on some diagnostic tests, as does the deterioration in forecasts commencing from 2008, at which point the effects of the Climate Change Act would not be known. Now the advantages of the robust device come into their own as panel (c) shows. The mis-specified model's 'forecasts' suffer systematic failure when $S_{\{2010\}}$ is excluded (all other indicators were included), lying outside the $\pm 2\widehat{\sigma}_f$ error bars for the last four observations, with a RMSFE of 36, whereas despite that omission, the robust 'forecasts' track the downward trend in emissions and have a RMSFE of 25.

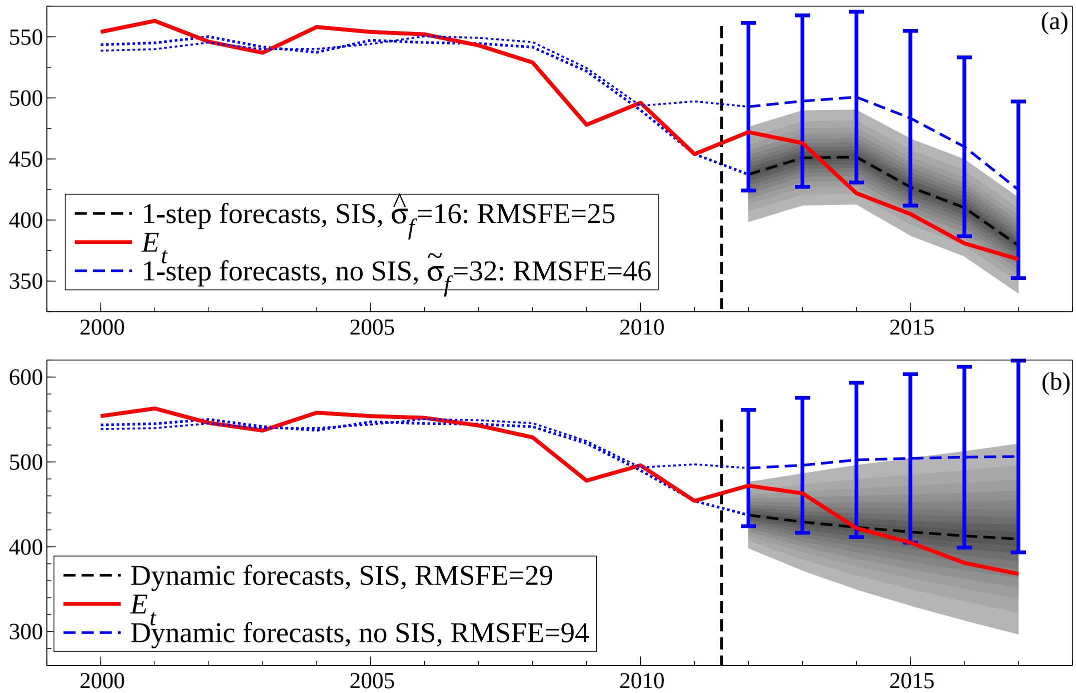

Figure 11: (a) Outcomes fitted values, and 1-step forecasts with and without step indicators, with $\pm 2\widehat{\sigma}_f$ respectively shown as bars and fans, plus RMSFEs; (b) Outcomes fitted values, and multi-step forecasts with and without step indicators, with $\pm 2\widehat{\sigma}_f$ respectively shown as bars and fans, plus RMSFEs.

To obtain unconditional forecasts and evaluate the role of IIS and SIS in model development and forecasting, a vector autoregression (VAR) with 2 lags was estimated for the five variables, E_t, C_t, O_t, g_t, and k_t, over the original sample of 1862–2011 with and without the indicators found for (4). In the former, those indicators were included in all equations. The VARs were estimated unrestrictedly without any selection to eliminate insignificant variables as that would lead to different specifications between the systems: Clements and Hendry (1995) demonstrate the validity of forecasting in this setting. Figure 11 reports the outcomes. Panel (a) shows the outcomes for 1-step ahead forecasts with and without step indicators and Panel (b) the multi-step forecasts going 1, 2, ..., 6 steps ahead. In both cases, indicator-based forecast intervals are shown as fans, and without step indicators by bars. In-sample, impulse indicators only have an impact on forecasts to the extent that they change estimated parameters, whereas step indicators can have lasting effects. As can be seen, including the step indicators greatly reduces $\pm 2\widehat{\sigma}_f$ for the forecasts in both Panels and leads to more accurate forecasts and much smaller RMSFEs in both cases as compared to when no step indicators are included. The outcomes lie within their own uncertainty intervals for both sets of forecasts.

12 Policy implications

The most important implication of the above evidence is that substantial CO_2 reductions are feasible, so far with little apparent impact on GDP. The UK's 2008 Climate Change Act established the world's first legally-binding climate-change target to reduce the UK's greenhouse-gas emissions by at least 80% by 2050 from the 1990 baseline (the UK carbon budget counts six greenhouse gas emissions, not just CO_2). A range of policy initiatives was implemented, with an updated carbon plan in 2011 (again covering more than just CO_2 emissions), with carbon budgets to limit greenhouse gas emissions to 3018 Mt CO_2-equivalent over the five years 2008–2012 and 2782 over 2013–2017. While only counting the CO_2 component, which is approximately 80% of the total, emissions over 2008–2012 cumulated to 2477 Mt, and to date over 2013–2017, to 2039 Mt, both below the sub-targets, allowing 20% for other greenhouse gas emissions while still hitting those overall targets.

To test the UK's achievement of its 2008 Climate Change Act targets for CO_2, the above 5-year total targets were translated into annual magnitudes, starting 20Mt above and ending 20Mt below the average target for the period. However, our test does not depend greatly on the within-period allocation, which affects any apparent residual autocorrelation (not significant, but the sample is small). We then scaled these annual targets by 0.8 as the share of CO_2 in total greenhouse gases emitted by the UK, shown in Figure 12 (a). As a decade has elapsed since the Act, there were 10 annual observations on CO_2 emissions to compare to the targets, and we calculated a test of the difference between targets and outcomes being zero, but starting in 2009 as the Act could not have greatly influenced the emissions in its year of implementation. A graph of those differences is shown in Figure 12 (b).

The null of "emissions=targets" is strongly rejected on the negative side with a mean of -18 and a zero-innovation error t-test value of -2.67 ($\mathsf{p} < 0.03$: $\mathsf{t} = -1.99$ correcting estimated standard errors for residual autocorrelation and heteroskedasticity), or as in panel (b), a downward step of -46.8 starting in 2013 with a t of -5.9. A similar approach could be used to evaluate the extent to which countries met their Paris Accord Nationally Determined Contributions or NDCs, given the relevant data. Thus, the UK has reduced its emissions faster than the targets and in 2017 was already below the implicit target for 2018. Indeed, the budget for 2018–2022 of 2544 Mt, roughly 410 Mt p.a. of CO_2, is undemanding given the 2017 level of 368 Mt, but should not induce complacency, as the easiest reductions have been accomplished with coal use now almost negligible. The NDCs agreed at COP21 in Paris are insufficient to keep temperatures below 2°C so must be enhanced, and common time frames must be adopted to avoid a lack of transparency in existing NDCs: see Sam Rowan (2019). Since the baseline dates from which NDCs are calculated is crucial, standardised dates, 5-year NDC reviews and evaluation intervals are needed.

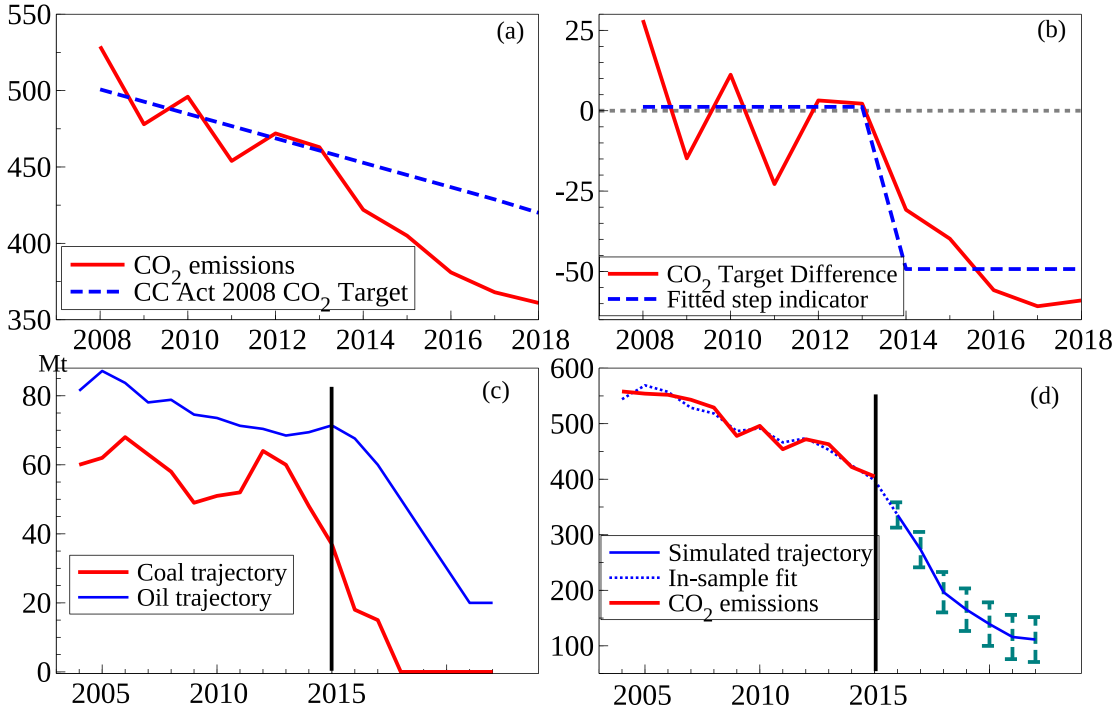

Figure 12: (a) UK CO_2 emissions and Climate Change Act 2008 CO_2 targets; (b) deviations from targeted values with a step indicator; (c) scenario reductions required in coal and oil use for original 2050 target; (d) resulting reductions in CO_2 emissions from (6). In (c) & (d), the horizon is compressed to 5-year intervals after 2017.

12.1 Can the UK reach its 2008 Act CO_2 emissions targets for 2050?

For CO_2 emissions to meet their share of the 80% drop from the 1990 baseline of 590 Mt, they would need to fall to about 120 Mt pa. To illustrate, we simulate a scenario with no coal usage, quite a possibility now that coal is banned for electricity generation from 2025, and a 70% fall in oil use, to around 20 Mt p.a., from greatly increased use of non-gasoline vehicles sustained by expanded renewables and alternative engines. The outcome is shown in Figure 12 panel (c). The horizon is compressed after 2017, as the timing of such dramatic reductions is highly uncertain. Implicitly, reduced dependence on natural gas to under 35 Mtoe p.a. (a 75% reduction) is required, potentially replaced by hydrogen as the UK used to burn (then made from coal gas) before the switch starting in 1969. With about a quarter of CO_2 emissions coming from agriculture, construction and waste (currently about 100 Mt p.a.) a serious effort to much more than halve those must also be entailed. Panel (d) records the resulting trajectory for CO_2 emissions, falling from around the 2015 level of 400 Mt p.a. to about 120 Mt p.a., or around 1.8 tonnes per capita p.a., down from 12.4 tonnes per capita p.a. in 1970. The point and interval 'forecasts' are at constant K and G, and assume the parameters of (6) remain constant despite the major shift. Increases in K and G would make the targets harder to achieve unless they were carbon neutral. However, given the key role of the capital stock in explaining the UK's CO_2 emissions since 1860, as K embodies the vintage of the technology at the time of its construction and is long lived, transition to zero carbon has to be gradual, and necessitates that new capital, and indeed infrastructure in general, must be zero carbon producing. As a 'policy' projection, together these measures would reach the UK's target for 2050 announced in 2008–but only if such reductions, perhaps with offsetting increases, could be achieved. In 2019, the UK Government amended the target to zero net emissions by 2050. Then all the sources must go to a level such that carbon capture and sequestration (CCS), possibly combined with atmospheric CO_2 extraction methods, would remove the rest. An excellent target, incredibly difficult to achieve, and as yet no sensible strategy to do so...

A probable reason for the sharp fall in coal use in 2017 is a rise in its price relative to those of other energy sources, with the UK carbon tax doubling in 2015 to £18 per tonne of CO_2. Conversely, natural gas use has increased 3.5 fold since the mid-1980s, so although producing less than half the CO_2 emissions of coal per Btu, still contributes about 140 Mt p.a. to CO_2 emissions. Natural gas is mainly used for electricity production and household indoor and water heating. The former could be handled in part by increased renewable sources, and the latter by households adopting solar panels and (e.g.) air heat pumps, as well as switching the gas system back to hydrogen. To meet the zero net target is demanding, and natural gas use would need to be reduced to near zero. Nevertheless, over the next 20–30 years with ever improved technologies, and consequential cost reductions in renewables electricity generation, a zero target does not seem impossible for electricity and gas without requiring reductions in UK GDP growth, perhaps even increasing it with opportunities arising from new technologies. However, air transport, agriculture, construction and waste management look more problematic, although some progress is occurring with electric cars and hydrogen driven trains in Germany and the UK (see https://www.birmingham.ac.uk/research/spotlights/hydrogen-powered-train.aspx).

The UK's total 'consumption induced' CO_2 equivalent emissions are higher than the domestic level through CO_2 embodied in net imports,[6] although the large reductions achieved to date have a major domestic component, and of course 'consumption induced' CO_2 will fall as the CO_2 intensity of imports falls with reductions in exporting countries. Unfortunately, targeting consumption emissions rather than production has the unwanted consequence of removing any incentives for emitting industries or exporting countries to improve their performance, as these would not be counted against them (e.g., if NDCs used a consumption basis). Border carbon taxes have a role to play in improving both exporters and importers performance. Similarly, allocating emissions from transport and packaging to (say) the food sector would again alleviate those intermediate sectors of the responsibility to invest to reduce what are in fact their emissions by attributing them to retail outlets or consumers. Conversely, the purchasing clout of large retail chains can pressure suppliers to improve, as (e.g.) Walmart is doing.[7]

The aggregate data provide little evidence of high costs to the reductions achieved in CO_2 emissions, which have dropped by 186Mt from 554Mt to 368Mt (34%) so far this century, during which period real GDP has risen by 35%, despite the 'Great Recession'. Historically, those in an industry that was being replaced (usually by machines) lose out and bear what should be the social costs of change, from cottage spinners, weavers and artisans in the late 18th–early 19th centuries (inducing 'Luddites'), to recent times (from a million coal miners in 1900 to almost none today). There is a huge difference in the impacts of substitutes and complements for existing methods: motor vehicles were a major advance, and created many new jobs directly and indirectly, mainly replacing horses but indirectly destroying their associated

[6] See http://www.emissions.leeds.ac.uk/chart1.html and https://www.biogeosciences.net/9/3247/2012/bg-9-3247-2012.html.

[7] See https://corporate.walmart.com/2016grr/enhancing-sustainability/reducing-energy-intensity-and-emissions.

workforce. Although not a direct implication of the aggregate model here, greater attention needs to be focused on the local costs of lost jobs as new technologies are implemented: mitigating inequality impacts of climate induced changes ought to matter centrally in policy decisions.

The rapidly falling costs of renewable-energy sources like solar cells and wind turbines (see e.g., Doyne Farmer and François Lafond, 2016), combined with improved storage methods should substantially reduce oil and gas use in electricity production. Table 5 records recent estimates of electricity generating costs in £/MWh by different technologies. Onshore wind turbines have fallen in cost and increased in efficiency so rapidly over the past two decades that for the UK at least they offer the lowest cost alternative, even below natural gas combined-cycle turbines before the costs of carbon capture and storage (CCS) are included. Solar photovoltaics come next (and this is the UK!) if CCS is enforced, though both require large backup electricity storage systems for (e.g.) windless nights.

Power generating technology| costs £/MWh	Low	Central	High
Nuclear PWR (Pressurized Water Reactor) (**a**)	82	93	121
Solar Large-scale PV (Photovoltaic)	71	80	94
Wind Onshore	**47**	**62**	76
Wind Offshore (**b**)	90	102	115
Biomass	85	87	88
Natural Gas Combined Cycle Gas Turbine	65	66	**68**
CCGT with CCS	102	110	123
Open-Cycle Gas Turbine	157	162	170
Advanced Supercritical Coal Oxy-comb. CCS	124	134	153
Coal IGCC with CCS (**c**)	137	148	171

Table 5: Electricity generating technology costs in £/MWh (megawatt hour). Lowest cost alternatives shown in bold. (**a**) New nuclear power guaranteed strike price of £92.50/MWh for Hinkley Point C in 2023; (**b**) Fell to £57.5MWh in late 2017. (**c**) IGCC = Integrated Gasification Combined Cycle. Source: *Electricity Generation Costs*, Department for Business, Energy and Industrial Strategy (BEIS), November 2016.

Increased outputs of renewable electricity will reduce the volume of emissions for a given level of energy production by also reducing usage of oil in transport through electric car use, but would not influence emissions conditional on the volumes of coal and oil included in the empirical models above. The use of oil in transport will take longer to reduce, but more efficient engines (with diesel being phased out completely given its toxic pollutants), and most vehicles powered from renewable sources, combined with much higher taxes on gasoline, offer a route to the next stage of CO_2 emissions reductions. Recently, the UK has banned new diesel and petrol cars from 2035. Facing an almost certain irreducible non-zero minimum demand for oil and gas, to achieve the Paris COP21 target of zero net emissions before 2050 requires really major technological change, almost certainly involving development of current research avenues into removing or using existing CO_2: see https://phys.org/news/2014-09-carbon.html.

Given the important role of the capital stock in the model above, 'stranded assets' in carbon producing industries are potentially problematic as future legislation imposes ever lower CO_2 emissions targets to achieve zero net emissions (see Pfeiffer *et al.*, 2016). As argued by Farmer, Hepburn, Matthew Ives and Thomas Hale *et al.* (2019) exploiting sensitive intervention points in the post-carbon transition could be highly effective, and they cite the UK's Climate Change Act of 2008 as a timely example that had a large effect.

An excellent 'role model' that offers hope for reductions in other energy uses is the dramatic increases in lumen-hours per capita consumed since 1300 (approximately 100,000 fold in the UK: see Roger Fouquet and Peter Pearson, 2006) yet at one twenty-thousandth the price per lumen-hour.

13 Climate-environmental Kuznets curve

The 'environmental Kuznets curve' is assumed to be a $\cap$ shaped relationship between pollution and economic development: see Susmita Dasgupta, Benoit Laplante, Hua Wang and David Wheeler (2002) and David Stern (2004). For a 'climate-environmental Kuznets curve', we estimated a regression of the log of CO_2 emissions, denoted e_t (lower case denotes logs) on the log of real GDP, g_t and its square g_t^2, which delivered:

$$\widehat{e}_t = -\underset{(1.6)}{31.5} + \underset{(0.27)}{6.13}\, g_t - \underset{(0.012)}{0.247}\, g_t^2 \tag{7}$$

$$\begin{gathered}\widehat{\sigma} = 0.091 \;\; \mathsf{R}^2 = 0.91 \;\; \mathsf{F}_{\mathsf{AR}}(2,145) = 37.3^{**} \;\; \mathsf{F}_{\mathsf{ARCH}}(1,148) = 0.26 \\ \mathsf{F}_{\mathsf{Het}}(3,146) = 1.70 \;\; \chi^2_{\mathsf{nd}}(2) = 68.3^{**} \;\; \mathsf{F}_{\mathsf{Reset}}(2,145) = 10.61^{**} \\ \mathsf{F}_{\mathsf{Chow}}(5,147) = 3.06^{*} \;\; \mathsf{F}_{\mathsf{nl}}(6,141) = 8.72^{**}\end{gathered}$$

Many of the diagnostic tests are significant, and both $\mathsf{F}_{\mathsf{reset}}$ and F_{nl} reveal that all of the non-linearity has not been captured by (7). Indeed, (7) has a borderline rejection on the parameter-constancy test, but the rejections on the other mis-specification tests makes that difficult to interpret. Full-sample impulse-indicator saturation (IIS) selected $\mathbf{17}$ indicators at a significance level of 0.1%, but still led to $\mathsf{F}_{\mathsf{nl}}(6,128) = 11.5^{**}$, and $\widehat{\sigma} = 0.055$.

The relationship between log CO_2 emissions and log real GDP is plotted in Figure 13. The large drop in CO_2 emissions while GDP more than doubled is notable, and reflects improved technology in energy use as well as a changing mix of fuels. Although the non-linearity is marked, there are large and systematic deviations from the fitted curve, shown inside ellipses for the start and end of the sample, 1921 & 1926, and the 1930s & 1940s.

Since the final model in (6) is linear in CO_2 emissions, and log-linear in GDP, a natural question is whether it can account for the non-linearity of the 'climate Kuznets curve' in Figure 13. This is answered in Figure 14 where the log of the fitted values from (6) are cross plotted against log(GDP) together with log(CO_2) data, to reveal the same non-linearity even though log(GDP) enters the equilibrium-correction mechanism in (5) linearly and is insignificant. The regression of log(CO_2) on the log of the fitted values from (6) had $\widehat{\sigma} = 0.019$. Of course that better explanation is greatly enhanced by using coal and oil, but conversely is after translation into logs.

Thus, the 'curvature' of an eventually declining relationship between log CO_2 emissions and log real GDP is an artefact of both being correlated with technology. Had electricity been discovered in 1300, batteries several decades later, rather than waiting for Volta in 1800, and solar cell technologies a few decades after that and so on, all of which depended on knowledge and understanding rather than income levels per se, an electrical world economy may have circumvented the need for coal. Conversely, if neither electricity nor the internal combustion engine had been discovered, leaving only coal as a fuel source, efficiency improvements or lower usage would have been the only routes to reductions in CO_2

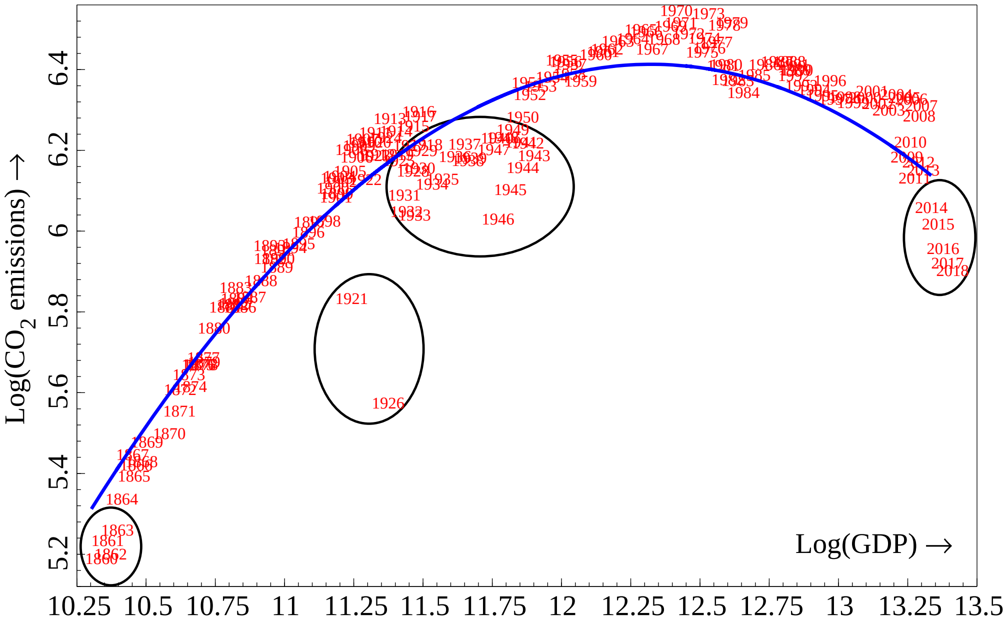

Figure 13: Scatter plot of log of CO_2 emissions against the log of GDP (shown by dates) with the fitted values from equation (7) (shown by the line).

emissions. Relative costs of energy provision matter, and Table 5 showed recent power generating costs, but the metaphor suggests a 'climate Kuznets curve' is mainly a technology-driven relation. Income levels may matter more for other environmental relations.

14 Conclusions on modelling UK CO_2 emissions

Having been first into the Industrial Revolution that has transformed the world's per capita incomes and wealth at the cost of climate change, the United Kingdom is one of the first out in terms of its CO_2 emissions. The UK's total CO_2 emissions have dropped below the level first reached in 1890, and in 2017 in per capita terms, are just 53% of that level, and below the level of 1860—when the UK was the 'workshop of the world'—despite per capita real incomes being more than 7-fold higher: major emissions reductions have not yet involved major *aggregate* sacrifices.[8]

The econometric approach to modelling such dramatic changes was explained in four steps. This was applied to develop a model of the observed CO_2 emissions data over 1860–2017 in terms of coal and oil usage, capital stock and GDP, taking account of their non-stationary nature, with many turbulent periods and major shifts over the 157 years. The key explanatory variables were coal usage and capital stock, with the estimated coefficients of coal and oil being close to their emissions factors. Renewable-generated electricity costs have fallen sharply, replacing carbon emitting methods. GDP had no long-run effect

[8]Carbon Brief (https://www.carbonbrief.org/) estimates that UK greenhouse gas emissions in 2016 were 42% below 1990 levels, but this estimate is much more uncertain than the CO_2-only figures.

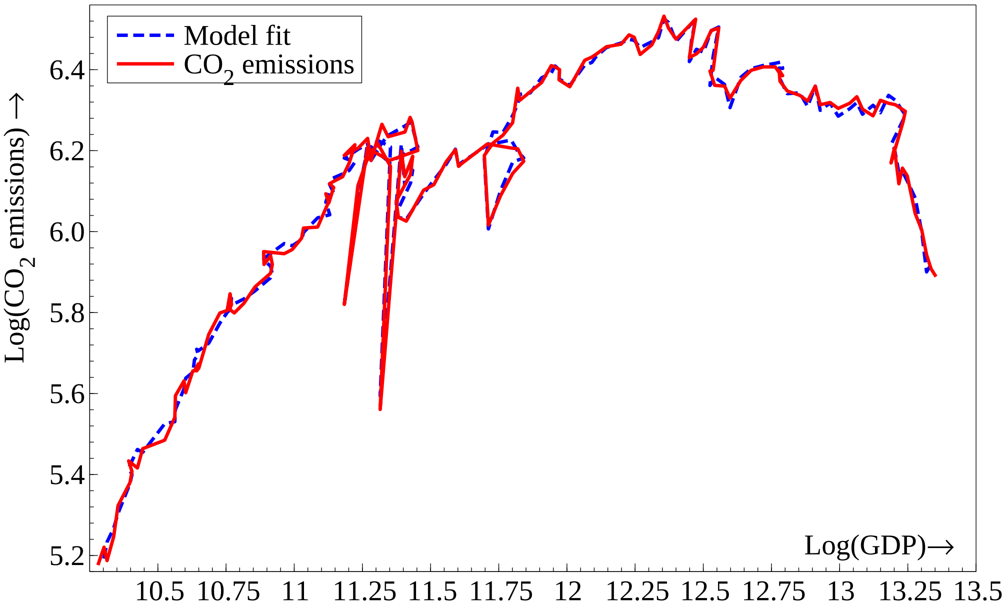

Figure 14: Plot of UK log(CO_2) emissions and log fitted values against log(GDP): re-creating a 'climate Kuznets Curve'.

given the other explanatory variables, probably reflecting an increased share of services, notwithstanding which, the model implies a non-linear 'climate Kuznets curve' between emissions and GDP. Compared to directly fitting a 'climate Kuznets curve' as in (7), the resulting model highlights the benefits of the more general methodology. Improvements in multi-step forecasts also highlighted the advantages of taking account of in-sample outliers and shifts using impulse- and step-indicator saturation, despite those creating more candidate variables to select over than observations.

The policy implications are that climate policy can be effective; that reducing CO_2 emissions to date has not had a large cost at the aggregate level, but local losses need to be addressed; that 'stranded assets' could be a potentially serious problem as legislation imposes even lower CO_2 emissions targets; that the UK's targets of an 100% reduction from the 1990 baseline of 590 Mt are only achievable with total elimination of coal, oil and gas use and in other emissions sources or increased re-absorption.

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