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Jennifer L. Castle
Institute for New Economic Thinking at the
Oxford Martin School and
Climate Econometrics at Nuffield College
University of Oxford
UK
jennifer.castle@magd.ox.ac.uk

David F. Hendry
Institute for New Economic Thinking at the
Oxford Martin School and
Climate Econometrics at Nuffield College
University of Oxford
UK
david.hendry@nuffield.ox.ac.uk

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Climate Econometrics: An Overview

Jennifer L. Castle[1] and David F. Hendry[2]

[1]*Institute for New Economic Thinking at the Oxford Martin School and Climate Econometrics at Nuffield College, University of Oxford, UK; jennifer.castle@magd.ox.ac.uk*
[2]*Institute for New Economic Thinking at the Oxford Martin School and Climate Econometrics at Nuffield College, University of Oxford, UK; david.hendry@nuffield.ox.ac.uk*

ABSTRACT

Climate econometrics is a new sub-discipline that has grown rapidly over the last few years. As greenhouse gas emissions like carbon dioxide (CO_2), nitrous oxide (N_2O) and methane (CH_4) are a major cause of climate change, and are generated by human activity, it is not surprising that the tool set designed to empirically investigate economic outcomes should be applicable to studying many empirical aspects of climate change.

Economic and climate time series exhibit many commonalities. Both data are subject to non-stationarities in the form of evolving stochastic trends and sudden distributional shifts. Consequently, the well-developed machinery for modeling economic time series can be fruitfully applied to climate data. In both disciplines, we have imperfect and incomplete knowledge of the processes actually generating the data. As we don't know that data generating process (DGP), we must search for what we hope is a close approximation to it.

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The data modeling approach adopted at Climate Econometrics (http://www.climateeconometrics.org/) is based on a model selection methodology that has excellent properties for locating an unknown DGP nested within a large set of possible explanations, including dynamics, outliers, shifts, and non-linearities. The software we use is a variant of machine learning which implements multi-path block searches commencing from very general specifications to discover a well-specified and undominated model of the processes under analysis. To do so requires implementing indicator saturation estimators designed to match the problem faced, such as impulse indicators for outliers, step indicators for location shifts, trend indicators for trend breaks, multiplicative indicators for parameter changes, and indicators specifically designed for more complex phenomena that have a common reaction 'shape' like the impacts of volcanic eruptions on temperature reconstructions. We also use combinations of these, inevitably entailing settings with more candidate variables than observations.

Having described these econometric tools, we take a brief excursion into climate science to provide the background to the later applications. By noting the Earth's available atmosphere and water resources, we establish that humanity really can alter the climate, and is doing so in myriad ways. Then we relate past climate changes to the 'great extinctions' seen in the geological record. Following the Industrial Revolution in the mid-18th century, building on earlier advances in scientific, technological and medical knowledge, real income levels per capita have risen dramatically globally, many killer diseases have been tamed, and human longevity has approximately doubled. However, such beneficial developments have led to a global explosion in anthropogenic emissions of greenhouse gases. These are also subject to many relatively sudden shifts from major wars, crises, resource discoveries, technology and policy interventions. Consequently, stochastic trends, large shifts and numerous outliers must all be handled in practice to develop viable empirical models of climate phenomena. Additional advantages of our econometric methods for doing so are detecting the impacts of important policy interventions as well as improved forecasts. The econometric approach we outline can handle all these jointly, which is essential to accurately characterize non-stationary observational data. Few approaches in either climate or economic modeling consider all such effects jointly, but a failure to do so leads to mis-specified models and hence incorrect theory evaluation and policy analyses. We discuss the hazards of modeling wide-sense non-stationary data (namely data not just with stochastic trends but also distributional shifts), which also serves to describe our notation.

The application of the methods is illustrated by two detailed modeling exercises. The first investigates the causal role of CO_2 in Ice Ages, where a simultaneous-equations system is developed to characterize land ice volume, temperature and atmospheric CO_2 levels as non-linear functions of measures of the Earth's orbital path round the Sun. The second turns to analyze the United Kingdom's highly non-stationary annual CO_2 emissions over the last 150 years, walking through all the key modeling stages. As the first country into the Industrial Revolution, the UK is one of the first countries out, with per capita annual CO_2 emissions now below 1860's levels when our data series begin, a reduction achieved with little aggregate cost. However, very large decreases in all greenhouse gas emissions are still required to meet the UK's 2050 target set by its Climate Change Act in 2008 of an 80% reduction from 1970 levels, since reduced to a net zero target by that date, as required globally to stabilize temperatures. The rapidly decreasing costs of renewable energy

technologies offer hope of further rapid emission reductions in that area, illustrated by a dynamic scenario analysis.

Keywords: climate econometrics; model selection; policy interventions; outliers; saturation estimation; *Autometrics*; Ice Ages; CO_2 emissions.

1

Introduction

Climate econometrics is a sub-discipline that has grown rapidly over the last few years, having held four annual international conferences (at Aarhus, Oxford, Rome and Milan) and with a global network.[1] A Special Issue of the *Journal of Econometrics* (https://www.sciencedirect.com/journal/journal-of-econometrics/vol/214/issue/1) has 14 contributions across a wide range of climate issues, and a second in *Econometrics* (https://www.mdpi.com/journal/econometrics/special_issues/econometric_climate) is in preparation. Because greenhouse gas emissions like carbon dioxide (CO_2), nitrous oxide (N_2O) and methane (CH_4) are the major cause of climate change, and are generated by human activity, it is not surprising that the tool set originally designed to empirically investigate economic outcomes should be applicable to studying many empirical aspects of climate change. Most climate-change analysis is based on physical process models embodying the many known laws of conservation and energy balance at a global level. Such results underpin the various reports from the Intergovernmental Panel on Climate Change (IPCC: https://www.ipcc.ch/). Climate theories can also be

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[1] See https://www.jiscmail.ac.uk/cgi-bin/webadmin?A0=climateeconometrics: its planned 5th Econometric Models of Climate Change Conference at the University of Victoria has had to be postponed till 2021 because of the SARS-CoV-2 pandemic.

embedded in models of the kind familiar from macroeconomics: for example, Kaufmann *et al.* (2013) link physical models with statistical ones having a stochastic trend, and Pretis (2019) establishes an equivalence between two-component (i.e., atmosphere and oceans) energy-balance models of the climate and a cointegrated vector autoregressive system (CVAR). Even in such a well-understood science, knowledge is not complete and immutable, and there are empirical aspects that need attention. For example, CO_2 and other greenhouse gas emissions depend on changeable human behavior; volcanic eruptions vary greatly in their climate impacts; the rate of loss of Arctic sea ice alters the Earth's albedo and such feedbacks affect warming.

Our approaches at Climate Econometrics (our research group, shown capitalized to differentiate it from the general research area) are complementary to physical process models, and use a powerful set of modeling tools developed to analyze empirical evidence on evolving processes that are also subject to abrupt shifts, called *wide-sense non-stationarity* to distinguish from the use of 'non-stationarity' purely for unit-root processes that generate stochastic trends: see Castle and Hendry (2019). A key reason is that differencing a wide-sense non-stationary time series does **not** ensure stationarity as is often incorrectly assumed in economics. Because the data are wide-sense non-stationary time series observations, the data generating process (DGP) is inevitably unknown and has to be discovered. The model selection methodology described below has excellent properties for locating an unknown DGP when it is embedded within a large set of potential explanations. Thus, we advocate commencing from a general specification that also includes variables to allow for dynamics, outliers, shifts, and non-linearities. We use a variant of machine learning called *Autometrics* that explores multi-path block searches to discover a well-specified and undominated model of the processes under analysis (see Doornik, 2009). Hendry and Doornik (2014) analyze the properties of *Autometrics*: also see §2.3.[2] The approach is available in R by Pretis *et al.* (2018a) at https://cran.r-project.org/web/packages/gets/index.html, and as the

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[2] For summaries, see http://voxeu.org/article/data-mining-more-variables-observations and https://voxeu.org/article/improved-approach-empirical-modelling-0.

Excel Add-in *XLModeler* (see https://www.xlmodeler.com/). Other model selection algorithms include the Lasso (see Tibshirani, 1996) and its variants.

Our methods are designed to select models even when there are more candidate variables, N, than the number of observations, T. *Autometrics* employs a variety of saturation estimators that inevitably create $N > T$. Each is designed to match the problem faced, namely impulse-indicator saturation (denoted IIS) to tackle outliers, step-indicator saturation (SIS) for location shifts, trend-indicator saturation (TIS) for trend breaks, multiplicative-indicator saturation (MIS) for parameter changes, and designed-indicator saturation for modeling phenomena with a regular pattern, applied below to detecting the impacts on temperature of volcanic eruptions (VIS). Importantly, saturation estimators can be used in combination, and can be applied when retaining without selection a theory-model that is the objective of a study, while selecting from other potentially substantive variables. Saturation estimators, and indeed our general approaches, have seen applications across a range of disciplines including dendrochronology, volcanology, geophysics, climatology, and health management, as well as economics, other social sciences and forecasting. Although theory models are much better in many of these areas than in economics and other social sciences, modeling observational data faces most of the same problems, which is why an econometric toolkit can help.

Below, we explain our econometric methods and illustrate some of their applications to climate time series. The first illustration investigates past climate variability over the Ice Ages, where a simultaneous-equations system is developed to characterize land ice volume, Antarctic temperature and atmospheric CO_2 levels as non-linear functions of measures of the Earth's evolving orbital path round the Sun. The focus is on system modeling and how we implement that despite $N > T$, as well as the difference in how saturation estimation is applied in systems. Few economists will ever have the opportunity to consider multi-step forecasts over 100,000 years as we do here! The second illustration is a detailed study of the UK's CO_2 emission over 1860–2017 that walks through the various stages of formulation, model specification, selection while tackling outliers and location shifts, then investigating cointegration, and on to model simplification for forecasting and policy analyses. A key aim is establishing the possible impacts of past policy interventions though we also discuss possible future developments.

As Pretis (2019) remarks

> Econometric studies beyond IAMs (integrated assessment models) are split into two strands: one side empirically models the impact of climate on the economy, taking climate variation as given . . . the other side models the impact of anthropogenic (e.g., economic) activity onto the climate by taking radiative forcing—the incoming energy from emitted radiatively active gases such as CO_2—as given . . . . This split in the literature is a concern as each strand considers conditional models, while feedback between the economy and climate likely runs in both directions.

Examples of approaches conditioning on climate variables such as temperature include Burke *et al.* (2015), Pretis *et al.* (2018b), Burke *et al.* (2018), and Davis (2019). Hsiang (2016) reviews such approaches to climate econometrics. Examples from many studies modeling climate time series include Estrada *et al.* (2013), Kaufmann *et al.* (2011, 2013) and Pretis and Hendry (2013). Pretis (2017) addresses the exogeneity issue in more detail. Most of the research described in this monograph concerns the second approach, although the methods are applicable both to the first and to investigating exogeneity as shown in Section 6. The resulting econometric tools also contrast with the methodology predominantly used in the first approach of a quasi-experimental framework using panel regressions under the assumption of strict exogeneity of climate variables.

The structure of the monograph is as follows. First, Section 2 describes econometric methods for empirical climate modeling that can account for wide-sense non-stationarity, namely both stochastic trends and location shifts, with possibly large outliers, as well as dynamics and non-linearities. Model selection is essential as the behavioral processes determining greenhouse gas emissions are too complicated to be known a priori. A basic question then concerns what is model selection trying to find? This is answered in §2.1 on the roles therein of theory models and DGPs by trying to find the latter, or at least a good approximation to its substantive components. §2.2 first discusses the formulation of models for wide-sense non-stationary time series, then §2.3 describes model selection by *Autometrics* and §2.4 explains its block multi-path selection algorithm. Next, §2.5 turns to understanding why automatic model selection can work well despite $N > T$. Saturation estimators are described in §2.6, commencing with impulse-indicator saturation (IIS) to tackle outliers. IIS is illustrated in §2.6.1, and its properties are described in §2.6.2. Then §2.6.3 considers step-indicator saturation (SIS), §2.6.4 the extension to super saturation estimation combining IIS and SIS, §2.6.5 explains a variant to handle trend saturation estimation (TIS), followed in §2.6.6 by multiplicative-indicator saturation (MIS) which interacts SIS with regressors for detecting parameter changes. Then §2.6.7 illustrates designed-indicator saturation by formulating indicators for modeling the impacts of volcanic eruptions on temperature reconstructions (VIS). §2.7 summarizes the various saturation estimators. §2.8 considers selection, estimation and evaluation of simultaneous equations models, addressing identification in §2.8.1. Facing forecasting in a wide-sense non-stationary world, §2.9 discusses the consequences of not handling location shifts and describes forecasting devices that are more robust after shifts than 'conventional' forecasting models.

Section 3 considers hazards confronting empirical modeling of non-stationary time-series data using an example where a counter-intuitive finding is hard to resolve. The framework has a clear subject-matter theory, so is not mere 'data mining', yet the empirical result flatly contradicts the well-based theory. §3.1 considers whether assessing the constancy and invariance of the relationship can reveal the source of the difficulty, but does not. An encompassing evaluation of the relationship in §3.2 fortunately does.

Section 4 provides a brief excursion into climate science, mainly concerned with the composition of the Earth's atmosphere and the role of CO_2 as a greenhouse gas. §4.1 considers whether humanity can alter the planet's atmosphere and oceans, and demonstrates we can—and are. §4.2 discusses the consequences of changes in the composition of the atmosphere, focusing on the impacts of climate change on 'great extinctions' over geological time.

Section 5 considers the consequences, both good and bad, of the Industrial Revolution raising living standards beyond the wildest dreams of those living in the 17th century, but leading to dangerous levels of CO_2 emissions from using fossil fuels.

Against that background, we consider applications of climate econometrics. Section 6 illustrates the approach by modeling past climate variability over the Ice Ages. §6.1 describes the data series over the past 800,000 years, then §6.2 models ice volume, CO_2 and temperature as jointly endogenous in a 3-variable system as a function of variations in the Earth's orbit, taking account of dynamics, non-linear interactions and outliers using full information maximum likelihood. The general model is formulated in §6.2.1, and the simultaneous system estimates are discussed in §6.2.2. Their long-run implications are described in §6.3 with one hundred 1000-year 1-step and dynamic forecasts in §6.3.1. Then, §6.3.2 considers when humanity might have begun to influence climate, and discusses the potential exogeneity of CO_2 to identify its role during Ice Ages. §6.4 looks 100,000 years into the future using the fact that the eccentricity, obliquity and precession of Earth's orbital path is calculable far into the future, to explore the implications for the planet's temperature of atmospheric CO_2 being determined by humans at levels far above those experienced during Ice Ages. Finally, §6.5 summarizes the conclusions on Ice-Age modeling.

Section 7 models UK annual CO_2 emissions over 1860–2017 to walk through the stages of modeling empirical time series that manifest all the problems of wide-sense non-stationarity. §7.1 provides data definitions and sources, then §7.2 discusses the time-series data. §7.3 formulates the econometric model, then §7.4 highlights the inadequacy of simple model specifications. The four stages of model selection from an initial general model are described in §7.5, then implemented in §7.6–§7.8. §7.9 conducts an encompassing test of the linear-semilog model against a linear-linear one. §7.10 presents conditional 1-step 'forecasts' and multi-step forecasts from a VAR. §7.11 addresses the policy implications of the empirical analysis, then §7.12 considers whether the UK can reach its 2008 Climate Change Act (CCA) CO_2 emissions targets for 2050. Finally, §7.13 estimates a 'climate-environmental Kuznets curve'.

Section 8 concludes and summarizes a number of other empirical applications.

To emphasize the different and interacting forms of non-stationarity, Figure 1.1 records time series from climate and economic data. Panel (a) shows the varying trends in global monthly atmospheric CO_2 concentrations in ppm measured at Mauna Loa over 1958(1)–2019(6); Panel (b) records the dramatically non-stationary UK per capita CO_2 emissions, with up and down trends, outliers and shifts; Panel (c) reports the log of UK GDP, again with changing trends and large shifts; and (d) plots the log of the UK wage share, with large shifts and outliers.

The lockdowns round the world in response to SARS-CoV-2 will doubtless cause a sharp drop in global CO_2 emissions in early 2020 needing modeled. The indicator saturation estimators described in Section 2 are designed to tackle such multiple shifts of unknown magnitudes and directions at unknown dates as countries gradually bring their pandemics under sufficient control to 'restart' their economies.

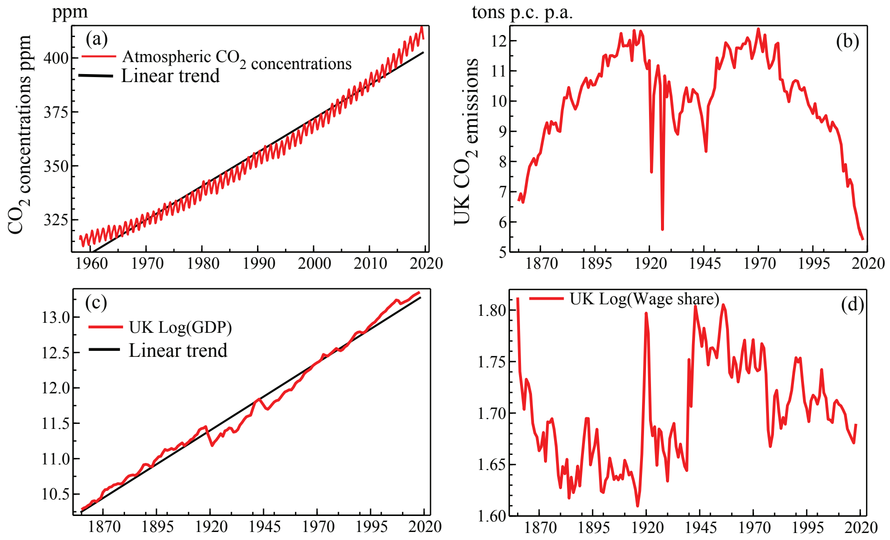

Figure 1.1: (a) Global monthly atmospheric CO_2 concentrations in parts per million (ppm) measured at Mauna Loa, 1958(1)–2019(6); (b) UK CO_2 emissions in tons per capita per annum; (c) the log of UK GDP; (d) log of the UK wage share. (b)–(d) are all annual over 1860–2018.

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