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Introduction

Abstract The evolution of life on Earth—a tale of both slow and abrupt changes over time—emphasizes that change is pervasive and ever present. Change affects all disciplines using observational data, especially time series of observations. When the dates of events matter, so data are not ahistorical, they are called non-stationary denoting that some key properties like their means and variances change over time. There are several sources of non-stationarity and they have different implications for modelling and forecasting. This Chapter introduces the structure of our book which will explore how to model such observational data on an ever-changing world.

Keywords Change · Observational data · Stationarity · Non-stationarity · Forecast failure

Earth has undergone many remarkable events in its 4.5 billion years, from early forms of life through the evolution and extermination of enormous numbers of species, to the present day diversity of life. It has witnessed movements of continents, impacts from outer space, massive volcanism, and experienced changing climates from tropical through ice ages, and recent changes due to anthropogenic interventions following the devel-

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opment of homo sapiens, especially since the industrial revolution. The world is ever changing, both slowly over time and due to sudden shocks. This book explores how we can model observational data on such a world.

Many disciplines within the sciences and social sciences are confronted with data whose properties change over time. While at first sight, modelling volcanic eruptions, carbon dioxide emissions, sea levels, global temperatures, unemployment rates, wage inflation, or population growth seem to face very different problems, they share many commonalities. Measurements of such varied phenomena come in the form of time-series data. When observations on a given phenomenon, say CO_2 emissions, population growth or unemployment, come from a process whose properties remain constant over time—for example, having the same mean (average value) and variance (movements around that mean) at all points in time—they are said to be *stationary*. This is a technical use of that word, and does not entail 'unmoving' as in a traffic jam. Rather, such time series look essentially the same over different time intervals: indeed, a stationary time series is ahistoric in that the precise dates of observations should not matter greatly. However, almost all social, political, economic and environmental systems are non-stationary, with means, variances and other features, such as correlations between variables, changing over time. In the real world, whether an event under consideration happened in 1914, 1929, 1945 or 2008 usually matters, a clear sign that the data are *non-stationary*.

Much of economic analysis concerns equilibrium states although we all know that economies are buffeted by many more forces than those contained in such analyses. Sudden political changes, financial and oil crises, evolution of social mores, technological advances, wars and natural catastrophes all impinge on economic outcomes, yet are rarely part of theoretical economic analyses. Moreover, the intermittent but all too frequent occurrence of such events reveals that disequilibrium is the more natural state of economies. Indeed, forecast failures—where forecasts go badly wrong relative to their expected accuracy—reveal that such non-stationarities do happen, and have adverse effects both on economies and on the verisimilitude of empirical economic models. Castle et al. (2019) provide an introduction to forecasting models and methods and the properties of the resulting forecasts, explaining why forecasting mishaps are so common.

To set the scene, the book begins with a series of primers on non-stationary time-series data and their implications for empirical model selection. Two different sources of non-stationarity are delineated, the first coming from evolutionary changes and the second from abrupt, often unanticipated, shifts. Failing to account for either can produce misleading inferences, leading to models that do not adequately characterise the available evidence. We then go on to explore how features of non-stationary time-series data can be modelled, utilising both well-established and recent innovative techniques. Some of the proposed new techniques may surprise many readers. The solution is to include more variables than you have observations for, which is important to capture the ever changing nature of the data. Nevertheless, both theoretical analyses and computer simulations confirm that the approach is not only viable, but has excellent properties.

Various examples from different disciplines demonstrate not only the difficulties of working with such data, but also some advantages. We will gain insights into a range of phenomena by carefully modelling change in its many forms. The examples considered include the underlying causes and consequences of climate change, macroeconomic performance, various social phenomena and even detecting the impacts of volcanic eruptions on temperatures. However, valuable insights from theoretical subject-matter analyses must also be retained in an efficient approach and again recent developments can facilitate doing so. Forecasting will inevitably be hazardous in an ever-changing world, but we consider some ways in which systematic failure can be partly mitigated.

The structure of the book is as follows. In Chapter 2, primers outline the key concepts of time series, non-stationarity, structural breaks and model selection. Chapter 3 explores some explanations for change and briefly reviews the history of time-series modelling. Chapter 4 looks at how to use the ever changing data to your advantage: non-stationarity in some form is invaluable for identifying causal relationships and conducting policy. Chapter 5 shows how various forms of break can be detected and hence modelled. Chapter 6 examines an empirical example of combining theory and data to improve inference. Chapter 7 looks at forecasting non-stationary time series, with hints on how to handle structural breaks over the forecast horizon, and finally Chapter 8 concludes.

Reference

Castle, J. L., Clements, M. P., and Hendry, D. F. (2019). *Forecasting: An Essential Introduction*. New Haven, CT: Yale University Press.