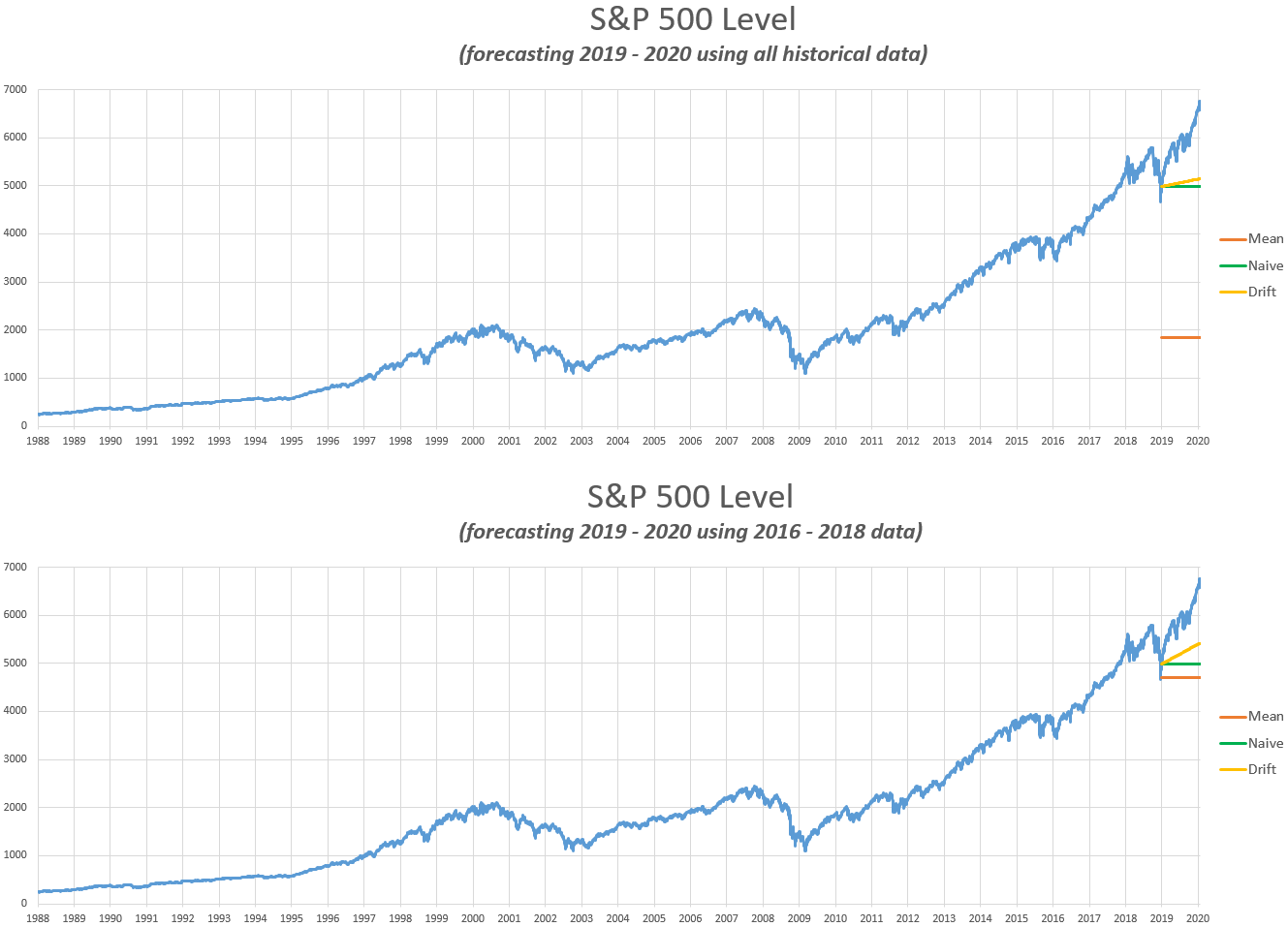
**Chapter 3 – The Forecaster’s Toolbox**

§3.1 Some Simple Forecasting Methods

Some forecasting methods are very simple and surprisingly effective. These simple methods include:

1. Mean
2. Naïve
3. Seasonal Naïve
4. Drift

**Figure 1** The mean, naïve, and drift methods used to forecast the S&P 500 level for differing historical data timeframes.

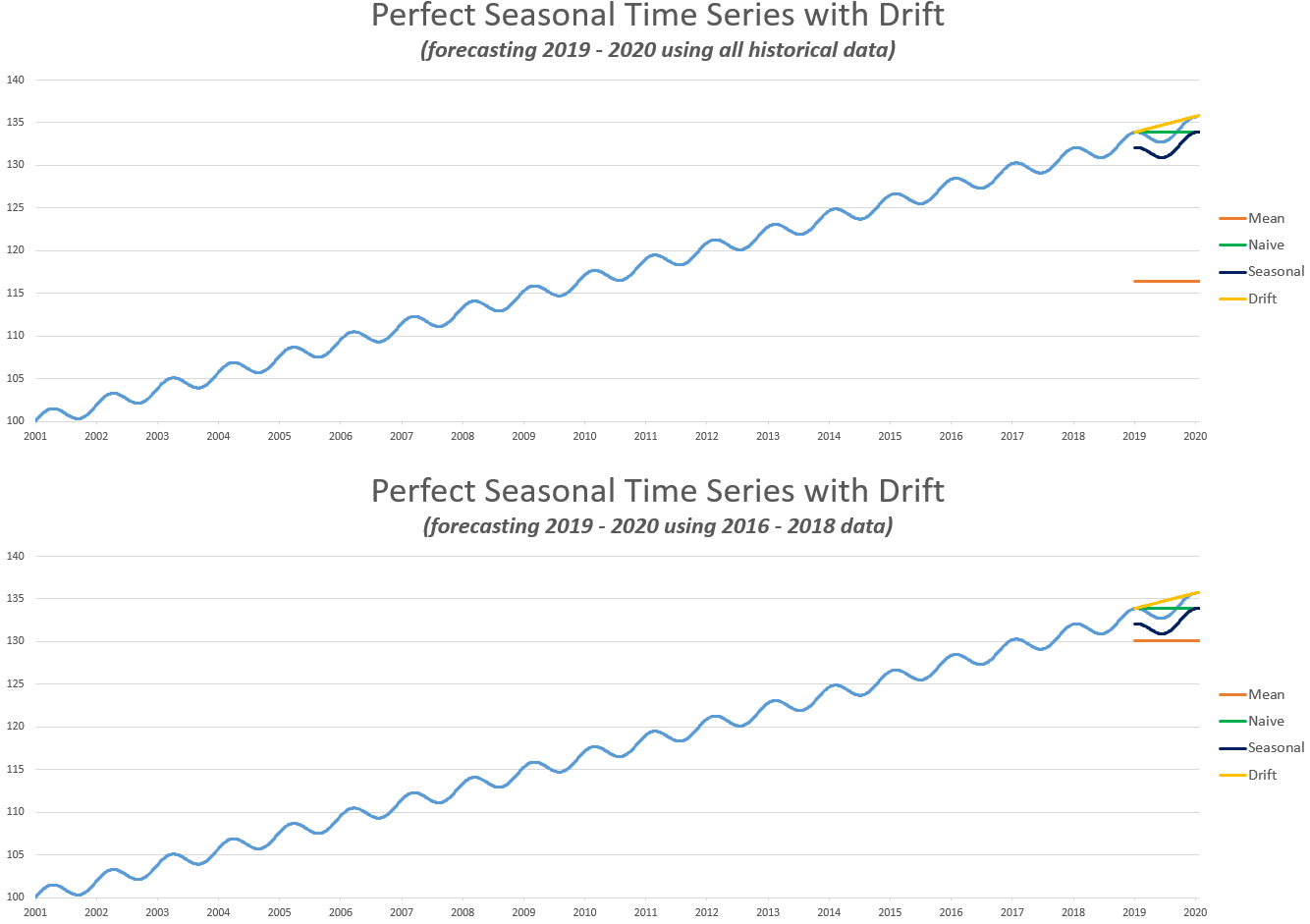
The naïve method works remarkably well for many economic and financial time series because it is the optimal method when data follow a random walk. This is why the naïve method is also referred to as the random walk forecast.

The seasonal naïve method (seasonal method), equation looks more complicated than it really is. For example, with monthly data, the forecast for all future February values is equal to the last observed February value. Similarly, with quarterly data, all future Q1 values is equal to the last observed Q1 value.

The drift method is equivalent to drawing a line between the first and last observation and then extrapolating that line into the future.

In many cases, these simple methods will serve as benchmarks rather than the actual implemented method. This is a critical concept because any new method we develop will be compared to these simple methods. If the new method does not perform better than these simple methods then it will be discarded and the forecaster has to start at square one.

**Figure 2** The mean, naïve, seasonal naïve, and drift methods used to forecast a perfectly seasonal time series with drift for differing historical data timeframes.



§3.2 Transformations and Adjustments

Adjusting historical data can often lead to a simpler forecasting task and this in turn can lead to more accurate forecasts. There are four primary kinds of adjustments:

1. Calendar – removes variation due to simple calendar effects. For example, using average monthly data instead of cumulative monthly data eliminates the variation stemming from differing days in each month.
2. Population – for most data that are affected by population changes, it is best to use per-capita data (per thousand people or per million people) rather than the totals.
3. Inflation – data affected by the value of money is best adjusted for changes in the value of money. For example, instead of using nominal house prices, house prices may be stated in base year dollars. To do this a *relevant* price index is required. In the context of house prices, the core rate of inflation (excludes food and energy components) is a good barometer for inflation relevant to the housing market.
4. Mathematical Transformations

The purpose of these adjustments is to simplify patterns in the historical data by removing know sources of variation or by making the pattern more consistent across the whole data set.

*Programmatic Note: find the Python equivalent of the R function monthdays()*

df