Vienna 2019 Abstract Submission

Title
Future trends in global beer wine and spirits consumption

I want to submit an abstract for:
Conference Poster Session

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Keywords
Alcohol consumption, forecasting

Research Question
To forecast future per capita beer, wine, and spirits consumption by country for all major global markets

Methods
Forecasts are derived from bayesian structural time series models and ARIMA models using country level data from 1961 to 2017

Results
Description of market size, by country, for beer wine and spirits consumption in 2017 and 2027

Abstract
The alcoholic beverage market is large. For example, in 2016, expenditure on alcoholic beverages in the 50 largests markets was $US 1,338,819 million.

In this research country level per capita alcohol consumption data will be used to investigate trends in consumption patterns and forecast future consumption trends.

Forecasts from ARIMA models are compared to forecasts from bayesian structural time series models, and reasons for the different estimates of future consumption are explored.

In terms of understanding the steps involved in developing forecasts using the ARIMA methodology it can be easier to think of using a two-step process.

The first step is to determine the order of integration, and the second step is to determine the appropriate number of moving average (MA) and autoregressive (AR) parameters to use.

A structural time series model is defined by two equations. The observation equation relates the observed data yt to a vector of latent variables αt known as the "state."

The transition equation describes how the latent state evolves through time.
The error terms ϵt and ηt are Gaussian and independent of everything else. The model may contain parameters in the statistical sense, but often they simply contain strategically placed 0's and 1's indicating which bits of αt are relevant for a particular computation.

The simplest useful model is the "local level model," in which the vector αt is just a scalar μt . The local level model is a random walk observed in noise.

Structural time series models are useful because they are flexible and modular. The analyst chooses the structure of αt based on things like whether short or long term predictions are more important, whether the data contains seasonal effects, and whether and how regressors are to be included.

The problem with the the local level model is that as the state evolves according to a random walk the variance increase to infinity for long term forecasts. An alternative is to replace the random walk with a stationary AR process. This means that uncertainty grows to a finite asymptote, rather than infinity, in the distant future. The asymptote is a function of the AR parameter value.

A hybrid model modifies the local level model by replacing the random walk on the slope with a stationary AR(1) process, while keeping the random walk for the level of the process. Such a model allows short term autoregressive deviations from the long term trend, with memory determined by ρ . Values of ρ close to 1 will lead to sustained deviations from trend.

So that the trends in alcohol consumption patterns can be understood, beer, wine, and spirit consumption data will be displayed via a series of ternery plots. In a ternary plot the size of the point can be used to represent the total level of consumption and the location of the dot provides information on the relative importance of each beverage type.

Density plots of forecasts at a point in time, and timeseies plots comparing alternate future forecasts are also used.

To complement the visual analysis using a range of formal metrics, for example the coefficient of variation (standard deviation divided by mean), and the similarity index introduced in Anderson (2014).

To describe the changes in consumption patterns, the level of consumption will be compared at 10-year intervals. All pair-wise comparisons of consumption changes will rely on Bayesian estimation methods. The specific approach used will follow the approach outlined in Kruschke (2013).

To create country level consumption time series data available in Anderson and Pinilla
(2017) is merged with data from the Euromonitor database.

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