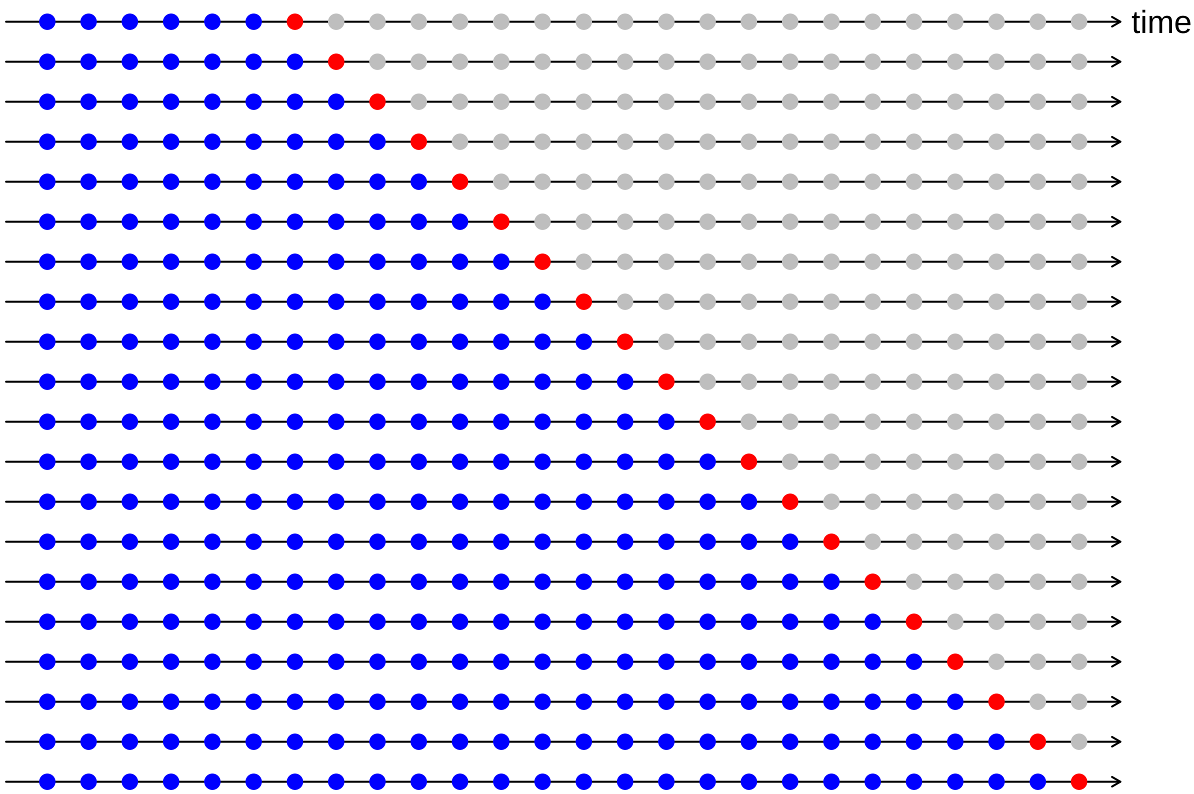
Verhuisfrequenties voorspellen

trond

Contents

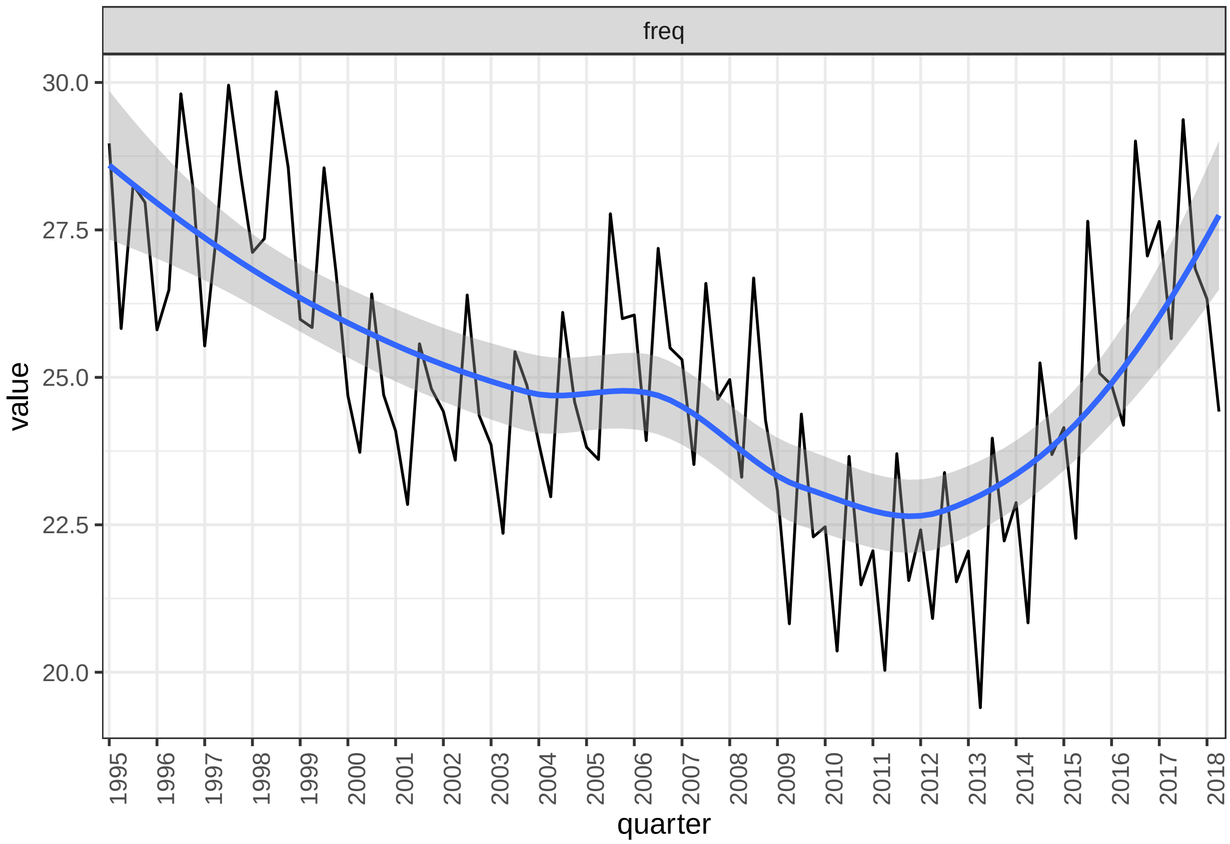


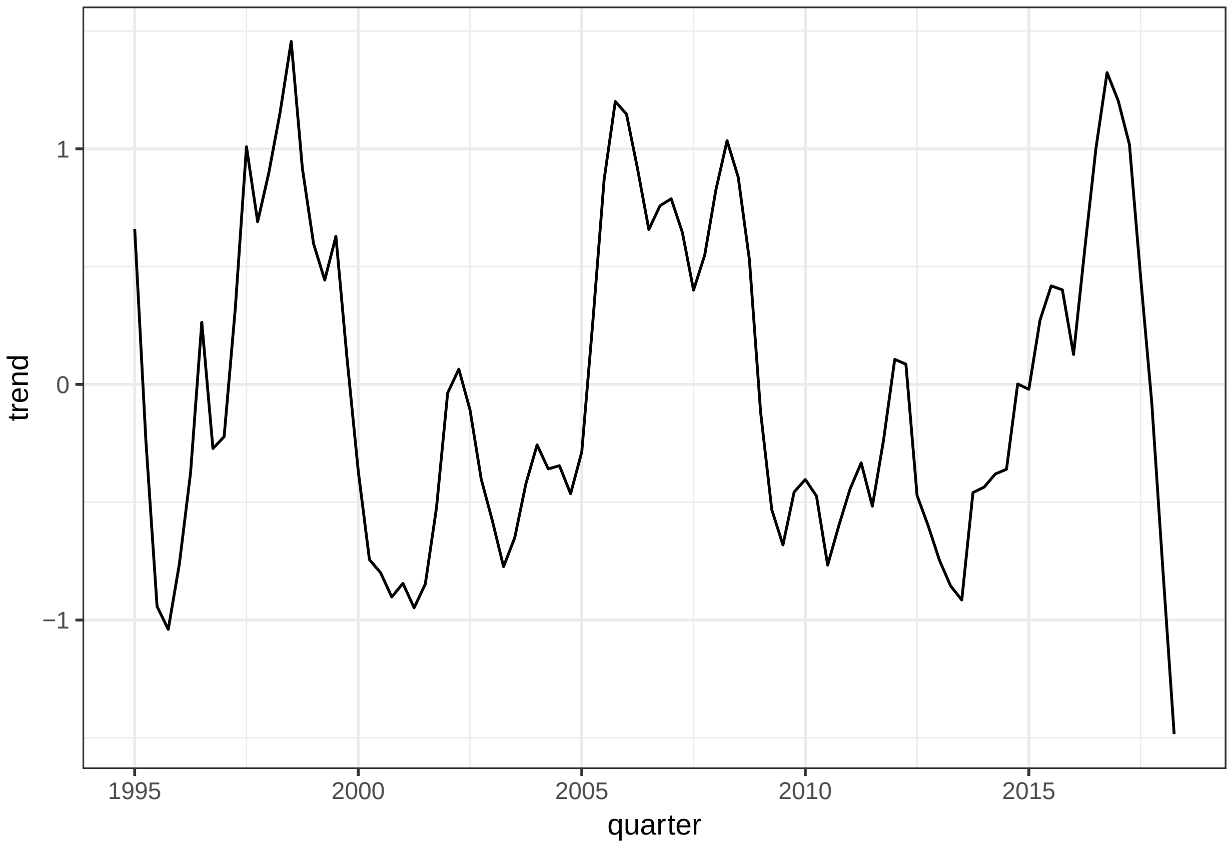
1 Introduction

Long-term projections of migration are key inputs to regional-level demographic population forecasts. Such long-term projections usually do not take the business cycle into account; instead techniques are employed that treat the business cycle as noise, effectively filtering it out. However, it is occassionally useful to analyse the short- to medium dynamics of demographic components, forecasting along the business cycle. This paper develops several state space models for short-to medium term forecasts of quarterly frequency of mobility.

The frequency of mobility, defined as the sum of intra- and inter-municipal moves per 1000 inhabitans, is generally the main driver of population change on a regional level. The interaction with housing market dynamics that knowledge about regional mobility is interesting also outside Spatial demography.

- ARIMA models, often used for long-term forecasts, are highly influenced by the last observations in the data on which they are estimated: a long-term forecast made at the peak of a business cycle may give misleading results.
- A short- to medium term analysis of the business cycle is one way of ameliorating this problem. Such an analysis often entails decomposing the time series into elements such as trend, cycle and seasonality, subsequently forecasting each element separately. Bayesian estimation.
- An important advantage of state space models is modularity: a basic model can easily be extended with other components, and different models can be compared by analysing their fit with the data. This paper develops four state space models for a two-year forecast of the frequency of mobility. Our data is quarterly, covering the period 1995 (first quarter) to 2018 (second quarter).





2 Models

2.1 Local level

$$
\begin{aligned}
y_t &= \mu_t + gamma_{1,t} + \epsilon_t & \epsilon_t &\sim N(0, \sigma^2_\epsilon) \\
\mu_t &= \mu_{t-1} + \eta_{t-1} & \eta_t &\sim N(0, \sigma^2_\eta) \\
\gamma_{1,t} &= -\gamma_{1,t-1} - \gamma_{2,t-1} - \gamma_{3,t-1} + \omega_t & \omega_t &\sim N(0, \sigma^2_\omega) \\
\gamma_{2,t} &= \gamma_{1,t-1} \\
\gamma_{3,t} &= \gamma_{2,t-1}
\end{aligned}
$$

2.2 Local trend

$$
\begin{aligned}
y_t &= \mu_t + \nu_t + gamma_{1,t} + \epsilon_t & \epsilon_t &\sim N(0, \sigma^2_\epsilon) \\
\mu_t &= \mu_{t-1} + \eta_t & \eta_t &\sim N(0, \sigma^2_\eta) \\
\gamma_{1,t} &= -\gamma_{1,t-1} - \gamma_{2,t-1} - \gamma_{3,t-1} + \omega_t & \omega_t &\sim N(0, \sigma^2_\omega) \\
\nu_t &= \nu_{t-1} + \zeta_{t-1} & \zeta_t &\sim N(0, \sigma^2_\zeta)
\end{aligned}
$$

2.3 Local trend and fourier seasonality

$$\begin{aligned}
y_t &= \mu_t + \nu_t + c_t + \epsilon_t & \epsilon_t &\sim N(0, \sigma^2_\epsilon) \\
\mu_t &= \mu_{t-1} + \eta_t & \eta_t &\sim N(0, \sigma^2_\eta) \\
\nu_t &= \nu_{t-1} + \zeta_t & \zeta_t &\sim N(0, \sigma^2_\zeta) \\
c_t &= \rho[\cos(\lambda_c)c_{t-1} + sin(\lambda_c)c^*_{t-1}] + \kappa_t & \kappa_t &\sim N(0, \sigma^2_c(1-\rho^2)) \\
c^*_t &= \rho[-\sin(\lambda_c)c_{t-1} + \cos(\lambda_c)c^*_{t-1}] & \kappa^*_t &\sim N(0, \sigma^2_c(1-\rho^2))
\end{aligned}$$

2.4 Local trend and AR(2)

$$\begin{aligned}
y_t &= \mu_t + \nu_t + \gamma_{1,t} + \epsilon_t & \epsilon_t &\sim N(0, \sigma^2_\epsilon) \\
\mu_t &= \phi_1\mu_{t-1} + \phi_2\mu_{t-2} + \varepsilon_t & \varepsilon_t &\sim N(0, \sigma^2_\varepsilon) \\
\gamma_{1,t+1} &= -\gamma_{1,t} - \gamma_{2,t} - \gamma_{3,t} + \omega_t & \omega_t &\sim N(0, \sigma^2_\omega) \\
\nu_{t+1} &= \nu_t + \zeta_t & \zeta_t &\sim N(0, \sigma^2_\zeta)
\end{aligned}$$