Time-Varying Parameter Models for Discrete Valued Time Series

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Summary

This dissertation contains four chapters on time varying parameter models. We summarize the main findings of each chapter.

In Chapter 2 we presented a non-Gaussian state space model for the analysis and forecasting of football matches. The model is a novelty in the sports and statistics literature because it takes a match result as a pairwise observation that is assumed to come from a bivariate Poisson distribution with intensity coefficients for the number of goals scored by the two teams and a dependence coefficient for measuring the correlation between the two scores. The intensity coefficients are functions of the strengths of attack and defence of the teams which evolve stochastically over time. Extensions of the model including amendments for the over representation of draws in data sets, breaks in strengths of attack and defence after summer and winter breaks, and a team-specific home advantage were considered. Since the match results of the teams are analysed for all teams in the competition, and over a period of several seasons, the resulting model is a high dimensional panel time series. Due to promotion and relegation of teams the panel increased with every season and has many missing values. We showed that football match results from a high dimensional panel can be analysed effectively within a non-Gaussian state space model. The statistical analysis is based on exact maximum likelihood and signal extraction methods which rely on efficient Monte Carlo simulation techniques such as importance sampling.

In Chapter 3 we modelled tick-by-tick discrete price changes for U.S. stocks listed on the New York Stock Exchange by a dynamic modified Skellam distribution with a variance parameter that evolves stochastically over time. The price changes were expressed in multiples of the tick size and are therefore in $\mathbb{Z}$. The Skellam distribution is congruent with the discrete price change data and we analysed the model with state space and importance sampling methodology. The new model accounts for a stable importance sampling estimation procedure, a good in-sample fit, an adequate diagnostic performance, and an accurate out-of-sample forecasting performance in comparison to a number of relevant benchmark models. We conclude that the new dynamic modified Skellam model provides a flexible modelling framework that can be effectively employed to capture the dynamics in high-frequency tick-by-tick data with many missing entries. Since the model

produces intraday patterns of high-frequency volatility dynamics, it may provide an interesting comparison with the usual stochastic volatility models that are typically associated with the time varying variance in time series of daily continuously compounded rates of returns.

In Chapter 4 we introduced a general dynamic model for Skellam distributed difference in counts. Our version of the Skellam distribution has two intensity parameters that correspond to the intensities of Poisson distributed counts. We opted for a likelihood-based analysis of the model using importance sampling methods. In particular, we showed how to estimate the parameters and states of the dynamic Skellam model using a bivariate extension of the numerically accelerated importance sampling method of Koopman et al. (2014). In the application, we modelled the difference between the number of goals scored by the home and away team in a high dimensional unbalanced panel of football match results. We also extended our benchmark model to a model that included regression effects, heterogeneous dynamics in the panel, and extensions of the Skellam distribution that assign different probability mass to zeros. A key example of the latter is the dynamic zero inflated Skellam model. We conclude that the new dynamic Skellam model is robust and computationally feasible for large unbalanced panels. Our flexible modelling framework for time series may provide a useful benchmark for empirical applications based on integer outcomes that can take both positive and negative values.

In Chapter 5 we continued the modelling of tick-by-tick discrete price changes and extended our research to capture the intraday seasonal pattern of dependence between discrete tick-size price changes of different stocks. We captured the intraday dynamic features of dependence using an observation driven model-based copula approach with discrete marginals. The complete dependence model is composed of dynamic Skellam marginal distributions for the discrete price changes combined with a time varying copula structure. We applied a range of bivariate copulas and the Gaussian copula fitted the data best. For four liquid U.S. financial stocks we found that the dependence structure varies over time during the trading day. There is a steep increase in dependence within the first hour of trading, and a steep decrease within the last 15 minutes of trading. We attribute these changes in dependence to the existence of more idiosyncratic risk components in the discrete price changes during the opening and closing hours of trading, in particular overnight firm-specific information accumulation when the market opens and the unwinding of inventory positions when the market closes.