Chapter 6

Conclusion

In this thesis, four articles are presented in four main chapters. Each chapter applies dynamic factor modeling techniques, often based on state space methods, to a credit risk modeling problem at hand.

In Chapter 2, we propose and motivate a novel non-Gaussian panel data time series model with regression effects to estimate and measure the dynamics of corporate default hazard rates. The model is the first to combine a non-Gaussian panel data specification with the principal components of a large number of macroeconomic covariates. The model integrates different types of factors, i.e., common factors from macroeconomic and financial time series, an unobserved latent component for (discrete, count) default data, and ‘observed’ contagion factors at the industry level. At the same time we allow for standard measures such as equity returns, volatilities, and ratings. In an empirical application, we continue to find a large and significant role for a dynamic frailty component even after taking account of more than 80% of the variation from more than 100 macroeconomic and financial covariates, while controlling for contagion at the industry level and equity returns and volatilities. Our findings support earlier research which points out the need for a latent component to prevent a downward bias in the estimation of extreme default losses on portfolios of U.S. corporate debt. Our results indicate that the presence of a latent factor may not be due to a few omitted macroeconomic covariates, but rather appears to capture different omitted effects at different times.

Chapter 3 introduced a new latent dynamic factor model framework, the mixed-measurement dynamic factor model (MM-DFM), for time series observations from different families of distributions and mixed sampling frequencies. Such models are particularly useful for the analysis of credit risk data, but they have applications also beyond that setting. Parameter and latent factor estimates can be obtained by e.g. Monte-Carlo maximum likelihood methods based on importance sampling. We provide two extensions
of that framework. First, we obtain increased computational speed by collapsing observations into a lower-dimensional space such that less observations are passed through the Kalman Filter and Smoother for each evaluation of the log-likelihood. Second, we consider a less complex observation-driven alternative model, the mixed-measurement generalized autoregressive score model (MM-GAS), where the factors are driven by the scaled score of the (local) log-likelihood. Missing values arise due to mixed frequencies and forecasting, and can be accommodated straightforwardly in either the MM-DFM and MM-GAS framework. In an empirical application of the mixed-measurement framework we model the systematic variation in US corporate default counts and recovery rates from 1982Q1 - 2008Q4. We estimate and forecast intertwined default and recovery risk conditions, and demonstrate how to obtain the predictive credit portfolio loss distribution. While the MM-GAS model is simpler and computationally more efficient than the MM-DFM, we do not find that its reduced complexity comes at the cost of diminished out-of-sample (point) prediction accuracy.

Chapter 4 presents a decomposition of systematic default risk based on a new modeling framework. Observed default counts are modeled jointly with macroeconomic and financial indicators. The resulting panel of continuous and discrete variables is analyzed to investigate the drivers of systematic default risk. By means of a dynamic factor analysis, we can measure the contribution of macro, frailty, and industry-specific risk factors to overall default rate volatility. In the empirical study for U.S. data, we found that approximately a third of default rate volatility at the industry and rating level is systematic. The share of systematic risk caused by macroeconomic and financial activity ranges from about thirty for speculative grade up to sixty percent for investment grade companies. The remaining share of systematic risk is captured by frailty, closely followed by industry factors. These findings suggest that credit risk management at the portfolio level should account for all three sources of risk simultaneously. In particular, typical industry models that account for macroeconomic dependence only, do not account for substantial parts of systematic risk. This could be detrimental from a financial stability perspective.

Chapter 5 proposes a framework for the measurement of world default conditions. The model allows us to track credit risk conditions around the globe. In an empirical study of world default data from 1981Q1 to 2009Q4, we estimate model parameters and multiple latent risk factors for firms in four geographical regions. The high-dimensional model allows for the differential impact of world business cycle conditions on regional default rates, additional latent geographical risk factors, as well as a region-specific impact of world-wide latent industry sector dynamics. To visualize latent common default stress for a given set of firms in a given region, we present a novel indicator based on the nonlinear
non-Gaussian factor model for disaggregated defaults. The indicator allows us to take account of macroeconomic, frailty, and industry-specific effects simultaneously. Finally, we suggest that the magnitude of ‘frailty’ effects at a given point in time can serve as an early warning signal for macro-prudential policy makers. Frailty effects have been pronounced during bad times, such as the savings and loan crisis in the US leading up to the 1991 recession, and exceptionally good times, such as the years 2005-07 leading up to the recent financial crisis, when defaults were much lower than implied by macro data.