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Operational risk via Bayesian inference: modeling dependence and combining different data sources

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To quantify the operational risk capital charge under Basel II requirements, more and more banks adopt the Loss Distribution Approach. Under this approach, the bank's internal model must include the use of internal data, relevant external data, scenario analysis and factors reflecting the business environment and internal control systems. Historical internal operational risk loss data have limited ability to predict future behaviour moreover, banks do not have enough internal data to estimate low frequency high impact events adequately. Historical external data are difficult to use due to different volumes and other factors. The idea of scenario analysis is to estimate frequency and severity of risk events via expert opinions. Scenario analysis is forward looking and can reflect changes in the banking environment. By itself, scenario analysis is very subjective but combined with loss data it is a powerful tool to estimate operational risk losses.

Bayesian inference is a statistical technique well suited for combining expert opinions and historical data. Often, ad-hoc methods are used in practice to combine these data sources. Lambrigger, Shevchenko and Wüthrich (The Quantification of Operational Risk using Internal Data, Relevant External Data and Expert Opinions. The Journal of Operational Risk 2(3), 3-27, 2007) introduced a novel approach that allows for combination of three data sources (relevant external data, bank's internal data and expert opinions) simultaneously using Bayesian inference. Here, we develop the model further by allowing risk profiles to evolve in time and to be dependent. The approach allows for dependence between frequencies of different risk categories and between severities of different risk categories as well as within risk categories. The model is estimated using Bayesian inference methodology that allows for combination of internal data, external data and expert opinion. We utilise a special Markov Chain Monte Carlo simulation methodology known as slice sampling

within Gibbs. In addition to exploring the utility of this algorithm in a financial risk model we examine the mixing properties of the chain when tempering is included.