be based on scores which depend on the explanatory variables in a predefined form.

Methods that allow a more flexible modelling approach are non-parametric GLMM extensions (see Hastie and Tibshirani, 1990), classification and regression trees (Brieman, Friedman, Olshen, and Stone, 1984), the k-nearest neighbour classifier (Hand and Henley, 1996), or neural networks (West, 2000). A major drawback of the latter approaches is also their advantage: they are able to recognize and incorporate non-monotone relations between explanatory variables and the probability of default in various, non-parametric forms (e.g. the size of a company and its default probability can be non-monotone, ceteris paribus). Unfortunately, the resulting non-monotonicity often lack economic plausibility and therefore the acceptance from credit risk measure users. It is often difficult to tell statistical artifact from genuine, economic relevant, non-monotonicity.

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COMPARISON OF DEFAULT PROBABILITY MODELS: RUSSIAN EXPERIENCE

Under the Basel II accord, improving probability of default models is a key risk-management priority. There are four main aspects of this research: suggesting the bank default classification; using a wide time horizon (quarterly Russian banking statistics from 1998 to 2011); investigating the macroeconomic and institutional characteristics of the banking sector environment and finally, testing the accuracy of the models developed.

We have employed nonlinearity and automatic classification of the independent variables in our models, paying attention to the structure of the banking market as well as to the reliability of the models developed. We have compared several models for estimating default probabilities. From the results of this comparison, we have chosen the binary logit – regression with quasi panel data structure. Our key findings are:

- There is a quadratic relationship between bank’s capital adequacy ratio and its probability of default.
- The “too big to fail” hypothesis does not hold for the Russian banking sector.
- There is a negative relationship between the Lerner index and bank’s PD.
- Macroeconomic, institutional and time factors significantly improve the model quality.

We believe that these results will be useful for the national financial regulatory authorities as well as for risk-management in commercial banks. Moreover, we think that these models will be valuable for other emerging economies.

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UNDERSTANDING OPERATIONAL RISK CAPITAL APPROXIMATIONS: FIRST AND SECOND ORDERS

We set the context for capital approximation within the framework of the Basel II/III regulatory capital accords. This is particularly topical as the Basel III accord is shortly due to take effect. In this regard, we provide a summary of the role of capital adequacy in the new accord, highlighting along the way the significant loss events that have been attributed to the Operational Risk class that was introduced in the Basel II and III accords. Then we provide a semi-tutorial discussion on the modeling aspects of capital estimation under a Loss Distributional Approach (LDA). Our emphasis is to focus on the important loss processes with regard to those that contribute most to capital, the so called "high consequence, low frequency" loss processes.

This leads us to provide a tutorial overview of heavy tailed loss process modeling in OpRisk under Basel III, with discussion on the implications of such tail assumptions for the severity model in an LDA structure. This provides practitioners with a clear understanding of the features that they may wish to consider when developing OpRisk severity models in practice. From this discussion on heavy tailed severity models, we then develop an understanding of the impact such models have on the right tail asymptotics of the compound loss process and we provide detailed presentation of what are known as first and second order tail approximations for the resulting heavy tailed loss process. From this we develop a tutorial on three key families of risk measures and their equivalent second order asymptotic approximations: Value-at-Risk (Basel III industry standard); Expected Shortfall (ES) and the Spectral Risk Measure. These then form the capital approximations.

We then provide a few example case studies to illustrate the accuracy of these asymptotic captial approximations, the rate of the convergence of the assymptotic result as a function of the LDA frequency and severity model parameters, the sensitivity of the capital approximation to the model parameters and the sensitivity to model miss-specification.