

Chapter 6

Conclusion

In the beginning of this work, it has been asserted that, despite the material relevance of concentration risk concerning the survival of banks and the stability of the whole banking system, the variety of literature and the public attention on this topic have been rather scarce. Against this background, within this work economical as well as regulatory aspects of concentration risk have been presented and some models for measuring concentration risk in credit portfolios have been explained, modified, and compared in detail. Moreover, several research questions regarding name and sector concentration risk, which have been discussed during this work, have been raised in the introduction.

In Chap. 2, the risk measures VaR and ES have been introduced, which are the most common characteristic numbers for measuring risk in credit portfolios. In this context, the emphasis has been put on the (non-)coherency and estimation issues. Then, the asset value model of Merton (1974), the one-factor model of Vasicek (1987), and the ASRF model of Gordy (2003) have been presented. These models build the fundament of the IRB Approach of Basel II, which has been explained subsequently.

In the literature and in various discussions it could be found that there are very different interpretations and characteristics of concentration risk. First of all, banks often only look at one side of concentration risk – the diversification effect. Thus, it is often argued that the requirements of Pillar 1 are the non-diversified benchmark and therefore an upper barrier for the true capital requirement. But as the Basel II formulas have been calibrated on well-diversified portfolios with low name and low sector concentrations, it is indeed possible that banks should have an additional capital buffer to capture concentration risk. Furthermore, some theoretical models as well as empirical studies have demonstrated that concentrated banks can be less risky than diversified banks, which is mainly due to better monitoring abilities of specialized financial institutions. However, even if it can be economically reasonable to be focused on particular industry sectors or geographical regions, the capital requirements should still be higher than for diversified banks. The main argument is that although a specialized bank could benefit from the ability to invest in firms with higher quality (of course it is not even clear that a higher risk-return premium is

earned through lower risk), the bank would still be very vulnerable if the specific sector is in an economic downturn scenario. But exactly such a downturn scenario, often quantified with the VaR, plays the decisive role for the capital requirements. This point as well as regulatory requirements and industry best practices concerning the management of concentration risk have been highlighted in Chap. 3.

In Chap. 4, we have focused on the measurement of name concentrations. After presenting the first-order granularity adjustment, a second-order granularity adjustment has been derived, which results from a Taylor series expansion taking elements of higher order into account. Although during this work and in the literature it was expected that the resulting formula could improve accuracy, it has to be stated that the standard first-order granularity adjustment leads to more convincing results. As it is not analyzed sufficiently in the literature in which cases the ASRF formula leads to a convincing approximation of the true risk, we have analyzed this issue with a detailed numerical study. For this purpose, it has been determined how many credits a portfolio should at least contain if a bank intends to ignore name concentrations; this would be the case if only the ASRF formula was applied. It has been shown that the result is highly dependent on the probability of default and the asset correlation. For a high-quality portfolio, the minimum number of credits varies between 1,371 and 23,989 (A-rated), whereas the critical number of credits for a low-quality portfolio is in the bandwidth 23–205 (CCC-rated). These numbers correspond to an accepted error of 5%. The difference between high- and low-quality portfolios can be explained with a higher anticipation of unsystematic defaults for low-quality portfolios. Furthermore, we have raised the question whether the granularity adjustment is able to overcome the shortcomings of the ASRF model, which has only been analyzed rudimentarily before. The results of our study demonstrate that the granularity adjustment provides a very good approximation of the risk stemming from name concentrations. We find that a consideration of the granularity adjustment can reduce the required minimum portfolio size by on average 83.04% compared to the ASRF model.

Because of the theoretical shortcomings of the VaR and since, differently from the ASRF framework, these can be problematic if there is concentration risk, the ES has been considered, too. At a first glance, it is problematic that the ES is by definition higher than the VaR, which leads to higher capital requirements. As the change of the risk measure should solve the problem of superadditivity but should not inevitably lead to higher capital requirements, we have adjusted the confidence level of the ES in a way that the Pillar 1 formulas still lead to an almost identical level of measured risk. We find that a confidence level of $\alpha = 99.72\%$ for the ES leads to a very good concurrence between the ES and the 99.9%-VaR for all relevant credit qualities and correlations. By application of the same analyses as before for the VaR-based granularity adjustment, we find that this approach works very well. The ES-based granularity adjustment does not only reduce the required number of credits by 91.64% compared to the ASRF solution, but the minimum number of credits is also 49.05% lower compared to the VaR-based granularity adjustment. These results show that for portfolios with a significant amount of name concentrations, the ES-based granularity adjustment is really well-suited.

An additional robustness check using stochastic LGDs has confirmed these findings. However, the postulated accuracy should also be obtained in many real-world portfolios if the VaR-based granularity adjustment is applied.

In Chap. 5, we have analyzed risks stemming from sector concentrations. For this purpose, the design of multi-factor models has been explained. Since additional input parameters are needed when applying a multi- instead of a single-factor model, a methodology has been developed to parameterize intra- and inter-sector correlations consistent with the one-factor model of Pillar 1. Given the inter-sector correlation structure of the MSCI EMU industry indices, a formula for the implied intra-sector correlation has been determined. With these parameters, the results of the multi-factor model and of the Basel II formula are almost identical if the portfolio is well-diversified as it had originally been assumed when calibrating the Basel II formula. However, if the degree of concentration is higher, the capital requirement can increase significantly. Using these parameters, an extensive numerical study has been performed, which is similar to Cespedes et al. (2006). The result of our numerical study is a closed form approximation formula in a multi-factor setting, which is consistent with the Basel framework. In contrast to the resulting formula of Cespedes et al. (2006), our formula is able to measure not only the benefit from sectoral diversification but also the additional risk from sectoral concentrations if these are higher than assumed in Basel II for a typical well-diversified portfolio of large internationally active banks. Moreover, we have used the theoretically more convenient ES instead of the VaR. In addition, we have demonstrated how the extensive numerical calibration of the model can be accelerated significantly without leading to worse approximations. Using the risk measure ES, we have also performed the calibration procedure of Düllmann (2006). Furthermore, we have demonstrated how these models can be applied on bucket instead of borrower level, which accelerates the computation of the corresponding formulas considerably.

Based on the preceding findings, we have implemented our multi-factor setting and compared different models by means of a simulation study. We find that the accuracy of the models of Pykhtin (2004) and the developed formula, which is based on Cespedes et al. (2006), lead to quite good results, whereas the model of Düllmann (2006) performs rather poorly. Especially in the case of heterogeneous exposures, the model in the style of Cespedes et al. (2006) shows the best accuracy. Since the extensive numerical calibration of this model only has to be done once for a given correlation structure, and then, it is possible to perform ad-hoc analyses, this model seems to be well-suited for many real-world applications if sector concentrations shall be considered. A last very interesting result could be obtained when the VaR and the ES have been compared within the simulation study.³³² In almost all simulation runs, the relative error of the VaR compared with the ES was lower than 1%. Thus, in contrast to some contrived portfolio examples, the usage of VaR seems to be unproblematic within this more realistic setting from a practical

³³²The confidence level of the ES has been reduced to 99.72% as argued in Chap. 4.

point of view, even if there is a high degree of sector concentration risk in the portfolio.

In this work, several aspects of concentration risk have been highlighted. However, there is a variety of open issues in the context of concentration risk that could not be addressed in this work. One important topic is the consideration of concentration risk in the pricing of individual credits and credit derivatives, especially of credit portfolio derivatives like CDOs. In particular, the sensitivity of the price depending on existing risk concentrations has hardly been analyzed. Beyond that, it would be interesting to take into consideration whether a bank is exposed to the risk of a security until maturity or whether instruments of active portfolio management are employed to reduce risk concentrations. Secondly, during most of the work, it has been assumed that LGDs are deterministic or at least stochastically independent. An open issue is how portfolio risk is affected by risk concentrations stemming from collateral. In this context, concentrations in individual positions and in sectors could both have relevant effects. For example, in the financing of objects like ships or airplanes, there are usually several financiers investing in one object; hence, the impact of the individual risk component of the collateral can be even higher than that of the obligors. Similarly, in retail financing there usually is a low degree of concentration risk of the obligors but if most of a bank's loans are secured by mortgages or by cars, there can be a relevant impact of sector concentrations in collateral. Thirdly, credit contagion through micro-structural channels could only be touched upon. One challenging aspect in this area is the estimation of business relations, since micro-structural dependencies cannot be restricted to the most important firms of a bank's actual portfolio but firms that are not financed by the bank can affect the credit portfolio through their business relationships as well. Thus, additional research should address how these effects of micro-structural dependencies can be implemented in practice despite the substantial data requirements.