Chapter 15
Concluding Remarks

OTHER CREDIT RISK EXPOSURES

In this book, we have focused on credit risk exposures for loans and loan portfolios. Other sources of credit risk exist, and, as mentioned in the introductory chapter, they include fixed income securities (e.g., bank, corporate, and sovereign bonds), securitization investments, contingent credit exposures (loan commitments and guarantees), credit derivatives, and over-the-counter (OTC) derivatives.

Securitization credit risk models often build on credit portfolio loss distributions where simulated credit portfolio losses are tranched. The risk profile of the credit portfolio is driven by all credit risk parameters: probabilities of default (PDs), exposures at default (EADs), losses given default (LGDs), and asset correlations. The risk of a tranche is determined by the rules that specify the allocation of free cash flows from the underlying collateral portfolio to the tranche investors. Important elements are the credit enhancement (attachment level, subordination) and thickness of a tranche. Banks often sell these tranches to nonbank investors but may retain the equity tranche (i.e., the most subordinate tranche) and invest in more senior tranches for liquidity reasons (i.e., to maintain the liquidity coverage ratio and the net stable funding ratio above 100 percent). Example contributions in the literature that focus on the risk measurement of securitizations include Das and Stein (2011) and Rösch and Scheule (2016a).

The Basel Committee on Banking Supervision computes the capital for retained and invested tranches by offering a Ratings Based Approach (RBA) (i.e., a lookup table that allocates risk weights to the ratings provided by credit rating agencies) and a Supervisory Formula Approach (SFA). The Supervisory Formula Approach is the equivalent of the Internal Ratings Based approach for loans and includes the required capital for the underlying credit portfolio, as well as the credit enhancement and thickness of a tranche as additional risk characteristics. For details, we refer to Rösch and Scheule (2012) for the SFA, and Lützenkirchen, Rösch, and Scheule (2013) for the RBA.

Generally speaking, credit guarantees and loan commitments are comparable to standard loans and loan portfolios from a modeling perspective. The challenge for loan commitments lies mainly on the determination of drawdown rates of credit lines, and these details were discussed in our EAD chapter (Chapter 11).

Credit derivatives expose financial institutions to the credit risk of large financial institutions and other corporates. Credit derivative instruments include credit default swaps (CDSs), CDS portfolios, and CDS portfolios tranches. For example, common CDS portfolios are the CDX.NA.IG, which includes 125 North American corporate CDSs, and the iTraxx Europe index, which includes 125 European corporate CDSs. Different maturities are available and generally lie between 3 and 10 years. Tranche prices are quoted for some credit portfolio indexes: for example, 0–3, 3–7, 7–15, 15–100 (all in percentage of the underlying CDS portfolio) for CDX.NA.IG and 0–3, 3–6, 6–9, 9–12, 12–22, 22–100 (all in percentage of the underlying CDS portfolio) for the iTraxx Europe index. The risk is generally modeled by explaining the market prices for these instruments. For details, we refer to Löhr et al. (2013) and Jobst et al. (2015). The credit risk of CDS derivatives is modeled by trading book value at risk (VaR) models, which are based on a 99 percent confidence level and a time reference period of 10 days.

The credit risk in relation to OTC derivatives is computed like standard credit facilities with the distinction that the exposure is the sum of the current exposure (the amount by which a derivative is in-the-money; i.e., an actual credit exposure exists) and the potential future exposure that results from the application of credit conversion factors (see the EAD chapter for more details).

LIMITATIONS OF CREDIT RISK ANALYTICS

Consistency

The product-modularized risk architecture in banking and banking supervision led to credit risk analytics that match this modularity, which is one of the many reasons for model inconsistencies within a bank and across banks. The European Banking Authority (2015) has surveyed 43 banks in 14 countries and found that risk weights and hence risk models differ across financial institutions. The sources of risk weight variations have been identified as follows:

a. definition of default;
b. application of regulatory floors (e.g., minimum 10% LGD floor for exposures secured by real estates);
c. mapping into regulatory portfolio categories (SMEs, Corporate versus Retail, Retail secured by real estate versus Housing loans);
d. differences in reporting and LGD calibration for exposures only partially secured;
e. heterogeneity in the margin of conservatism, data sources, length of the time series and approaches used for the calibration of PD models;
f. different practices in the frequency and triggers for the re-development and re-estimation of internal models;
g. use of global IRBA models for exposures located in different countries; LGD estimation (defaulted and non-defaulted);
h. different practices in the estimation of the LGD parameter on defaulted and non-defaulted assets (inclusion of incomplete workout positions, level of discount rates and legal and administrative costs, internal haircuts estimates, repossession likelihood and use/definition of cure rates);
i. banks try to capture downturn conditions in the LGD computation using broadly similar approaches but with different final outcomes;
j. a wide range of practices followed by banks in the treatment of defaulted assets (varying interpretation and use of different approaches for the computation of the best estimate LGD and RWA on defaulted assets) and in the calculations of the IRB shortfall.

Parallel to this, the Institute of International Finance (2015) and the Basel Committee on Banking Supervision (2013) have conducted similar studies and find considerable variation in risk weights. A big industry effort in the upcoming years is needed to standardize credit risk and other risk models.

Another related issue is the link between the risk parameters (PD, LGD, EAD, and asset correlations), which are often modeled independently. Dependence is sometimes considered by means of conditioning on economic downturns (as in the case of worst-case default rates, downturn LGD, and downturn EAD), or by modeling correlated default events by asset correlations and other dependence parameters. However, many economic dependencies remain unconsidered in contemporary risk models. This is an area where integration models are important. One interesting approach for integration models is offered by random effect modeling. For example, it has been observed that the PD and LGD parameters are positively correlated. One way to account for this correlation may be to include random effects in both measurement equations and estimate the empirical correlations between these processes after controlling for covariates (see Rösch and Scheule 2005). Similar integration models may be provided for other dependencies.

Accuracy

Complementary Models

In various applications we have found that in empirical credit risk analytics strategic concepts matter more than the actual implementation framework. For example, logit and probit models forecast very similar default probabilities. Likewise, life cycle time variation can be addressed by continuous time models or by strategic use of time stamps as covariates in discrete time models. Hence, the consideration of risk drivers such as origination, macroeconomic, and maturity profiles in the models is important. Very often, it is better to have a simple model that is robust and easily understood by the managers than a complex model that is not.

Statistical versus Economic Significance

Generally speaking, economic intuition is essential, in particular in situations where the dependent variables are constrained. Every statistical analysis should be accompanied by an economic impact analysis in which realistic variations in the covariates are compared with the model-implied variation of the dependent variables. For example, unobserved variations can be modeled by fixed and random effects that are clustered with reference to the borrower, collateral, lender, time, or other risk characteristics.

Model Comparison

It is a big challenge to compare credit (portfolio) risk measures for different portfolios over time. Most validation measures are subject to the risk characteristics of the time-varying underlying portfolio. Hence, the comparison of validation outcomes is very difficult, and financial institutions should not target minimum values for measures, as this may incentivize overfitting when these targets are not met. Good validation practice generally requires a balanced mix of a number of alternative measures, including out-of-sample and out-of-time validation techniques as well as qualitative robustness checks.

Model Risk

Various model validation measures suggest that parameter estimates and risk measures are subject to uncertainty. Following up on economic significance, credit risk analytics is still at an early stage when it comes to the understanding of the economics of the actual data-generating processes. The global financial crisis (GFC) has revealed that a large number of drivers have not been included in risk modeling in the past. Examples are credit product features, borrower behavior, collateral value changes, lending standards, and rating agency incentives. Model risk is typically multidimensional, and the confidence levels need to be tracked across the multiple dimensions; clustering should also be considered. It is often practical to address model risk using Monte Carlo simulations, as we have shown in our stress testing chapter.

Interaction with the Economy

Credit risk is cyclical and comoves with the macroeconomy. It is important to understand the degree of macroeconomic information that is included in models. Statistical models may underestimate the degree of macroeconomic variation, as many frailty/random effect studies show that unexplained systematic variation remains when controlling for idiosyncratic and systematic information. Risk measures based on market prices (e.g., share prices or CDS spreads) sometimes overestimate the systematic variation, as financial markets underprice risk in economic upturns and overprice risk in economic downturns; compare Borio and Drehmann (2009) and Cerruti et al. (2012) for critiques on market-based measures for financial system stability. As a result, correlations may be inaccurate, and consequently the tails of credit portfolio loss distributions and hence derived price and capital measures may be misestimated.

GUIDING PRINCIPLES FOR BUILDING GOOD CREDIT RISK MODELS

In order to build good credit risk models, special care should be taken in the data preprocessing, model estimation, model implementation, and model interpretation. The following list defines some guiding principles for building good risk models:

- Analyze the representation of historical data. Are past economic downturns representative for future economic states in terms of likelihood and magnitude?
- Check whether the data, model, and risk measures meet reasonable robustness checks, including prior expectations of the credit analyst and other stakeholders.
- Verify whether market-based risk measures and risk factors are subject to constraints and assumptions. Is there evidence for systematic underpricing or overpricing?
- Consider multiperiod outcomes in the risk models where appropriate. Many important risk aspects have multiperiod features. Examples are life cycle changes, loan amortization, rating migration, and the multiperiod funding constraints of borrowers and lenders during economic downturns (see Rösch and Scheule 2016b).
- Analyze the effect of the time value of money (interest rates and inflation rates) on the risk measures.
- Develop a proper understanding of financial instruments and financial innovations. Latest examples may include covered bonds, contingent convertible bonds, consumer credit lines, and reverse mortgages.
- Be aware that unexpected losses generally matter more for banks than do expected losses. Banks face regulatory constraints when the capital buffer (i.e., capital in excess of regulatory capital) is exhausted.
- Limit the maximum EAD through limit systems and exposure sharing.
- Understand that diversification is a very powerful risk mitigation instrument. Bank

portfolios are often concentrated in terms of geography and asset classes by the operating business model. Risk diversification strategies are available, and some include securitization and derivatives.

- Analyze how credit risk interacts with other risk categories. One important example is liquidity risk. Liquidity risk is of equal importance for lenders and borrowers/counterparties. Lenders have to cover liquidity risk under Basel III (i.e., have to meet liquidity ratios). However, liquidity risk is often only partially included in risk models. Current models often focus on net asset value and income of borrowers but exclude liquidity constraints such as income shocks, repayment step-ups, margin calls, or product maturity.
- Develop a deep understanding of the financial contract, the borrower behavior, and the interactions with the economy.
- Be aware that the data-generating process remains to a large extent unknown. Hence, our current understanding of the realization of losses may change in the future. A periodic update of risk models is important.

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