Theory and practice in risk-based capital assessment methodology

By Jimmy Skoglund (SAS Sweden) and Kaj Nyström (Umea University)

Jimmy Skoglund *is a risk expert with SAS and has more than five years experience developing and implementing risk methodologies. Prior to joining SAS, he was responsible for economic capital methodology development and implementation at Swedbank. Jimmy holds a Ph.D in econometrics from Stockholm School of Economics and is a published thought leader on risk technology. He has been published in Journal of Risk, Journal of Banking and Finance and Risk Books.*

Kaj Nyström *is currently an associated professor of mathematics in Sweden and works as consultant in the financial industry. As a researcher he is well established in the areas of harmonic analysis and partial differential equations and has published extensively in established mathematical journals. He also worked for a number of years for Swedbank within their project for economic capital, and he has published several papers on risk in Journal of Risk, Journal of Banking and Finance and Risk Books. Kaj holds a Ph.D. in pure mathematics from Umeå University, Sweden, and has held research positions at the University of Chicago and MIT in Boston, as well as at several Swedish universities.*

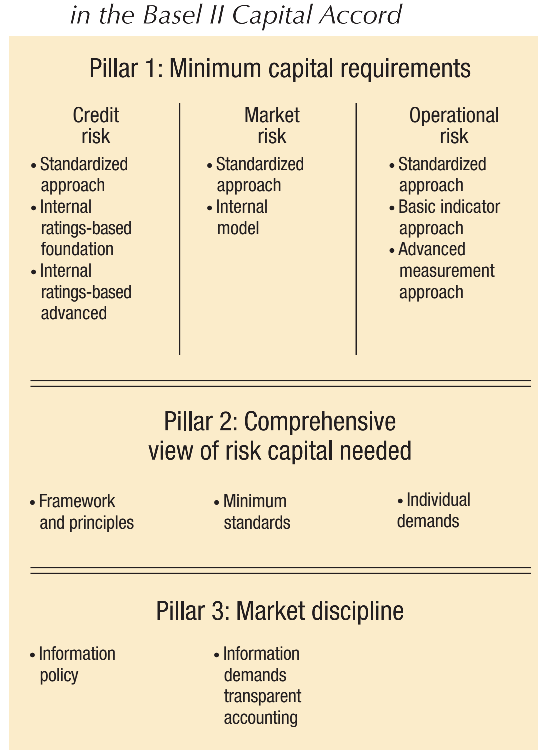
Introduction and overview

Banks are currently struggling with their Basel II implementations – addressing the Pillar 1 minimum capital requirements and any changes to existing economic capital models to comply with the Pillar 2 requirements on the internal capital assessment process. Among banks there is widespread support for migration to a regulatory environment with risk-based capital assessment. There is also awareness that this change poses several challenges well beyond the implementation of a credit risk rating system. In particular, the introduction of Basel II reconciles regulatory capital with risk management practice in focusing on the planning for and managing of tomorrow's risks. Though the Basel II guidance in this planning process is not so clear, regulators and banks agree that volatile movements in the level of capital held arising from changes in economic conditions is undesirable. The methodology developed at banks to address Pillar 2 risk-based capital assessment is, therefore, based on a *long-term risk assessment*, e.g., covering a complete business cycle. It may seem that the horizon of the risk assessment can be dictated by the existence or non-existence of a liquid hedge or secondary market. But banks generally, in case of existence, want to avoid speculations about their ability to function in adverse economic scenarios. Such speculation would also be unacceptable from the perspective of investors since, in that case, they would be the lenders of last resort in a situation they may have expected the bank to be protected against.

From a methodological perspective, the challenge in risk-based capital assessment is, therefore, to measure risk accurately through time. If capital is to provide the required cushion over the swings of a business cycle, then the evolution of risk through time becomes most important.

Figure 1 displays an overview of the three pillars in the new Basel II Capital Accord. Pillar 1 address minimum capital requirements for credit risk, market risk and operational risk. Pillar 2 addresses the need for a comprehensive view of risk capital, i.e. the bank's internal capital assessment process. Pillar 3 addresses the demands on market discipline and communication towards investors, rating agencies and others.

Figure 1: An overview of the three Pillars in the Basel II Capital Accord



The conceptual view that actual capital is based on a long-term risk assessment also has implications for how capital is implemented in business control, e.g. credit granting and risk-adjusted pricing. Allocated capital, as well as provisions, are based on a long-term risk assessment, regardless of the actual level of capital allocation (such as exposure level through internal transfer prices or business unit level). If pricing were dependent on the economic cycle, it would be counter to the interests of both banks and debtors, since generally it is the banks and not the debtors who are best positioned to hold capital buffers.

Figure 2 displays an overview of a bank's capital assessment process. Firstly, the ability to address the full impact of Pillar 2 resides in the bank's ability to integrate risks. This requires, among other things, a methodology for risk integration and consolidation of risk IT infrastructure. Secondly, actual capital is not assessed over one year but rather over a complete business cycle. Thirdly, capital needs to be incorporated in business control, both in terms of front-end credit granting and risk-adjusted pricing, and in terms of back-end strategic capital management, e.g. through securitisation structuring.

The level of capital in place should be able to cover losses arising as a result of economic scenarios possible during a business cycle. Banks are, therefore, addressing the need to define what they consider to be the key economic factors that drive their regulatory minimum capital requirements, loss rates and balance sheets. Specifically, they are focusing on developing a methodology and capturing data for these key risk drivers to factor their impact explicitly. How well banks achieve this will, for obvious reasons, be a core success factor in the disclosure requirements of Pillar 3. It will also affect how well they are able to integrate capital into strategic financial planning at the board level.

The push to define key risk drivers means that one of the goals of the risk methodologies they develop for Pillar 2 and 3 compliance is to make risk comprehensible, both in terms of inputs and projected impacts, Here, inputs would refer to economic scenarios and projected impacts would include changes in regulatory minimum capital requirements, loss rates and the bank's result and balance sheet.

In this process the explicit choice of scenarios is the key input to the analysis. And this is the most difficult point, both from a methodological as well as a communicative perspective. From the methodological perspective the question is to understand and capture the correct "transfer function" describing the impact of specific scenarios. From the perspective of communication it is important to be able to communicate how the scenarios are constructed. This communication is crucial if the people within the organisation are to understand the scenario and feel comfortable with its construction.

Figure 3 displays the components of sound risk methodology that could form the basis for risk integration and communication. One requirement of a risk methodology is that it should allow for the integration of expert views at the scenario level and that it should enable communication of scenarios as well as their effects.

Figure 2: An overview of the capital assessment process under the Basel II Accord.

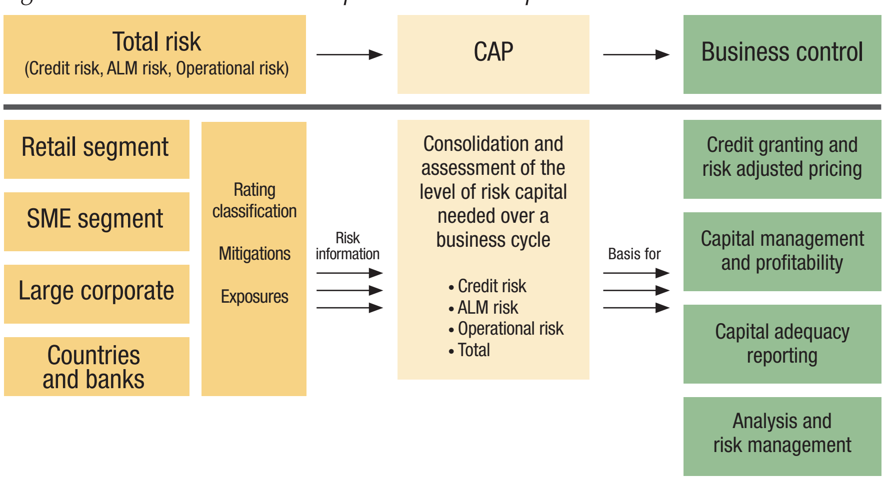
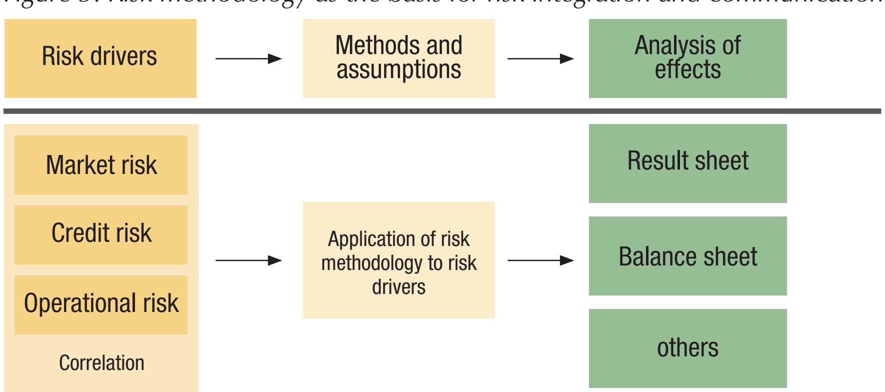


Figure 3: Risk methodology as the basis for risk integration and communication.



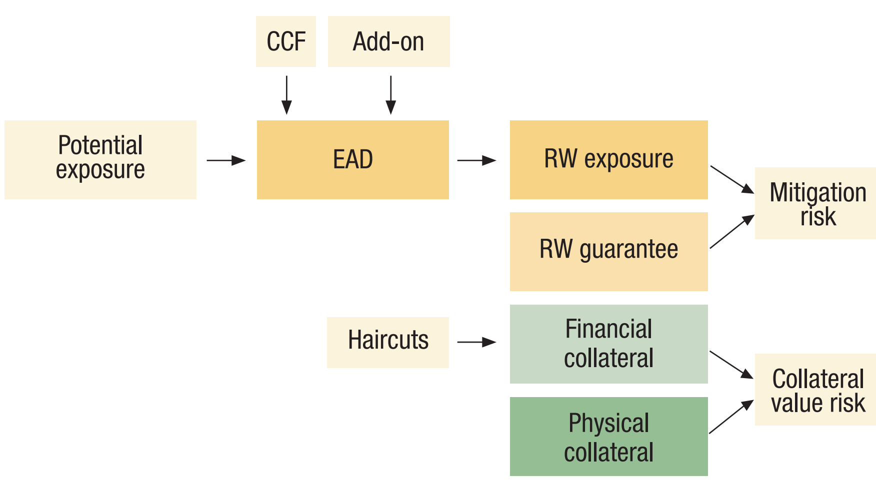
Capital assessment methodology for credit risk

For credit risk, the first step toward the explicit quantification of the impact of key risk drivers is the observation that changes in minimum capital requirements and loss rates over time are expected to be pro-cyclical. This is due to rating migrations (of borrowers and guarantors) and to changes in the value of exposures and collateral.

Figure 4 displays the components at risk in the Basel II IRB minimum capital requirements for credit risk – exposures at default (EAD), exposure risk weights (RW) due to rating migrations and loss given default (LGD) due to the risk in collateral values. In approaches to economic capital associated with credit risk, the business risk in future margin income due to competitive pressures must be properly addressed. If a tightening of the excess margin income earned by the bank occurs in the future, this would have a direct impact on future results and would have an indirect impact through the required adjustment of the level of economic capital.

Starting with migration risk and the associated rating methodology, we describe below and exemplify the methodological risk measurement process for the components that address portfolio credit risk.

Figure 4: Components at risk in Basel II IRB minimum capital requirements.



It is well known that the statistical power of a scorecard or rating decays rapidly with the prediction horizon of the assessment. This means that the preferred approach is a combination of short-term assessments (based on one year, for example) and a methodology for explaining the long-run systematic rating migrations based on key economic factors, such as unemployment rates, output gaps, stock indices and other financial indices. The methodology to assign a rating based on the average risk of default over the entire period to maturity is then based on the current risk grade and the sensitivity of the exposure to the economic cycle, which is derived from the methodology for explaining long-run systematic rating migrations. In this we may assign a loan with a low one-year scorecard or rating PD to a relatively high-risk grade, as we assess the fact that the longer-term viability of the borrower may be questionable based on its sensitivity to the business cycle.

The above two-step approach to rating methodology has several advantages. For example, it allows for back-testing of the rating systems of individual banks and for a comparison of ratings across banks. Moreover, diversification and concentration effects can be captured through the business cycle, since these effects are not subsumed in the rating itself but rather captured in the methodology for explaining long-run systematic migrations. One of the difficulties with a rating methodology that attempts to assign a rating directly according to a 'through the cycle' methodology is that it significantly complicates the tasks of back testing. In particular, that the average observed default frequencies for a given grade do not equal the associated one-year PD for the grade may not point to a flaw in the rating system or its application.

In general though, the effect of pro-cyclicality does exist regardless of the internal rating philosophy applied by the bank. Specifically, the observed pro-cyclicality in the empirical migration matrices used by the rating agencies shows that attempting a direct rating "through the cycle" is not an easy task. (See, for example, the empirical case studies on pro-cyclicality in Carling et al. (2001) and Segoviano and Lowe (2002).)

Using either rating approach, the pro-cyclicality of capital requires banks to develop methodologies to understand how rating migration effects capital. This involves defining and explicitly linking key economic factors capturing default and rating migration volatility.

Figure 5 displays the different rating migration risks experienced in practice and their applicability to the different segments, i.e. retail, Small and Medium sized Entities (SME) and large corporates. Systematic risk is a concern for all the segments and is also used to capture correlation between the rating migration of customers. For the retail segment the systematic factors include unemployment rates, interest rates and GDP growth. For the SME segment different industry-specific performance indices may be used, such as leading indicators. For large corporates the systematic

Figure 5: The different rating migration risks and their applicability to different segments.

		Systematic risk	Idiosyncratic risk	Domino effect
Asset class	Retail	✓		✓
	SME	✓		✓
	Large corporate	✓	✓	✓
Modeling method		Correlation analysis “Creditindex”	Specific index	Expert model

component in stock prices, such as a stock index, may be used as a systematic variable. However, in practice the actual linking of a systematic variable to a segment may be non-trivial due to a limited rating history of only a few years. If this is the case, the bank would have to adopt a combination of expertise, judgment and available data. As time progress and more data are captured a re-evaluation of the expertise judgment may be necessary.

Large corporates also need to capture idiosyncratic risk. And this might also be important for SMEs, depending on the size of the portfolio. The traditional approach is to split the systematic credit risk component into diversifiable idiosyncratic components akin to a traditional capital asset pricing model. Examples include several applications of the well-known Merton model.

Finally, the modelling of so-called domino effects or default contagions is at the heart of sound credit risk methodology. The idea is to capture direct default dependence links between firms – something that has been the occupation of traditional credit analysts for a long time. However, the formalisation of this concept in a credit risk methodology requires the actual modelling of this dependence. This involves expert judgments of, for example, the effect of the health of firm A on the health of firm B. Moreover, will changes to the health of either or both firms affect our SME portfolio and/or retail portfolio?

However, it is not sufficient to capture rating migration volatility and dependence. Loss Given Default and Exposure At Default may also display significant dependence on the economic cycle. In particular, the accurate measurement of LGD requires the validation of the process(es) for the valuation of collateral currently employed. It is equally important to capture the volatility in LGD, as well as its correlation with rating migration. This can be achieved by the mapping of collaterals to a set of collateral evolution models based on, for example, historical property and financial indices. (The historical indices being the base for capturing specific collateral volatility as well as, indirectly, the correlation with rating migration, through their correlation with systematic factors.)

Figure 6 illustrates the process of mapping collateral to a set of collateral evolution models based on indices.

This LGD measurement process must resolve the fact that the Basel definition of default does not coincide with the events or the timing of an actual firm bankruptcy, legal restructuring or customer settlement, i.e. the events that yield the ultimate losses. Indeed, as many banks do not sell their troubled assets there is a time dimension of default which needs to be explicitly accounted for through the measurement of the transitions between default states. For example, in the Basel definition of default high loan-to-value mortgages may be more likely to end up as forced sales of collateral than low loan-to-value mortgages. Of course, such information resides in the workout process of the bank.

Figure 6: The process of mapping collateral to collateral evolution models based on indices.

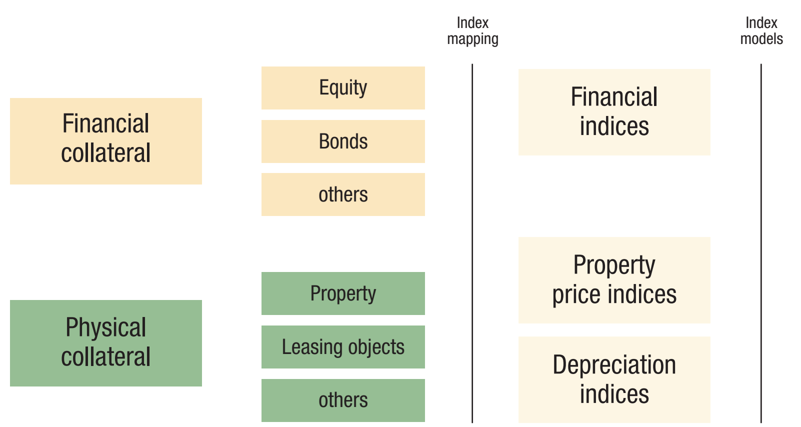


Figure 7 displays a potential default event chain defined by a bank. In this chain the Basel definition of default of 90 days due is a "technical" definition of default that does not necessarily coincide with the event of bankruptcy or customer settlement. Indeed, typically only a fraction of the exposures that are in Basel default end up in the state of settlement. Moreover, only a subset of those exposures that actually end up in settlement may be realised defaults in the strict sense. LGD can hence be measured on multiple levels in this process with LGD conditional on settlement being greater than or equal to LGD conditional on Basel default. In this regard, see also Peura and Soininen (2005) on the use of the Basel II minimum capital requirement formulas in the event of multitier LGD, as well as the connection between multitier LGD and credit risk impairment allowances under IAS 39.

Logically, portfolio segmentation is the first step in any application of the credit risk methodology introduced. Figure 8 displays a segmentation of the credit portfolio as may be used by a bank, as well as the steps needed to capture and explicitly factor the impact of key risk drivers of rating migrations and collateral values. In practice the portfolio segmentation is also the basis for capital allocation granularity in internal transfer prices. To apply the methodology introduced as well as exemplify the degree of pro-cyclicality in Basel II IRB-A capital that can be expected, figure 9 displays the upper limit on relative Basel II IRB-A capital, at the 99% confidence level, over a planning horizon of 10 years for a large retail and SME portfolio collateralised with property. The results obtained are based on a simulation-based approach to scenario analysis and stress testing that models explicitly the rating migration volatility based on systematic factors, and in the event of actual loss, the value of collateral. In figure 9 rating grade 1 indicates the exposures with the lowest initial PD (on average 0.01%) and rating grade 8 indicates the exposures with the highest initial PD (on average 21%). It is evident from figure 9 that the portfolio is dominated by exposures in 'good' rating classes and is therefore exposed to the risk of significantly higher minimum capital requirements in the future.

Figure 7: Potential default event chain.

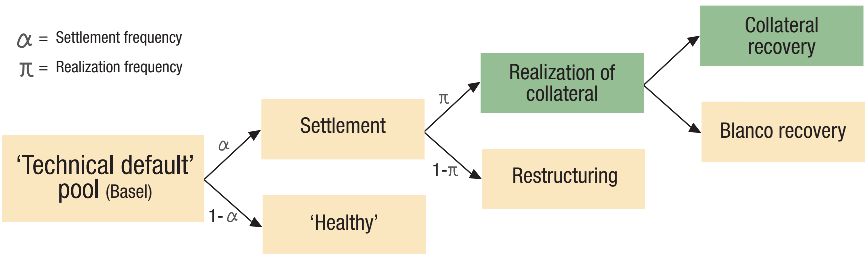
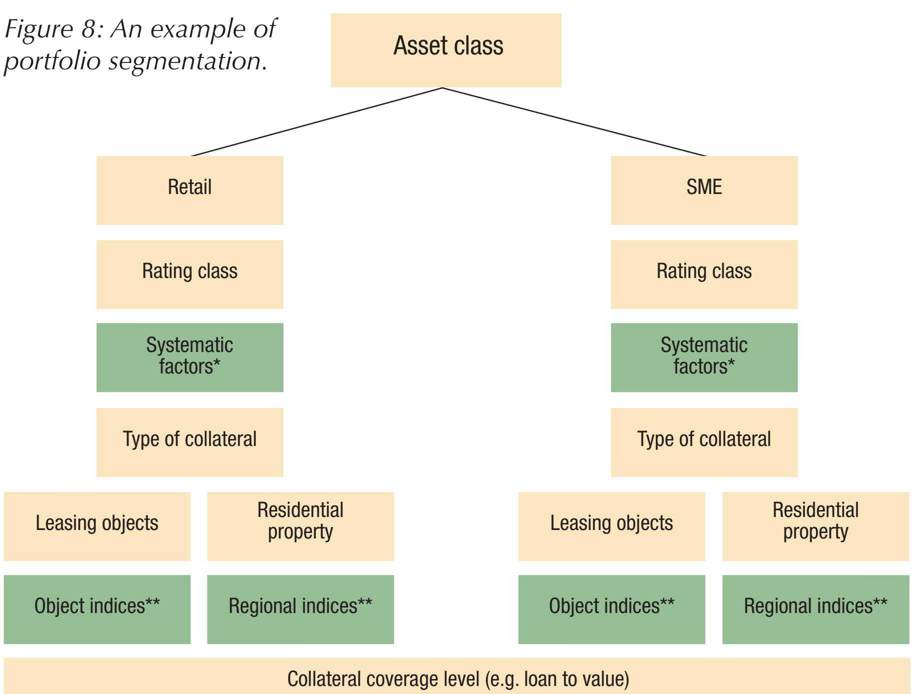


Figure 10 displays the lower limit on relative net cash flows, being the basis for credit risk economic capital, at the 99% confidence level, over a planning horizon of 10 years for the same large loan portfolio as in the case of the Basel II capital displayed in figure 9. This uses the models for systematic rating migration and collateral value used in the Basel II case and a model for the excess margin, at customer reset times. In our case a slight tightening over time of the excess margin is implemented (this tightening is due to increasing external competitive pressures). As can be seen from figure10, the effect that "good" grades are more risky and hence require, on a relative basis, more capital is true for economic capital as well, although to a lesser extent than for Basel II minimum capital requirements. The reason for this is that Basel II capital – as opposed to economic capital – is based on loss rates and on successive quality depreciation through rating migrations. For marked-to-market credit risk, however, the two would be equal in this regard.

Figure 8: An example of portfolio segmentation.



* Define systematic factors, define model for systematic factors, define segment exposure to systematic factors

**Define collateral indices, define model for collateral index, define haircuts, define LGD event type transition parameters

Figure 9: Upper limit on relative Basel II IRB-A capital, at the 99% confidence level, over a planning horizon of 10 years for a large loan portfolio collateralised with property.

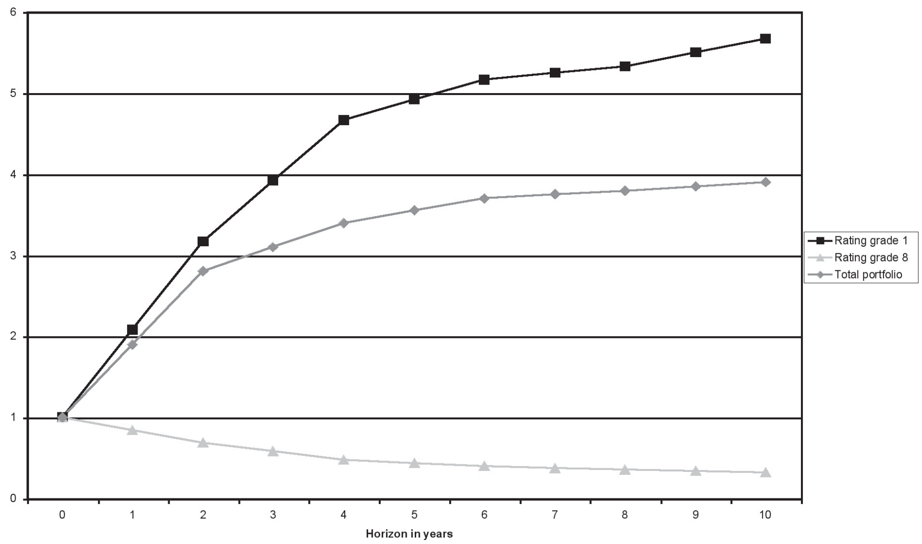


Figure 10: Lower limit on relative net cash flows, at the 99% confidence level, over a planning horizon of 10 years for a large loan portfolio collateralised with property.

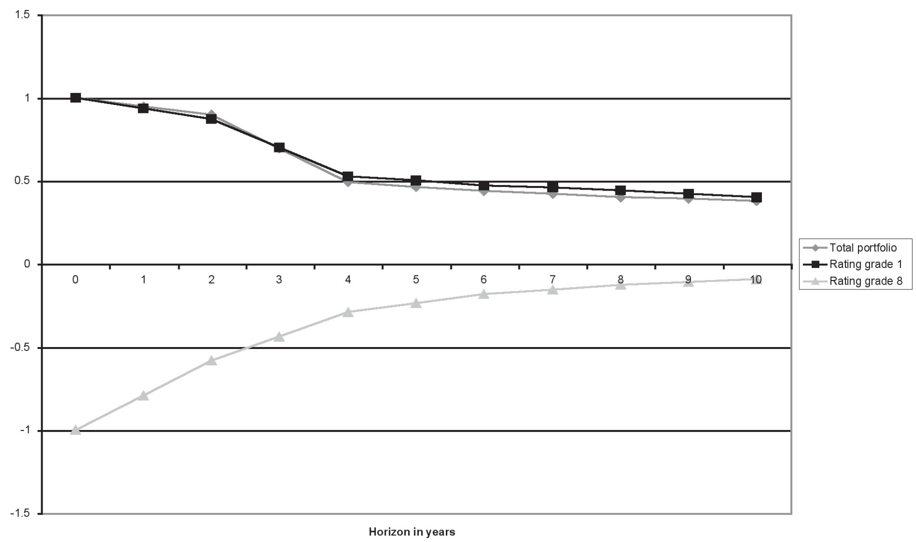


Figure 11: Evolution of credit risk methodology.

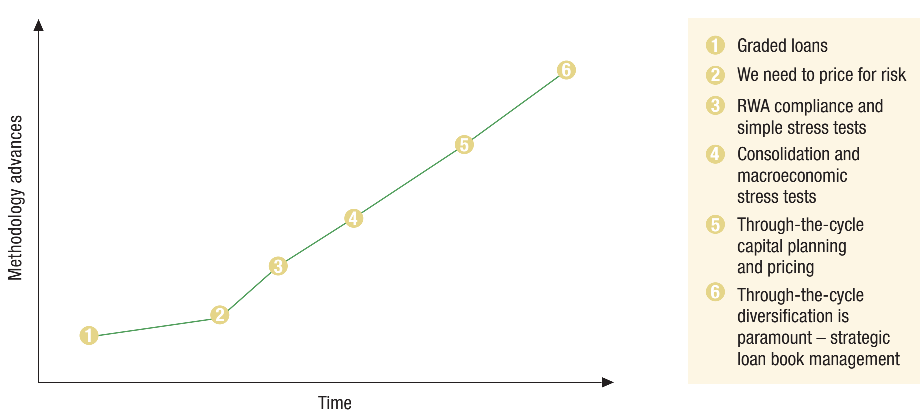


Figure 11 displays an evolution of credit risk methodologies to summarise our discussion. Steps 1, 2 and 3 in this evolution represent the implementation of credit risk rating systems, risk-adjusted pricing based on the current rating, and regulatory risk-weighted assets. Today most banks are at stage 3, and at this stage stress tests are defined strictly in terms of changes in PD and LGD, with no reference to underlying economic key-risk drivers. The next stage in this evolution is to consolidate the drivers of migration risk and the risk in collateral values and to assess the diversification and concentration effects. Finally, this will have an impact on how banks view their actual current capitalisation and their risk-adjusted pricing as well as the way they strategically manage their loan book.

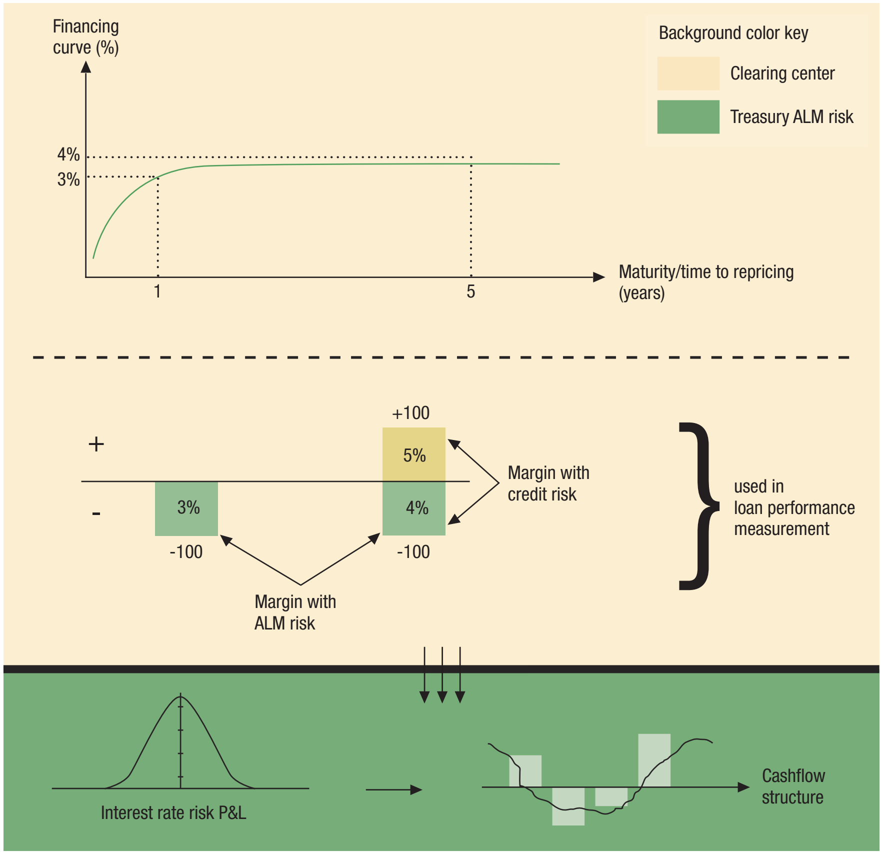
For further details on the methodology for portfolio credit risk presented here we refer to e.g., Wilson (1997) and in particular Nyström and Skoglund (2005).

Capital assessment methodology for ALM risk

The spread income between the assets a bank invests in (loans and securities) and the cost of its funds (deposits and other sources) should allow it to meet its operating expenses and earn a fair profit on its capital. In order to generate the spread income a bank takes on and faces several risks, in particular credit risk, interest rate (or funding) risk and liquidity risk. Often the funding base consists of deposits, outstanding short-term and long-term debt in the form of emitted instruments, and traditional deposit accounts, such as demand deposits, savings accounts and market time deposits.

Consistent with the demands of Pillar 2, banks do not only have to address key economic drivers for credit risk, but such drivers also have to be addressed for asset and liability management (ALM) and operational risk. Actual risk consolidation,

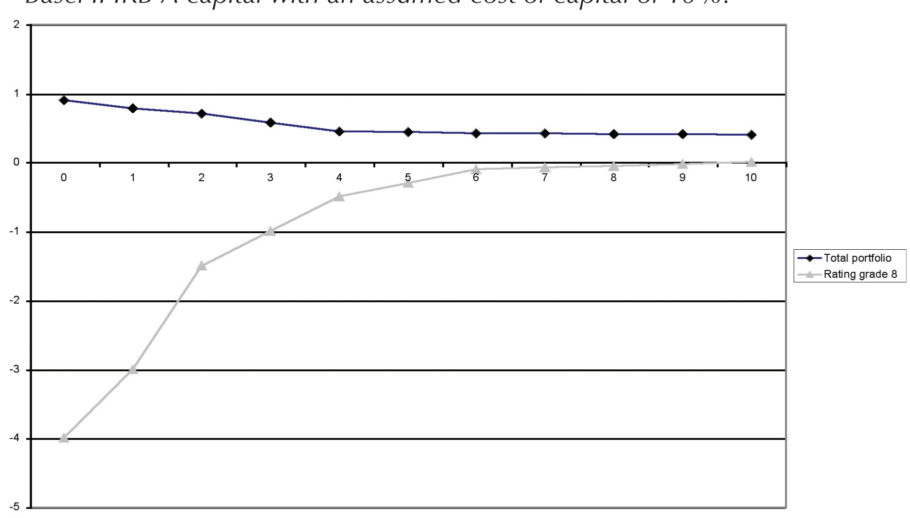
Figure 12: Traditional ALM risk clearing and management.



i.e. integration of the different risk types, then occurs at the level of key economic factors. The capturing of correlation effects for key economic factors, both within and between risk types, is of paramount importance if diversification and concentration effects are to be explicitly accounted for in scenario analysis and stress testing.

In traditional ALM analysis the bank is seen to consist of two legs, the funding leg and the loan or customer leg, and in most banks credit risk and ALM risks are separated at a clearing centre. One of the reasons that this centre exists is to allow performance measurement of loan originators to be based solely on return on credit risk, basically because loan originators typically have no influence on the actual funding. The short-term ALM risks in differences in cash flows in the funding and customer legs, and in particular the differences in timing of these flows, reside at Treasury, where the daily ALM management is executed with transactions on the funding leg. Figure 12 displays a situation where the ALM risk inherent in a customer exposure of 100 units of money is cleared at a clearing centre. The interest rate for the customer exposure is fixed for five years. On the funding side of this exposure is a financing of 100 units of money through, for instance, an emitted bond with one-year intervals between reset times (or maturity). The customer interest rate is 5% and the funding rate is 3%. The actual margin is therefore 2%. If the funding had been perfectly matched with the cash flow offered to the customer, in which case the ALM risk vanishes, the funding rate would be 4% with an actual margin of 1%. To achieve the higher margin, i.e. 2%, the bank therefore has to take on an interest rate risk, which is managed at Treasury. The 1% margin is the margin that would be used in loan performance measurement on the level of loan originators. Figure 13 displays the incremental expected economic profit, in percent, for the same loan portfolio as in figures 9 and 10. In figure 13 we have used a definition of actual capital as the maximum (over time) Basel II IRB-A capital in figure 9. The expected incremental profit is defined in two steps. In the first step we define a cost of risk as the incremental expected loss plus capital times the cost of capital – the cost of capital being set here to 10%. In the second step the incremental expected economic profit is defined as the margin with credit risk, i.e. the margin, as in figure 12, which contains no ALM risk and which is used for loan performance measurements, minus the cost of risk. In figure 13 the incremental expected

Figure 13: Incremental expected economic profit based on maximum Basel II IRB-A capital with an assumed cost of capital of 10%.



economic profit for the total portfolio is decreasing over time due to assumptions of tightening of excess margins and of decreasing volumes. Note that the increase over time in the incremental expected economic profit for the rating grade(s) with the highest initial PD cannot neutralise the decrease in the overall profitability of the portfolio.

A separation of credit and ALM risks, as described above, may seem to contradict demands to integrate the two risks, but this is not the case. The separation enables consistency in performance measurement in loan origination as exemplified in figure 13. However, from a treasury perspective credit risk cannot really be separated from other ALM risks – it is, by necessity, an integrated part of ALM. Where volumes, reset times, maturities and financing rates are deterministic on both the funding and the loan side, this integration is not difficult per se. But in reality an assumption of determinism is an oversimplification.

Figure 14 displays the generic loan structure defining the cash flows on the customer leg. A loan consists of a time to maturity, an amortisation structure, an exposure and an interest rate. The time to maturity can be deterministic as well as non-deterministic, the latter is the case when, for instance, prepayments are allowed. The interest rate can be fixed as well as variable. In the actual construction of a loan the loan structure is parameterised, i.e. all degrees of freedom are fixed and, as a result, the loan generates a deterministic or non-deterministic cash flow.

Focusing on the funding leg, figure 15 shows the generic flow of funds into customer deposits. At the top there is an inflow which can be assumed to equal the income level of the customer. The flow is divided into three sub flows, the transaction volume, the saving volume and other investments. The transaction volume is allocated to a transaction account and is used to fulfil the short time liquidity needs of the customer. The saving volume is allocated, based on a saving policy of the customer, between the different saving accounts offered by the bank. The differences between the accounts are defined through differences in the conditions offered and in particular through differences in the return per unit time and unit currency paid on the deposit. Parts of the inflow can also be assumed to be allocated to other investments, such as mutual funds. We refer to the choices or strategies applied by the customer over time and resulting in the evolution and allocation of funds as an investment policy. To parameterise an investment policy we need to know the current allocation and the current strategy for the allocation of the inflow. The latter strategy is non-trivial to parameterise. In practice, therefore, the factor that makes the problem of the valuation and risk management of the potential mismatch between the funding and customer legs complex is what can be referred to as optionality. Generally, banking books contain numerous implicit options, such as early withdrawal options, options to transfer from less to more profitable accounts, prepayment options on mortgages, borrowing options etc. In the structure for the funding and customer leg described above the customer has the option to switch, at the reset times, between loan structures and, in particular, at basically any time, change the policy applied for investments in the demand deposits. The result of the latter may be that the customer closes all of its accounts and withdraws the amounts deposited or that it transfers all cash available to the most profitable account offered by the bank. In both cases, this results in a

Figure 14: Generic loan structure defining the cash flows on the customer leg.

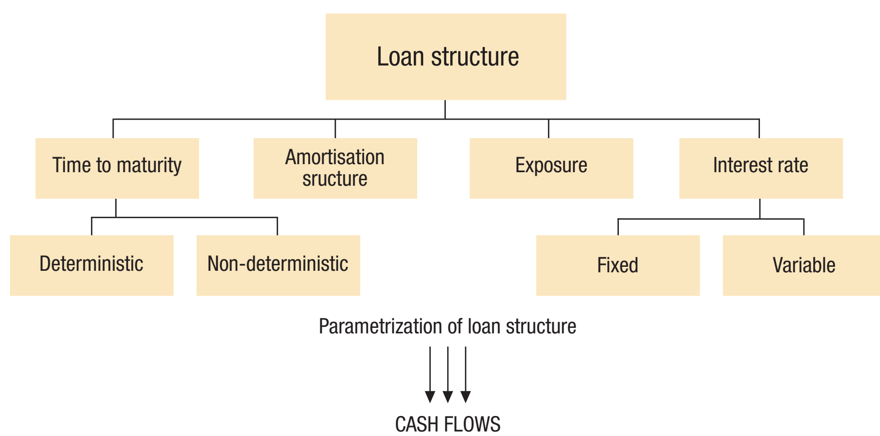
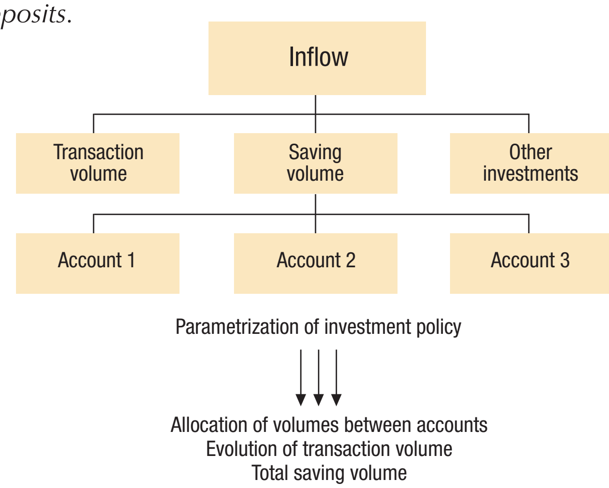


Figure 15: Investment policies define the evolution and allocation of funds into customer deposits.



higher funding rate for the bank. As any of these options are, to some extent, exercised in response to interest rate changes (i.e. market or administered rates), they induce non-linear interest rate risk. A bank that neglects to account for this optionality may end up overvaluing its assets and, potentially, mispricing its products.

Risk managers need a number of behavioural models if they are to perform dynamic analyses of future cash flows, estimate the likely path of future net interest income in line with various financial scenarios, including stress scenarios, and hedge interest rate risk. In particular banks need to model the choices made by the customer – we emphasise that optionality enters through choices of loan structure and investment policy and through changes in choices of loan structure and investment policies over time.

Because customers may make transitions between different loan structures and different investment policies, behavioural features need to be addressed in a dynamic and integrated model for ALM. Furthermore, the establishment of a sound pricing mechanism requires reliable behavioural models that spread economic-value-added commercial incentives across all business units. Indeed, such models are, properly designed, also of considerable assistance to the marketing department in the development and pricing of new products and offerings.

To create and calibrate the type of behavioural models referred to above we can assess these problems on a basis similar to that used to assess credit risk in, for example, retail portfolios. Firstly, the set of key risk factors must be identified. In our case these factors include interest rates (market rates, loan rates, deposit rates) that trigger the action of the customers to, for example, prepay or renegotiate their mortgage or to reconsider the amount deposited as well as its allocation. Secondly, in order to create a dynamic and integrated model for ALM and credit risk the portfolio credit risk model has to be complemented with additional dimensions and models in the portfolio segmentation in figure 8. In particular, on the asset side there is a need for a refined segmentation of the customer base, focusing on a classification of loan structure as in figure 14, and a model for loan structure transition behaviour. Similarly, figure 15 is the basis for segmentation of the funding leg together with models and key drivers for investment policy behaviour.

Capital assessment methodology for operational risk

Within banks there is pressure to manage and quantify operational risk in a formalised and structured way. This pressure mainly comes from regulators. But it also comes through a recognition that the increasing sophistication of financial products and systems. suggests that operational risk need not be a minor concern. Furthermore, banks are recognising that expected losses due to operational risk should be priced into their products. For example, the expected loss of credit card fraud should affect the pricing of credit cards.

At a basic measurement level this structuring of operational risk requires three sources of loss or potential loss information. In particular, there is a need for an internal loss database representing actual loss events, self-assessment and scenario analysis representing expert opinions on loss events that could potentially be experienced, and an external loss database collecting actual external loss events.

These basic measurement tools are required components if a bank is to qualify for Advanced Measurement Approaches (AMA) to operational risk. They also serve as a base for calibration, i.e. they are all, in combination, the information source for calibrating operational risk models. Specifically, their main use is for the calibration of the frequency and severity of identified operational risks. For a discussion of different models for the frequency and severity density used in operational risk see Ebnöther et al. (2001) and for a discussion of the issues that arise when pooling an internal and external database, which both are truncated from below, see Frachot et al. (2002).

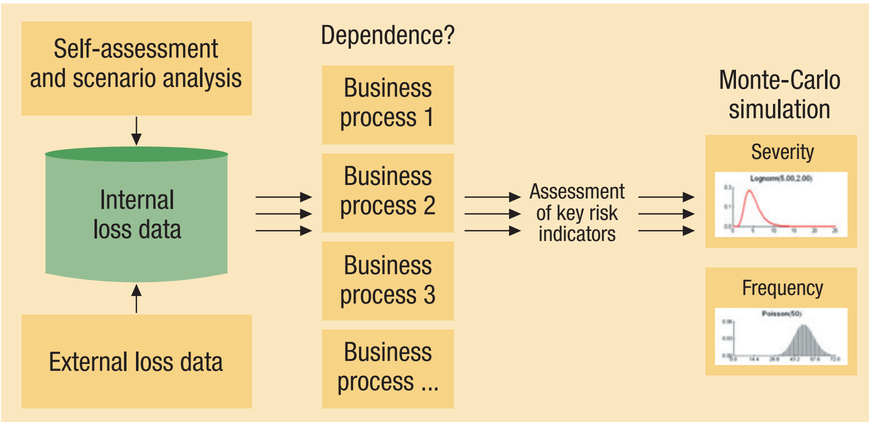
However, the actual risk identification process is not driven solely by the risk information acquired from the three measurement tools. The process of self-assessment also plays a part. One goal of the latter is to give a description of the internal flow of processes, e.g. the process of producing a product such as a loan. The objective of the process self-assessment as part of the risk identification process is threefold. Firstly, it serves as the basis for the allocation of operational risk capital, i.e. both unexpected and expected loss on the desired granularity level, such as business line, product line, etc. Secondly, a huge problem with the quantification of operational risks is the lack of actual data. Hence, a structured approach to risk identification based on process self-assessment and not simply loss data is required. The basic idea is that qualitatively structuring and documenting a bank's process would identify actual risks that would not have been recognised otherwise. Thirdly, a natural element of process self-assessment is the identification of dependencies in the process flow.

Having addressed risk identification, an important part of operational risk quantification involves identifying and assessing, by data or expertise, the impact of so-called key risk indicators on the frequency and severity of loss. Such indicators include business volume and employment turnover.

Figure 17 displays the elements of the risk identification and measurement process and their use in the calibration of operational risk models.

The identification of key risk indicators (KRI) is also of utmost importance from the active operational risk management perspective. The goal is to identify exposures towards KRI, by which the

Figure 17: Elements of the risk identification and measurement process and their use in the calibration of operational risk models.

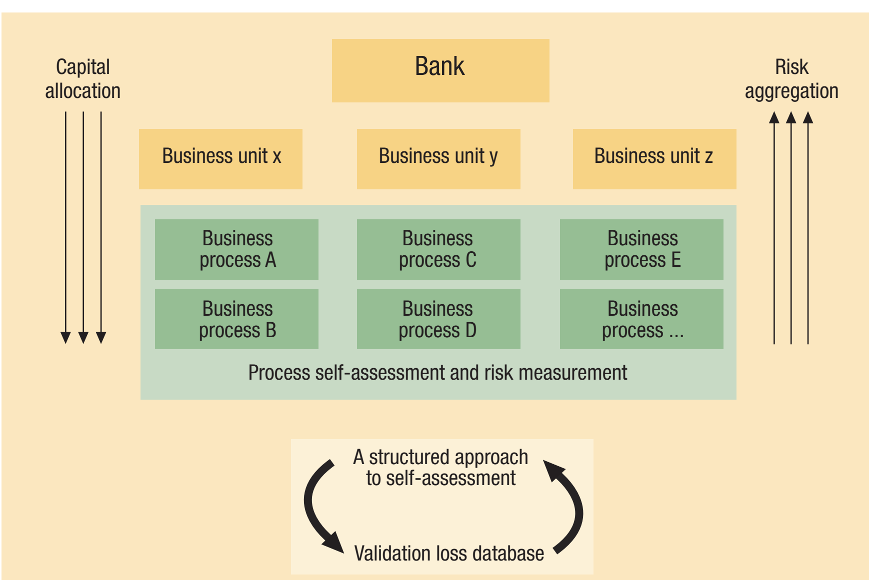


bank can actually steer the intensity and severity of loss. Of course, it may not be the KRI itself that the operational risk manager has control over. Instead, the control instrument available may be via the parameters linking the key risk drivers to the intensity and/or the shape of the severity loss density. These numerical control variates are therefore natural ways to manage and numerically measure "quality adjustment". In addition, the risk manager may also exercise control by the use of insurance programs in a similar way that the credit manager uses credit derivatives for insurance. In practice this means that the level of operational risk at the banks can, to some degree, be controlled through internal risk management activities. However, the application of a control is usually associated with a cost so that the decision to implement a control is based on a cost-benefit analysis. As the operational risk management unit will rarely have a budget for implementation of controls, such cost-benefit decisions are decentralised to the business units or product lines. The level of operational risk capital allocated to the business unit or product line then serves as an incentive for continuous control evaluation.

Figure 18 displays the components of an operational risk framework. This involves a structured approach to risk identification via process self-assessment and risk measurement, as well as methods for risk aggregation and capital allocation. An important part of the operational risk management framework is the method for validation. On a business process level the operational risk management unit must be able to measure quality in the (process) self-assessment. One way of doing this is through objective data as illustrated below. At the bank and business unit level, validation is based on external data and other benchmarks.

For further details on operational risk methodology we refer readers to Cruz (2004) and, for a mathematical AMA framework, to Nyström and Skoglund (2004).

Figure 18: Components in the operational risk framework.



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