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Bank Model Risks Incorporated into the Operational Risk Management Process

SUMMARY: The global economic and financial crisis substantiated the recognition that the mathematical and statistical models applied in the financial sector may lead to costly decision mistakes. The need for managing the risks associated with modelling also arises from the regulatory side. Since European regulations refer to modelling risks among operational risks, this article examines the process of evaluating and managing model risks and the possibility of integrating it into the operational risk management process. Based on practical experiences and the specificities of model risks, the basis of risk management in the case of model risks should be, instead of a capital cover, the formulation of a process replete with adequate controls. Moreover, a seamlessly functioning model risk management system can be designed within the process of operational risk management through the shared loss database, risk self-assessment and the definition of key risk indicators.

KEYWORDS: model risk, operational risk, bank
JEL CODES: G21, G32

The years of the economic and financial crisis erupting in 2008 made it abundantly clear that the increasing use of models in the financial sector may precipitate severe losses, especially in periods of high volatility in the market and in the environment (Danielsson, J. – James, R. K. – Valenzuela, M. – Zer I., 2016).

The increased focus on model risks set into motion two trends in the financial sector, driven primarily by the regulatory authorities. On the one hand, the idea arose that complex models should be simplified or even withdrawn. The first signs of this process are already present in the calculation of the regulatory capital requirement. The Basel Committee issued a recommendation on the withdrawal of the sophisticated models behind the estimation of operational risk regulatory capital and on the replacement of such complex models by a simple calculation method using controlling data (BCBS, 2016/a). On the other hand, the need increased for measuring and managing the risks surrounding models with a significant business impact: for establishing a model risk management system.

In setting up the model risk management framework, even the definition and measurement of model risks pose challenges to the organisation, but identifying model owners – which is the basis of any viable risk man-

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agement system – is even more problematic. The European banking regulation and supervisory practice (EBA, 2014) refer to model risks under Pillar 2 and envisage their management within the operational risk management framework, but they do so without offering a clear conceptual framework for this endeavour.

In the first chapter of the article, we review the changes in the regulation of model risk and put model risk regulation into the context of the regulatory responses given to the crisis. The second chapter presents an analysis of the concept of model risk and attempts to rethink and expand the model risk definition of relevant literature on the basis of practical experience. The third chapter offers a glimpse into the methodology of model risk assessment. The fourth chapter explores which methodology should be chosen for the management of model risk – given the nature and characteristics of the risk – to maximise harmony with regulatory expectations and to make efficient use of the existing risk management tools and expertise of financial institutions. The chapter discusses in detail the possibility of managing the operational risk management process and the methodology to be designed for the measurement and mitigation of model risk under the same umbrella.

CHANGES IN THE REGULATION OF MODEL RISKS

Iván Bélyácz (2013) analyses in detail the evolution of the distinction between uncertainty and risk in the history of economic thinking. Although the literature often refers to the two concepts as synonyms, it is extremely important to distinguish between the two terms. In the case of risk, it is possible to define the probability of future events, while the likelihood of uncertainty cannot really be readily quantified.

In the past few decades, experts concerned with the estimation of risks did their best to ignore uncertainty and capture all future events by way of mathematical models as a projection of historical events. The advancement of mathematics and the integration of mathematical and physical correlations into economics contributed to these efforts. The upsurge in the construction and application of models has become especially prevalent in the financial sector. We should, however, bear in mind that a model is a stylised image of reality that fails to handle any measure of uncertainty – such as a sudden shock to the economic or political environment – beyond risk. Consequently, the introduction and increasing popularity of models entailed the emergence and intensification of model risks.

The European regulation of the management of model risks has a short history. Although Basel II warns, under Pillar 2, that the capital requirement should be sufficient to cover all significant risks, there are no provisions on model risk specifically. In relation to the valuation of trading book elements, it stipulates that the models used for such purposes should be subject to periodic review and that the valuation adjustment should cover the uncertainty of the model valuation (BCBS, 2004).

In reference to the models used for the valuation of derivatives, the Regulatory Technical Standards (RTS) of the European Banking Authority (EBA) – on which public consultation was launched in 2013 before its adoption in 2015 – specifically prescribes adjustments for model risk (EBA, 2015).

Basel III, in turn, already identifies model risk and measurement error as a focal point of the regulation, as an important part of the regulatory response to the crisis. Banks should address the measurement errors of individual models and should provide an extra layer of protection against such risks. That notwithstanding, the regulation still does not include any definition for models and model risks and offers no guidance regarding their measurement. In terms of their management, the single tool identified in the document is the risk coverage of the capital framework (BCBS, 2011).

While the European Union CRD IV directive still fails to address the definition of models, it is the first document to define model risks, referring to them among operational risks. According to the directive, *"model risk means the potential loss an institution may incur, as a consequence of decisions that could be principally based on the output of internal models, due to errors in the development, implementation or use of such models"* (CRD IV, 2013).

Apart from the definition, however, the regulation does not provide for either the measurement or the management of model risks; it merely requires institutions subject to the directive to specifically address model risks within operational risks.

Compared to European Union regulations – which, apparently, have only recently started to assign more significance to this risk type –, the American provisions are far more detailed, thanks to the precise definition provided by the Board of Governors of the Federal Reserve System with respect to models and the model risk management framework. Accordingly, *"the term 'model' refers to a quantitative method, system, or approach that applies statistical, economic, financial, or mathematical theories, techniques, and assumptions to process input data into quantitative estimates" (Fed, 2011, p. 3).* According to the Fed's definition, the model consists of three components:

- input: an information input component, which delivers data, initial assumptions and hypotheses to the model;
- the model itself in the narrow sense: parameterisation, selected procedures;
- output: a reporting component, which translates the results of the model into decisions.

In this article, we adopted this model definition and applied it for the purposes of further analyses. Despite the precise definition, it is not easy to define the models used by the organisation in practice. Although the literature offers some recommendations for the distinction between a model and a simple computation by definition, actual boundaries can only be captured at the level of individual institutions by reviewing the internal frameworks of the given institution.

The EBA's SREP Guidelines (EBA, 2014) defines the activities where banks commonly make extensive use of models. These activities include trading in financial instruments, risk measurement and management and capital allocation (including lending policies and product pricing).

If the models are taken account of on a process basis, they will be found – based on our practical experience – in the following additional areas:

- risk management
  - capital calculation models
  - models estimating risk parameters (PD, LGD, EAD, CCF, etc.)
  - models supporting the definition of impairment rates
  - models for the definition of ratings and limits (e.g. country and counterparty risk management)
  - fraud prevention model
- liquidity management
  - models for liquidity risk management
- treasury activities
  - calculation of the value at risk values of trading activity (VaR models)
  - cost of capital calculation
  - margin requirement calculation
- supply of credits and loans
  - models used for the definition of internal financing premiums

- compliance
  - filtering models for the detection of money laundering
- strategic and controlling tasks
  - stress tests
  - planning models

Most models can be linked to risk management and, in particular, the prevalence of credit risk models is remarkable.

The majority of authors considering model risks rely and provide detailed analyses on the models used by financial institutions. Nevertheless, modelling practices are not uncommon outside of the financial sector either; examples include the pricing models of the energy sector, the models used for geothermal systems in environmental engineering, noise pollution or climate change models, the modelling of particle motion in physics or the forecast models applied in the agricultural sector. That notwithstanding, it is undoubtedly the deficiencies of the models used by financial institutions that may have a direct financial impact on retail, corporate or institutional clients or on the performance of the economy. In line with the main focus of the literature and our own practical experiences, in examining model risks, this article also concentrates on the financial sector in general and on banks in particular.

HOW CAN WE CAPTURE MODEL RISKS?

After the definition of models, we attempt to illustrate model risk through the presentation of the lifecycle of a model used by – but at least commonly known among – most banks.

Basel II permitted banks to adopt Advanced Measurement Approaches (AMA) for the purpose of determining their regulatory capital requirement. The AMA refers to an internal model using sophisticated and complex mathematical and statistical methods. This model is especially suitable for illustrating model risks because even its adoption was received with harsh criticism; subsequently, the Basel Committee proposed to standardise and tighten the parameterisation and environment of the model and eventually, it recommended the complete withdrawal of the methodology.

Parallel to the issue of the recommendations, the consultative documents published by banks, regulatory authorities and consultants effectively illustrated all of the possible deficiencies of the model and the risks arising from its application. This is the model that spurred the greatest controversy among experts and researchers; in addition, its entire lifecycle can be observed from its adoption to its withdrawal.

Before presenting the arguments for and against the model, we should review the concept and regulation of operational risks. Operational risk *"means the risk of loss resulting from inadequate or failed internal processes, people and systems or from external events, including legal risk"* (MNB, 2015, p. 67). This risk type is sector neutral and may materialise at any organisation in relation to external and internal fraud, customer complaints arising from human errors, natural disasters or IT system shutdowns, only to mention a few of the possible operational risks. This issue is all the more pressing for banks, as they are required – as of 1 January 2008 – to set aside the amount of capital required to cover their exposure to operational risks. The regulator permits the use of three options for the calculation of the capital requirement, the most sophisticated of which is the internal model based AMA method mentioned in the previous paragraph. This measurement approach simultaneously considers historical losses, the result of self-assessments estimating future risks and testing the quality of controls, scenario analyses aimed at the quantification of disastrous risks and the content of external databases collecting other banking losses.

Upon the introduction of the AMA model, maximising the precision of input data, prescribing a closed IT environment, management reports and periodic validation ensured the mitigation of model risks.

The nature of model risks is aptly reflected in the concerns raised in relation to the AMA model, the most important of which – based on the model's input, output and parameterisation component – can be summarised as follows.

- The Basel Committee justified its proposal to eliminate the methodology by stating that the modelling of operational risk for regulatory capital purposes is unduly complex and that the AMA has resulted in excessive variability in risk-weighted assets and insufficient levels of capital for some banks *(BCBS, 2016/c).*
- The AMA regulation is limited to defining the modelling framework and provides more room for the design of institution-specific conditions. As a result, the majority of models were calibrated on an expert basis, ignoring sound mathematical/statistical analyses and backtesting. As a result of low-level standardisation, calculations yield significantly different regulatory capital figures across institutions, which deteriorates transparency and comparability *(PwC, 2015).*
- We may conclude that, despite the initial requirements and thorough supervisory and internal model validations, lax regulatory frameworks made the institutionalisation of modelling errors across the banking sector inevitable.
- In determining the required regulatory capital figure, the AMA model relies far too heavily on historical-event data and thus, it does not reflect the true risk profile of the institution (PwC, 2015). Model risk is rooted in the assumption that future losses can be predicted from historical events. This train of thought, however, underestimates the significance of uncertainty. Once again, this criticism reflects the need to distinguish between risk and uncertainty.
- Reliable modelling, first and foremost, depends on the proper quality and quantity of data which, considering the data sources of operational risk management[1], are not always available. The time series is typically insufficient in the case of external and internal data, while expert estimates are distorted by subjectivity; in other words, the risk arising from input data is inherent in operational risk models *(Sherwood, J., 2005).*
- The risk related to the use of the model's output is the fact that banks, for the most part, view it as a tool for reducing the capital requirement and calibrate the model's parameters according to this objective. Therefore, the results of the model cannot be viewed as sufficient for promoting sound risk mitigating measures and risk management tools, and they are not integrated into day-to-day risk management *(Wyman, O., 2006).*

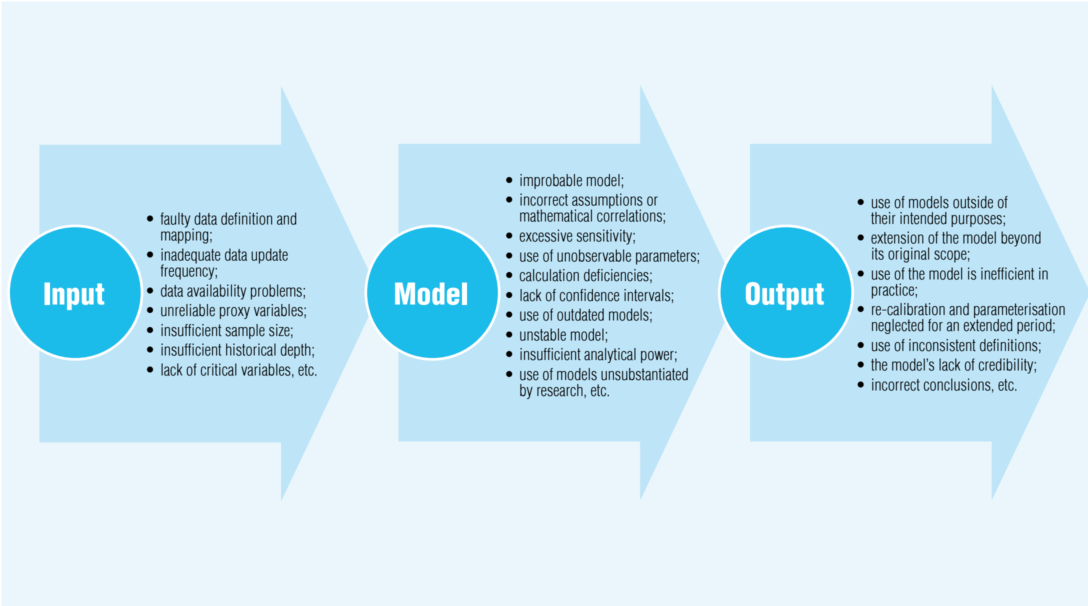
After this specific example, below we present an overview of the model risk approaches discussed in the literature. *Lebel* and *Gagnon (2014)* define model risk as errors within models and the misuse of models, while *Barrieu* and *Scandolo* (2015) simply consider the hazard of working with a potentially not well-suited model as model risk.

In measuring model risks in the narrow sense, our baseline assumption is that risks are present during the entire lifecycle of the model – development, implementation, monitoring, validation and audit – and typically derive from the previously mentioned three main sources, as illustrated by *Figure 1.*

As demonstrated by the examples, it is the models' parameterisation and matching problems that the authors consider relevant to modelling or model risks; in other words, the

Figure 1

TYPICAL MODEL RISKS AND THEIR SOURCES



Source: own editing based on Management Solutions (2014)

choice of statistical parameters used for the modelling and the extent to which the model matches real data. Practice and regulatory requirements, however, call for a broader interpretation of model risk. *Shi, Young* and *Cao* (2015) interpret the concept as financial loss or reputational damages caused by the use or the output of the model. This definition, however, offers no guidance as to where to look for model risk: where is the point at which it departs from the problems of the IT system operating the model or from the errors of experts participating in the development of the model.

The debate erupting around and the arguments expressed in connection with the withdrawal of the AMA, as well as our practical experience demonstrate that the definition of model risk should be expanded further.

Before formulating a broader definition, we should look at the model risk events of recent years.

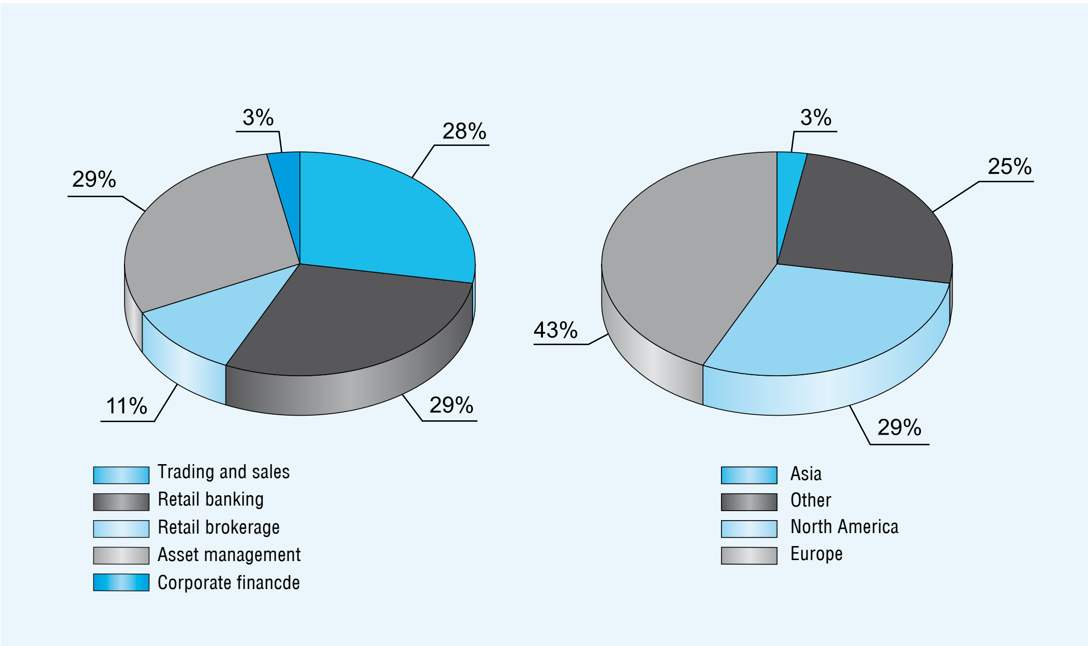
According to the SAS Global Data[2] database on the financial sector, the number of losses stemming from modelling errors is extremely low; only 28 out of nearly 30,000 publicly disclosed data items. As regards business lines, the most frequent model risk losses related to flawed product development occur during trading and sale, asset management and retail banking activities *(see Figure 2).*

As a result of model errors, financial institutions may need to pay compensation to customers, penalties and other, compliance related supervisory fines, or face significant reputation risk effects. Losses may range from tens of millions to thousands of billions of forints.

Among the greatest losses on record was the loss incurred by a Swiss financial institution due to erroneous option pricing during its trading and sale activities, which raised its hedging costs spectacularly. Losses resulting from the modelling risk of the retail sector

Figure 2

DECOMPOSITION OF THE NUMBER OF MODEL RISKS BY REGION AND BUSINESS LINE (2002–2015)



Source: SAS Global Data

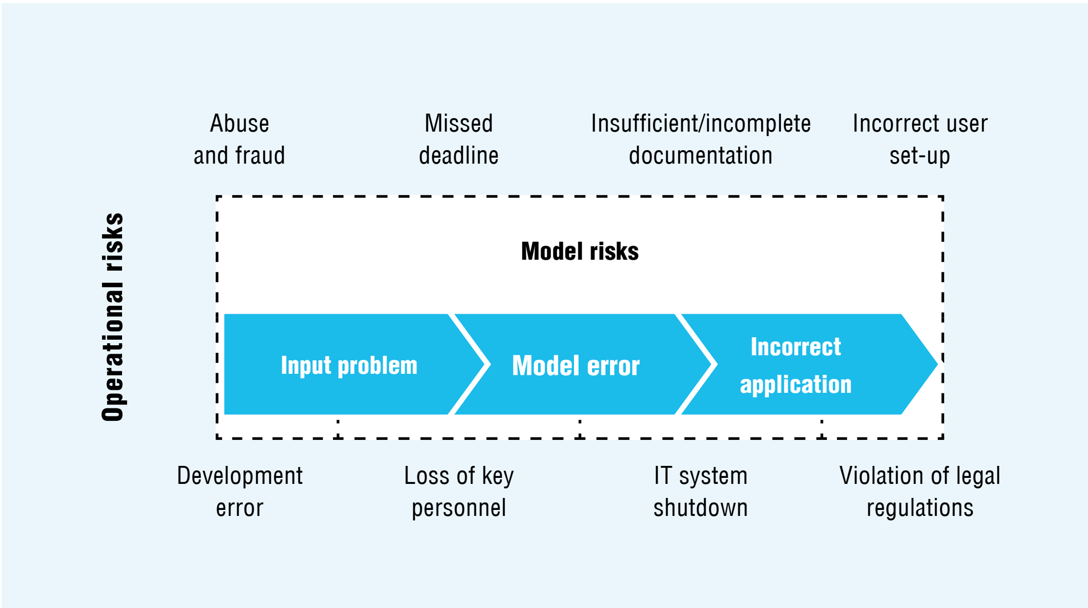
amounted to an extremely high figure for a Canadian bank that miscalculated the default interest of nearly 28,000 mortgage loan customers. When the error was discovered more than ten years later, the bank had to reimburse about USD 6 million to customers for overpayment.

The scarcity of model errors in the database can be explained by the lack of a consistent definition, the difficulties of quantification and the fact that model errors are often attributable to other operational risks – e.g. system shutdown, incorrect manual parameter setup, development deficiencies – and therefore, they are not classified as such. Apart from the public databases, there are consortium databases (pooled data sharing), through which financial institutions share their loss data anonymously. The most commonly known such database in Europe is the ORX Consortium Database. The close link between – and occasional inseparability of – modelling risks and operational risks is demonstrated by the fact that the ORX database does not even have a separate category for losses stemming from model risks; they appear among operational risks.

In short, actual loss events suggest that model risks are hard to interpret independently; their occurrence is often precipitated by operational factors. Incorrect calculations may result from system errors or power outages, but incorrect parameterisation could also involve user errors. Inconsistent interpretation of the definitions used during the modelling process is generally caused by insufficient/incomplete documentation, but the improper use of model results may also point to fraud or abuse. Bias in the data included in the database may be the result of data collection errors

Figure 3

BROADLY INTERPRETED MODEL RISKS



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or incorrect expert estimates. The correlations between modelling and operational risks are illustrated by *Figure 3.*

In considering the similarities between model risks and operational risks, we may conclude that the following is true for both risk types:

- both are sector neutral: while they occur more frequently at financial institutions, pricing or business models are not uncommon in the energy sector and the telecommunications sector, and the use of models has also become prominent in the field of engineering, medical sciences and the agricultural sector. Operational risks are also characterised with this sector neutrality;
- heterogeneous, hard-to-define risk types;
- the risk/return correlation is irrelevant in the case of model risks and operational risks; the undertaking of higher risks does not promise higher returns. Instead, considerations should be focused on the amount spent on risk mitigation;
- there is no uniform measurement method for model risks and operational risks; the reliability of measurement is low;
- risk management requires the participation of several units of the organisation;
- responsibility for model risks is assumed by the model owner professional unit and likewise, the given professional unit or process owner is responsible for operational risks.

Based on this line of thought, in our view modelling risks should be defined and managed in a broader sense, along with their operational risk implications.

Accordingly, based on our definition, modelling risks are losses stemming from the errors of the model's input data, parameterisation or application, including the operational risks arising during the operation and application of the model.

MEASUREMENT OF MODEL RISK

The truly painful losses an organisation may incur during the use of the models can be captured by the consequences of incorrect decisions. They may include the loss of customers caused by reputation risk; compensation to customers in response to customer complaints; the selection of loss-generating investment opportunities; model errors giving rise to external or internal fraud. Due to the diversity of models, quantifying the economic consequences of model risks is a challenging task. Essentially, two approaches can be distinguished:

- analytical estimation methods; and
- the use of expert estimates.

Several authors have attempted to propose an analytical estimation methodology, focusing their attention primarily on market risk models.

Danielsson, James, Valenzuela and *Zer* (2016) introduced the concept of risk ratio. Suppose we have *N* candidate models to forecast the same risk. In this case, the risk ratio can be defined as the ratio of the highest to the lowest risk forecasts produced by the models. If the various models yield very similar estimates, then the risk ratio will be close to 1, which corresponds to a low model risk. In such cases, mutually validating each other, the various models signal the suitability of the selected model.

Barrieu and Scandolo (2015) argue that the multiplier introduced by the Basel Committee as an ingredient in the assessment of the capital requirements for market risks is a sound measure of the risk associated with this model (BCBS, 2016/b).

In addition to comparison with potential candidate models, a typical way to identify the risks associated with a model is by backtesting; i.e. when the forecast calculated by the model is compared to the values of actual observations. However, once again we should bear in mind that, as Bélyácz (2013) pointed out, it is the uncertainty factor that cannot be captured by merely projecting historical data. Consequently, even backtesting is not fully capable of estimating the future performance of a model or filtering out its errors.

These examples illustrate that the quantification of model risk – the model's "goodness of fit" – is hard to define; it can only be compared against the results of other models of unknown quality, or historical time series.

The subjective expert estimation methods (self-assessment, scenario analysis) described in detail in the operational risk regulation (HFSA, 2008) represent another group of options. As part of this exercise, based on data available and historical experiences, banking experts produce the best possible forecast of expected losses.

According to the methodological guidelines for supervised financial institutions on the internal capital adequacy assessment process (ICAAP) and on its supervisory review process (SREP) (MNB, 2015), specific model deficiencies and their operational risk implications can be more easily identified and managed within model risk. They can be captured by such adequate models as sensitivity analyses and stress tests or conservative parameterisation. By contrast, the guidelines emphasise that estimating the economic and reputation impact of decisions made on the basis of incorrect results is an extremely challenging task. Given the difficulties of capturing the potential losses arising from model risk, the recommended method of safeguarding against such risks is the implementation of adequate risk management rather than the quantification of – and capital allocation for – model risks.

In the next chapter we analyse the management of model risk with this train of thought in mind.

RELATIONSHIP BETWEEN THE OPERATIONAL RISK MANAGEMENT FRAMEWORK AND MODELLING RISK

As mentioned before, European regulations consider model risk – as well as the similarly recently defined legal risk and conduct risk – to be a sub-type of operational risks under Pillar 2.[3]

The process of operational risk management

The regulation of operational risks can be divided into two parts. On the one hand, the regulation defines provisions for capital allocation (quantitative requirements); on the other hand, it describes in detail the requirements regarding the risk management framework of institutions (qualitative requirements). Of all the regulations and directives related to risk management, only those related to operational risks provide such detailed guidelines on the formulation of a risk management methodology; i.e. identification, assessment and monitoring of risks, risk mitigating measures (HFSA, 2008).

The operational risk management framework can be captured from various angles; we can examine:

- firstly, the risk management process itself;
- secondly, the practices implemented for the collection of the data required for efficient risk management;
- thirdly, the personnel network participating in the risk management process and the accumulated experience and expertise of the participants.

The risk management process, i.e. the identification, assessment and monitoring of risks and the design of risk mitigating measures, is a universal practice; this cyclically repeated process should be carried out for each risk type. In the case of operational risks, the regulation expects all financial institutions to carry out this process at least once a year (HFSA, 2008).

As regards the practices put in place for data collection, with a view to meeting qualitative requirements, the operational risk management framework consists of the following elements:

- The first element is the collection of loss data, which involves the collating of historical events into a database and data analysis. Data collection has a dual purpose: on the one hand, it provides input for the calculation of the capital requirement; on the other hand, it may serve as a basis for the targeted implementation of risk mitigating measures.
- The second element is the practice of risk and control self-assessment (RCSA): we explore the risks that the institution may face in the future in the case of the given process and examine the extent to which the existing control environment is suitable for filtering out these risks.
- Thirdly, the practice of scenario analysis serves a similar purpose as risk self-assessment, except for its focus on low-probability risks exerting a significant impact on the operation of the organisation.
- Finally, the fourth element is the key risk indicator system. The periodic measurement of risk indicators allows for the monitoring of risk deterioration and developments in loss events, and action can be taken, as required, to counteract the deteriorating trend.

In addition to these four risk management data sources and tools, the risk appetite framework can be another option to improve risk control functions. In the case of model risks, risk appetite should be interpreted in the same way as in the context of operational risks: in reality, organisations have no "appetite" for such risks; they merely tolerate their presence at some level *(Lamanda – Võneki, 2015).*

Apart from the process and the data sources, a typical characteristic of operational risk management systems is the fact that they cannot function properly without a well-trained and committed personnel network. The efforts of LORMs ("local operational risk managers") or process owners are intended to enable the organisation to manage this heterogeneous risk type despite the difficulties experienced in capturing and assessing it.

The process of model risk management

In consideration of the rules defined by the detailed American regulation (Fed, 2011), the process of model risk management can be summarised along the lines of the process illustrated in *Figure 4.*

The purpose of the process is to enable – after a thorough understanding of the models – the formulation of the control mechanisms that are designed with a view to minimising risks.

The first step in determining risk exposure is to identify the models and produce a model inventory. In view of the large number of the models identified, the need may arise for the classification of various model types according to some additional criteria. Easy-to-manage, transparency-enhancing model families can be created, for example, on the basis of model purpose, e.g. calculation of capital requirement, estimation of risk parameters, rating, limit-setting, pricing, ALM or planning models.

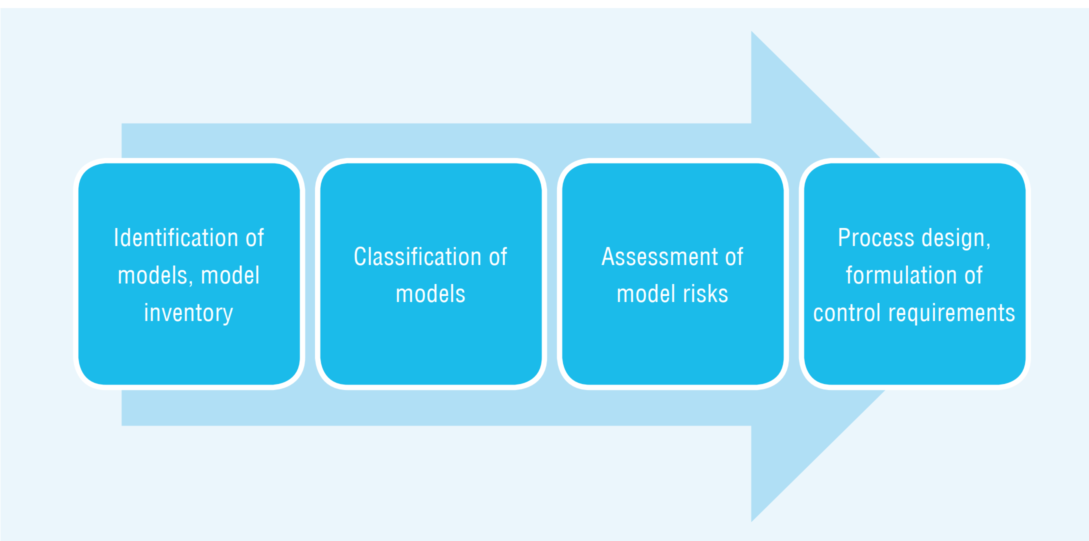
This step enables the institution to gain a consistent picture of the units using the models and to identify the areas associated with the most significant model risks *(Institute and Faculty of Actuaries, 2015).*

After their identification, models are evaluated. We perform the qualitative and quantitative evaluation of the models on the basis of the criteria proposed by Management Solutions (2014), supplementing them by practical experiences. The evaluation is performed on the basis of three criteria: complexity, impact on decision and materiality.

- Complexity: low-complexity models are constructed on the basis of simple operations

Figure 4

MANAGEMENT OF MODELLING RISKS



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and basic functions, while operating models of higher complexity categories requires mathematical or programming expertise. Control functions can be subsequently defined on the basis of complexity; for example, the performance of regular validation activities require different skills of the independent, internal validator.

- The "impact on decision" criterion refers to the extent to which the results of the given model influence sensitive decision-making processes or the preparation of critical financial statements or supervisory reports. Models classified into the high-risk category constitute the basis for decisions of key significance from the perspective of the institution, and affect not only internal reports but also reports prepared for third parties, e.g. regulatory authorities, rating agencies or shareholders. The evaluation should also weigh reputation risks.
- The definition of materiality means the quantification and assessment of model risks, as discussed in the previous chapter.

After the evaluation of the models on the basis of these three criteria, the institution can classify them – also in consideration of regulatory expectations – into categories and formulate standardised control requirements for the individual categories. It is important to perform this classification, as the impact of some models on business decisions is not as significant as the impact of others; therefore, the resources available for risk mitigation can be concentrated on the management of models with high loss potential.

In designing the control system, the following areas may come into focus:

- documentation of the modelling process;
- design of model lifecycle, the content and frequency of the review;
- independent external and internal validation;
- model utilisation and its constraints;
- change management;
- data quality controls;
- Model Governance and reports.

Although each criterion would deserve a separate analysis, discussing them in detail would be beyond the scope of this paper.

In the approach outlined above, the assessment of model risks is assigned a lesser significance – which is also justified by the lack of assessment methodologies –; instead, the focus is on the construction, execution and review of controls.

Integration of modelling risk management into the process of operational risk management

In the second chapter of this article, we provided an overview of the specificities of model risks and discussed their similarities with operational risks. We then proceeded to examine the operational risk management process prescribed by European regulations and, in the lack of European guidelines, presented an example for the individual steps of model risk management on the basis of the regulations prevailing in the United States. This chapter is intended to explore the possibility of implementing a combination of the two processes.

Identification

The first step in both processes is the identification of risks and the models. In the process of operational risk management, this step takes place in the context of workshops, with the participation of regularly trained contact persons appointed by the institution (LORMs or, in the case of process-based risk management, dedicated process owners). The communication channel put into place by the institution's operational risk management unit and a decentralised risk management approach can provide a suitable framework for the identification of the models operated by the bank. Since all units of the institution are represented during the identification of operational risks, the experts participating in the given forum are in possession of all information required for the reviewing and identifying the models.

Assessment

Operational risks are generally assessed at the same forum where risks are identified. Once again, the expertise required to assess and classify the models and to define the related model risks is readily available. The complexity of the measurement of model risks depends on the methodology chosen. If the institution prefers expert estimates to the quantitative methodologies outlined in the third chapter, these estimates can be actually made at the self-assessment meetings arranged for the purposes of operational risk management. The difficulties involved in the evaluation and quantification of losses arising from model risks are also present in the case of other, operational risk type events (estimating the business impact of IT system shutdowns, evaluating the events exerting a reputation impact). If the institution has already adopted procedures for these events in the framework of operational risk management, they can be efficiently adapted to estimate the consequences of model risks.

Monitoring

The next step is monitoring, a process designed to minimise identified risks. As mentioned before, in the opinion of the regulatory authorities the efficiency of the risk management framework hinges on a properly functioning modelling process and built-in controls. In the case of operational risks, this monitoring function is performed by the key risk indicator system. The construction and monitoring of such risk indicators should also be considered for modelling risks. Examples for the available indicators include (IFA, 2015):

- Number of models classified into the high-risk category;
- Cumulated amount and/or number of loss events arising from model errors;
- Number of models deemed unsuitable for their given purpose by the independent validation;
- Number/level of model enhancements aimed at the elimination of the model's errors and deficiencies;
- Overdue model review;
- Number of overdue model validations;

RISK MITIGATING MEASURES

In the case of operational risks, risk mitigating measures are defined along with the process of their implementation. If the institution decides to use key risk indicators for the control of model risks, their monitoring could be integrated into the existing practice.

Having reviewed the process, our proposed solution for managing modelling risks within the operational risk management framework is the following: the modelling should be considered to be a separate process, which should use the operational risk management toolset and involve the already established and trained expert network.

The proposed process is shown in *Figure 5.*

With the implementation of the process, the management of model risks would take place in the operational risk management framework of the institution, through the tools and methodology available therein.

CONCLUSIONS

Undoubtedly, the increasing prominence of models that constitute the basis of an increasing percentage of financial sector decisions carries severe risks. Regulatory authorities have attempted to manage these risks, although the level of detail regarding the requirements imposed on the financial sector differed from country to country.

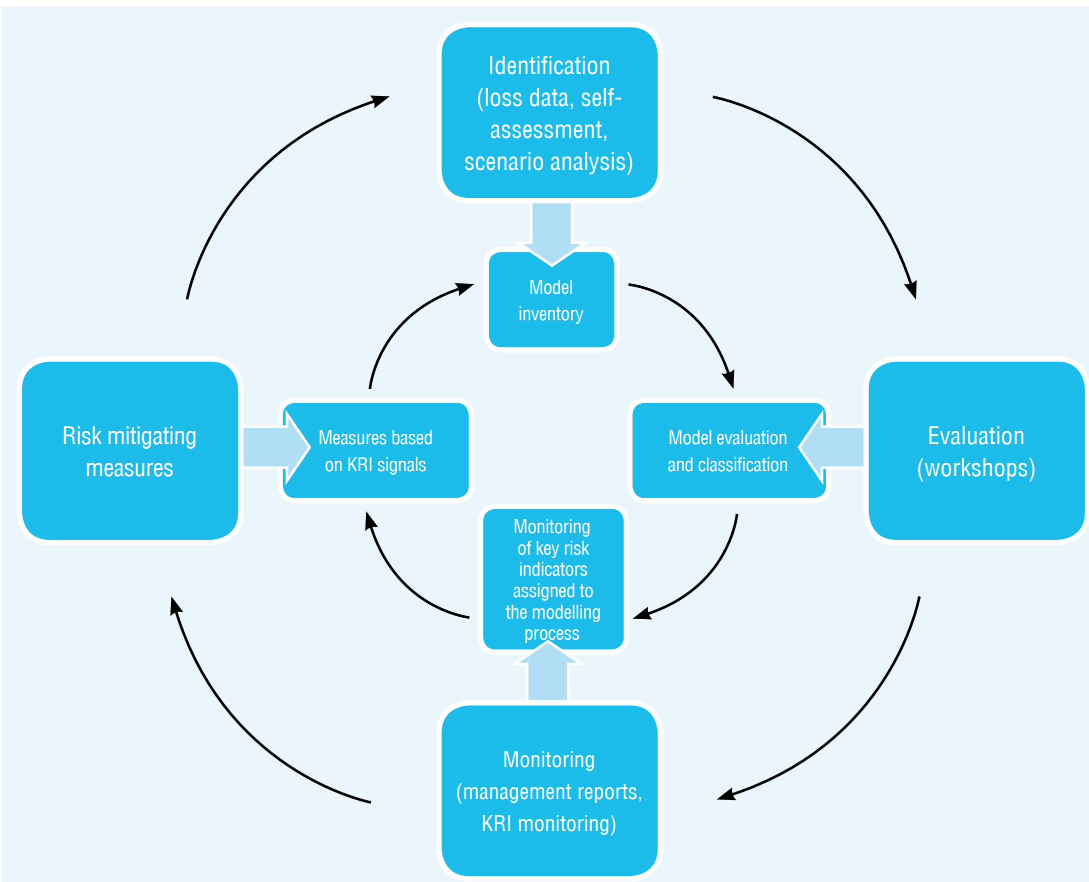
Participants of the financial market may face a number of obstacles during the practical implementation of modelling risk management. In the first step, even the identification of models and their separation from simple computation pose a challenge. Attempts to define modelling risks point to their close relationship with other risk types (especially operational risks), which often renders the identification of pure model risks impossible. The literature refers to several methodologies for the quantification of modelling risks, but they are typically applicable to a specific model type (e.g. market risk models).

In order to remove these obstacles, we propose the following approaches.

- Since European regulations refer to modelling risks among operational risks, it would be worth considering the utilisation of the results, network and methodology of the established operational risk management framework for the purposes of identifying, measuring and managing modelling risks.

Figure 5

MODELLING RISK MANAGEMENT WITHIN THE PROCESS OF OPERATIONAL RISK MANAGEMENT



Source: Own editing

Accordingly, the model inventory could be constructed and the models could be classified during the process of model identification and classification with the assistance of the existing expertise of the network established for the management of operational risks, in the context of workshops and brainstorming.

Measuring model risks is a complex task without a uniform methodology; therefore, the primary risk mitigating solution should be a properly designed modelling process, rather than the allocation of capital for covering model risks. This characteristic of modelling risks and the fact that such models are present across all units of the organisation make model risks similar to operational risks.

Consequently the management of modelling risk should be based on the construction of a proper control environment. Costly decision mistakes associated with the increasingly frequently used models could be mitigated by a process structured around the controls integrated into the modelling process, the periodic review of the models and internal/external validation.

By constructing and monitoring key risk indicators, developments in modelling risks could be controlled within the operational risk management framework.

Modelling risk is the most recent risk element emphasised by the regulator among operational risks, with special recommendations regarding its management. An additional direction of research could examine other risk factors that may receive special attention in the future as risks requiring separate methodologies and special attention on the part of organisations and supervisory authorities. In view of the expected regulatory changes, the question arises as to whether the simplification and standardisation of the models may lead to an increase in systemic model risks. In this article, we examined the management of model risks at financial institutions, but we believe that the issue should be also explored in the context of other sectors. The financial sector is privileged in the sense that it has advanced risk management regulations and an established risk culture. As risk management expectations may be lower or non-existent in other sectors, in such sectors the identification, measurement and management of model risks may pose a greater challenge.

Notes

[1] Based on legal regulations, the AMA model builds on four mandatory data sources (internal and external loss data, the results of self-assessment and scenario analysis).

[2] SAS OpRisk Global Data is one of the largest and most comprehensive information repositories of publicly reported operational losses in excess of USD 100,000. It has been collecting and storing operational risk data since 2002. It documents more than 30,000 loss events, which have been collected on the basis of published case studies and press information. *Source:* https://support.sas.com/documentation/onlinedoc/securedoc/index_oprisk.html

[3] According to the definition of the MNB's review guidelines, conduct risks are a part of the legal risks associated with operational risks and they mean the current or prospective risk of losses to an institution arising from inappropriate supply of financial services including cases of wilful or negligent misconduct (MNB, 2015).

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