Institute
and Faculty
of Actuaries

DISCUSSION PAPER

Operational risk dependencies

P. O. J. Kelliher*, M. Acharyya, A. Couper, E. Maguire, P. Nicholas, N. Pang, C. Smerald,
D. Stevenson, J. Sullivan and P. Teggin

*Corresponding author. Patrick Kelliher, c/o Research and Knowledge, Institute and Faculty of Actuaries' Operational Risk Working Party, Level 2 Exchange Crescent, 7 Conference Square, Edinburgh, EH3 8RA, United Kingdom. Email: patrick_oj_kelliher@yahoo.co.uk

Abstract

This paper explores dependencies between operational risks and between operational risks and other risks such as market, credit and insurance risk. The paper starts by setting the regulatory context and then goes into practical aspects of operational risk dependencies. Next, methods of modelling operational risk dependencies are considered with a simulation study exploring the sensitivity of diversification benefits arising from dependency models. The following two sections consider how correlation assumptions may be set, highlighting some generic dependencies between operational risks and with non-operational risks to assist in the assessment of dependencies and correlation assumptions. Supplementary appendices provide further detail on generic dependencies as well as a case study of how business models can lead to operational risks interacting with other risks. Finally, the paper finishes with a literature review of operational risk dependency papers including correlation studies and benchmark reports.

Keywords: Operational Risk; Dependency; Diversification; Correlation; Copulas

1. Introduction

The Operational Risk Working Party aims to assist actuaries and others in the modelling and management of operational risk. One of the key challenges in modelling operational risk is the modelling of dependencies between operational risks and between operational and non-operational risks such as market, credit and insurance risk. This paper seeks to assist in this regard and help develop good practice in setting assumptions and modelling operational risk dependencies.

In terms of structure, the paper starts by outlining why we model operational risk dependencies and makes some general observations on the nature of these. It then considers methods for modelling dependencies and how we might set correlation and other assumptions. This includes some generic sources of operational risk dependency which can be used to inform the modelling of dependency and the setting of correlation and other dependency assumptions. Lastly, we outline a review of literature pertaining to operational risk dependencies.

The paper focuses on financial services companies and in particular banks, asset managers and insurers, but it is hoped that this also has wider relevance.

2. Why Model Operational Risk Dependencies?

The primary reason to model operational risk dependencies is to understand the nature of operational risk exposures and how disparate risks may be connected. This feeds into the assessment of economic capital and other resources required to be able to withstand extreme yet plausible combinations of operational and other loss events at a desired level of confidence. It is unlikely that all

operational risks will crystallise at the same time, and it is appropriate to allow for a diversification benefit to reflect this, that is, the economic capital requirement for all operational risks should be less than the sum of stand-alone requirements for individual operational risks. Allowances for dependencies between operational risks will affect the level of this diversification benefit.

The Working Party also believes that it is appropriate to allow for diversification between operational and non-operational risks as again it is unlikely that these will all crystallise at the same time. There is thus a need to understand dependencies between operational and non-operational risks to model the degree of diversification between these risks.

As well as modelling operational risks and associated economic capital requirements, there is also a regulatory context in that banks and insurers need to hold regulatory ("Pillar 1") capital to cover operational risks, and dependencies may affect the amount of capital held.

2.1. Banks

An explicit requirement to hold operational risk capital was introduced for banks as part of Basel II which was finalised in June 2006 (Basel Committee on Banking Supervision (BCBS), 2006, part 2.V). There were three alternatives for assessing this capital requirement. The Basic Indicator Approach and the Standardised Approach (TSA) were based on set percentages of gross income, with the latter refined by type of business. As an alternative to these, a bank could apply to use its own model of operational risks for setting capital requirements as part of the advanced measurement approach (AMA), subject to this model meeting quantitative and qualitative standards.

As part of the AMA, a bank could allow for diversification between operational risks subject to satisfying regulators about their system for identifying and modelling dependencies between risks. Note, however, that the Basel II framework did not allow for diversification between operational and non-operational risks. The Working Party feels that this was unduly prudent in that it did not recognise that operational and credit and markets risks are not perfectly correlated, particularly over the 1-year time horizon used to assess capital requirements under Basel II. Worse, it may have introduced bias to operational risk assessments as a high stand-alone operational risk requirement may have been unpalatable to senior management when combined with credit and market risk requirements with no allowance for diversification.

In any case, in the aftermath of the financial crisis of 2007/09, conduct and other losses often exceeded regulatory operational risk requirements, pointing to the need to strengthen requirements.[1] By March 2016, this and regulatory dissatisfaction with the complexity of AMA and the lack of comparability between bank operational risk requirements prompted BCBS to propose dispensing with internal models of operational risk and replace all approaches with a Standardised Measurement Approach (BCBS, 2016[2]). This was adopted as part of wider Basel III reforms in December 2017 (BCBS, 2017).

With internal models no longer permitted to be used for regulatory capital requirements, models of operational risk dependencies and diversification benefits no longer affect regulatory requirements. However, banks should still assess their economic capital requirements for operational risks including for the ("Pillar 2") Individual Capital Adequacy Assessment Process (ICAAP) required by regulators. The Working Party believes that such assessment should allow not just for dependencies and diversification between operational risks, but also for diversification

---

[1]For example, at the end of 2010, LBG reported that its capital requirement under TSA was just over £2.5bn (see LBG's Basel II Pillar III disclosures document, 31/12/2010, page 100 – see http://www.lloydsbankinggroup.com/globalassets/documents/investors/2010/2010_lbg_pillar3_disclosure.pdf). However, within 6 months, they would have to set aside £3.2bn to cover payment protection insurance (PPI) claims and £500 m for customer goodwill payments relating to issues with the wording of HBOS mortgage contracts. The cost of PPI to LBG would ultimately increase to over £17 m.

[2]The Institute and Faculty of Actuaries response to this can be found at https://www.actuaries.org.uk/system/files/field/document/06-03%20IFoA%20response%20to%20Basel%20Committee%20on%20Banking%20Supervision-%20Consultative%20Document%20Standardised%20Measurement%20Approach%20for%20Operational%20Risk.pdf

benefits between operational and non-operational risks. This provides a more realistic picture of risks, and in distinguishing between stand-alone operational risk requirements and their marginal contribution to overall diversified requirements, helps foster a realistic assessment of exposures.

2.2. Asset Managers

Asset managers are in a similar position to banks in having to produce a Pillar 2 ICAAP for regulators. Operational risk is often the main risk faced by asset managers so the assessment of economic capital requirements for operational risks, and the diversification assumed between these operational risk requirements, will be key to this assessment. Diversification with non-operational risks will generally be less important given often limited exposure to non-operational risks.

2.3. Insurers

Insurers have in some ways moved in the opposite direction to banks. Prior to the introduction of Solvency II in 2016, regulatory requirements for UK insurers did not explicitly reflect operational risks. However, UK insurers were required to produce their own assessment of economic capital requirements for operational risks as part of individual capital assessments required by the regulators, similar to banks' ICAAP. While approaches to assessing operational risk requirements varied, these generally allowed for diversification both between operational risks and between operational and non-operational risks.

Solvency II introduced an explicit regulatory capital requirement for operational risk as part of the Pillar 1 Solvency Capital Requirement (SCR). Under the standard formula, this is based on percentages of metrics such as premium income and reserves which were calibrated based on those insurers who were already using internal models of operational risk for internal economic capital assessment (section 3.6, 325–336, Committee of European Insurance and Occupational Pension Supervisors (CEIOPS), 2010).

Due to differences in sample sizes of insurers contributing pre- and post-diversification figures to CEIOPS, economic capital requirements after allowing for diversification with non-operational risks were perversely greater than those before such diversification, so the post-diversification figures were discarded and standard formula percentages were based on figures before diversification with non-operational risks.

Not only is the standard formula operational risk requirement based on assessments before allowance for diversification with non-operational risk, but also there is no allowance in the standard formula aggregation module for such diversification. Whereas allowance is made for diversification between market, counterparty and insurance risk in the calculation of the Basic SCR, the operational risk requirement is simply added to this without allowance for diversification between operational and these other risks.

However, while the standard formula does not allow for diversification between operational and non-operational risks, firms may apply to use their own internal models of risks to set regulatory capital requirements instead of the standard formula, subject to satisfying regulatory requirements. These models can and generally do allow for dependencies between operational risks and between operational and non-operational risks.

Even for standard formula firms, there is a requirement to assess economic capital requirements for operational and other risks as part of the Own Risk and Solvency Assessment (ORSA), which is akin to banks' ICAAP. As part of the ORSA, there is a need to consider the appropriateness of the Standard Formula, including the addition for operational risk. The Working Party understands that the assessment of operational risk requirements and the appropriateness of standard formula for operational risk will typically include allowance for dependencies and diversification between operational risks and between operational and non-operational risks, though these allowances may not be as rigorous as those used in internal models.

3. The Nature of Operational Risk Dependencies

Based on their review, the Working Party would note the following aspects of operational risk dependencies both between operational risk and with non-operational risk.

3.1. Indirect Nature of Dependencies

Unlike market risks, say, where, for example, base rate changes may directly affect equity markets and vice versa, most operational risk dependencies are indirect in nature. There is usually no obvious direct link between operational risks, but often there will be underlying risk drivers which affect disparate operational risks. For instance, poor governance could lead to operational failing across different types of risk (see section 4.1 below). Similarly, a flu pandemic may lead to business continuity losses as well as higher life insurance claims and market falls.

There are some instances where a direct link can be observed between non-operational risk events and operational losses. For instance, a fall in stock markets could trigger mis-selling claims related to the sale of equity-linked products.

3.2. Asymmetry

Where there is a dependency between operational and non-operational risks, this will generally be asymmetric as while market, insurance and credit events may trigger operational losses, the reverse does not apply as operational losses tend to be idiosyncratic with little impact on markets, the wider economy and insured experience.

3.3. Operational Losses Contingent on Non-Operational Risk Drivers

Often operational losses will only crystallise depending on the occurrence of other events. For example, an investment product may be mis-sold, but losses might only arise if markets fall. This occurred with LTSB's Extra Income and Growth Plan, where falling stock markets over 2001/03 led to customer losses of 30–48% of amounts invested, and a £100 m loss for LTSB.[3]

Similarly, the severity of operational losses may also be dependent on market, credit or insurance experience. An example of this would be the US$250 m loss suffered by Sphere Drake in the 1990s as a result of fraudulent collusion between underwriters.[4] This resulted in it being wrongly exposed to US workers compensation claims at a time when the claims experience of this line of business was deteriorating, hence the large loss.

By the same token, there are many instances of "near misses" where an operational failing has not crystallised due to favourable non-operational risk experience, or where losses could have been even more severe.[5] Analysis of dependencies should therefore consider not just operational failings but also how the subsequent crystallisation of loss is connected to other risks. It should also consider "near misses" where favourable experience may mask an underlying dependency.

---

[3]See Financial Services Authority's (FSA's) final notice to LTSB, 25 September 2003 at https://www.fca.org.uk/publication/final-notices/lloyds-tsb_24sept03.pdf

[4]See "FSA bans four individuals for dishonest behaviour in the reinsurance market", 14 December 2007 at http://www.fsa.gov.uk/library/communication/pr/2007/127.shtml

[5]An example of this might be the FSA's decision not to proceed with a full-scale review of mortgage endowments in October 2000 as the indications were that most policyholders were better off with a mortgage endowment based on returns to that date – see "FSA acts on mortgage endowment complaints", 3 October 2012 at http://www.fsa.gov.uk/library/communication/pr/2000/121.shtml

3.4. High-Frequency, Low-Impact versus Low-Frequency, High-Impact Losses

Operational losses typically comprise lots of small-impact losses coupled with infrequent, large-scale losses. Economic capital requirements will generally be driven by infrequent, high-impact losses, and it is the dependencies of these with other risks which matter to capital assessment, though analysis of dependencies of lower level losses can prove useful to business as usual (BAU) operational loss management.

There may be different drivers to each type of loss, with different dependencies to other risks. For example, there may be little correlation between low-impact, high-frequency losses under two operational risk categories (e.g. manual processing errors and card fraud), but these may be correlated at the tail (e.g. weak IT system implementation leads to systemic processing errors and also exposes a firm to large-scale cyber theft).

Similarly, in terms of correlation with non-operational risks, an insurer may experience frequent, low-level financial reporting errors which might not be correlated with market conditions. In distressed markets, however, there may be a greater reliance on mark-to-model valuations with the related risk of significant errors in such valuations.

Note, however, it is not always the case that operational losses at the tail are more highly correlated with other risks. For example, there may be strong correlations between low-impact, high-frequency losses in two categories (e.g. weakness in customer service recruitment leads to manual processing errors and petty theft), and there may be less connection between high-impact, low-frequency events (e.g. large-scale system processing errors and rogue trading).

Considering non-operational risk dependencies, a general insurer may experience low-level manual processing losses linked to claim volumes (e.g. data entry errors), but the tail of processing risk may revolve around system failure which may be unrelated to claim volumes.

The important thing to note is that care should be exercised in assessing dependencies based on high-frequency, low-impact data as it may under- or overstate dependence at the tail, which is critical to economic capital assessment.

3.5. Loss Components and Fines

The Working Party would highlight a potential pitfall in assessing dependencies. Operational risks such as business continuity failings may generate Financial Conduct Authority (Financial Conduct Authority (FCA) fines[6], but the Working Party believes that such fines should be considered as part of the overall operational losses rather than separate conduct risk events. Treating the fine separately would result in two separate yet perfectly correlated loss events which would give a distorted view of conduct risk correlations.

In general, in assessing dependencies between operational risks, care needs to be exercised to avoid treating a single loss as two separate loss events under different categories, which would distort the analysis of dependencies between categories.

3.6. Implicit Allowance for Operational Losses in Other Data

Another issue in the assessment of dependencies is the implicit allowance for operational losses in other loss data, and hence the implicit allowance for operational risk in non-operational risk capital. For instance, insurance claims data will implicitly include an element of non-disclosure and claim fraud as well as underwriting and process errors to the extent these are not detected. Such errors will add not just to the base level of claims, but also to the volatility of insurance risk data and hence insurance risk capital.

---

[6]For example, in October 2018, the FCA fined Tesco Bank £16.4 m for failings in protecting client data against cyber attack (−https://www.fca.org.uk/news/press-releases/fca-fines-tesco-bank-failures−2016-cyber-attack), while TSB Bank is likely to be fined for its 2018 systems disruption due to migration problems.

In terms of the dependence between these operational risks and insurance risk, to the extent that insurance risk provisions and capital implicitly reflect these sources of loss, then we can say these implicitly allow for the aggregation of underlying claims experience with these operational risks, and there is a risk of double counting these risks if a strong correlation assumption is then used between insurance and operational risk.

Ultimately, the Working Party believes that if claims experience includes a significant element of fraud and processing errors, then the assessment of these operational risks should seek to focus on the scope for errors above and beyond what may normally come through in claim data, for instance, the risk of systematic processing errors in underwriting systems as opposed to what may be termed BAU underwriting errors.

There may still be a strong correlation between these exceptional losses and insurance experience. For instance, catastrophic claim experience could lead to a breakdown in claims controls and much higher levels of claim fraud and processing errors. On the other hand, the systematic failure of an underwriting system may be more idiosyncratic.

3.7. Lags in the Emergence of Operational Losses

A final observation on operational risk dependencies relates to the time it takes for many operational losses to crystallise. For instance, PPI mis-selling claims arise in many cases from policies sold before 2000, yet banks only started making provisions for these from 2011 onwards. As we shall see in Appendix B, while there may be a link between, say, compliance breaches and weak loan underwriting, the fines and other losses associated with the former may crystallise some years after credit losses in respect of the latter.

From the perspective of a 1-year economic capital assessment, frequently we will be looking to aggregate operational risk requirements based on past failures crystallising alongside market, credit and insurance losses arising over the year. There is thus an element of temporal dislocation which should be borne in mind when setting dependencies: while we might argue for a link between operational losses and other risks in the long term, this may be less relevant in the short term.

4. Methods for Modelling Dependencies

Based on benchmarking studies (Institute of Risk Management (IRM), 2015) and what the authors have observed in practice, the most common methods for modelling dependencies are, in increasing order of sophistication:

- correlation matrices;
- copula aggregation:
  - Gaussian copula;
  - T- and other copulas;
- Bayesian Networks. Simpler methods include:
  (a) no allowance for diversification (i.e. aggregate operational risk requirement is the sum of capital requirements for individual operational risks, which is then added to requirements for non-operational risks without allowance for diversification);
  (b) as (a) but with an arbitrary "haircut" applied to aggregate requirements to allow for diversification;
  (c) the square root of the sum of individual operational risk requirements squared – effectively a simplification of correlation matrix aggregation with 0% correlation;
  (d) as (c), but with an arbitrary loading to allow for dependencies between operational risk; and
  (e) assess capital requirements at a lower confidence level and simply add these up.

The Working Party does not believe that such simpler approaches are appropriate to modelling economic capital requirements, though they could be useful in assessing standard formula appropriateness (e.g. assessing the haircut in (b) that would equate to the marginal standard formula addition for operational risk).

4.1. Correlation Matrices

A fuller description of correlation matrix (aka variance–covariance matrix) aggregation is supplied in section 7 of Shaw *et al.* (2010) on modelling of dependencies in economic capital, but the Working Party would highlight the following limitations.

- It assumes that individual risk distributions are elliptically distributed, but in practice individual operational risk distributions will be highly skewed – depending on the frequency of an individual risk occurring, the operational loss will be £0 at most percentiles, but large, potentially catastrophic losses at the tail.
- Linked to this, correlation matrix aggregation may produce materially higher economic capital requirements.
- It focuses on aggregating economic capital requirements at a particular percentile and does not produce aggregate requirements at other percentiles, providing a limited view of aggregate operational losses.
- As such, it is not consistent with the requirements to provide the holistic distribution of own funds impacts required of internal models under Article 228 of Solvency II Delegated Regulations.

The Working Party is of the view that correlation matrix aggregation is not appropriate for internal models of operational risks. However, it does have the advantage that it can be readily implemented and easily understood and as such may be appropriate for the assessment of standard formula appropriateness.

4.2. Copulas

The bulk of insurance internal models aggregate operational risks using a Monte Carlo approach with copulas in order to produce a holistic distribution of aggregated operational losses, which can in turn be combined with distributions of non-operational risks to form an overall distribution of losses. A fuller description of copulas is given in section 8 of the Shaw *et al.* (2010), but in essence these allow random percentiles of individual risk distributions to be simulated which nonetheless reflect dependencies between risks.

Copulas are flexible in that they can cater for different distributions of individual risks and do not assume that these are elliptical. They do not even require individual risks to follow a certain distribution but may instead sample from Monte Carlo simulations of individual risks (the Iman Conover approach).

One limitation with copulas is that it can prove challenging to address asymmetric dependencies. For example, using a copula approach with a high correlation between say mortality catastrophe (flu pandemic etc.) and business continuity risks will generate loss simulations where mortality catastrophes are accompanied by business continuity losses – as we might expect – but also where business continuity losses are accompanied by excess mortality levels even though many business continuity events, such as an office being flooded, should have no impact on mortality rates.

To get around this problem of asymmetry, correlation assumptions are often adjusted downwards, but this can result in understatement of operational losses simulated in non-operational

risk scenarios where we might expect operational losses to be higher. Simulations of combined losses need to be examined to ensure that any adjustment does not lead to material understatement.

4.2.1. Choice of copula

Among UK life insurers, the most common copula used is the Gaussian copula which is based on a multivariate normal distribution. This is relatively easy to implement and does not require any assumption beyond a matrix of correlations between risks. However, an oft-cited limitation of the Gaussian copula is that it has a zero co-efficient of tail dependency so that the conditional probability of risk A exceeding (or undershooting) a certain percentile given risk B exceeds (or undershoots) that percentile will tend to zero for extreme percentiles. It is noteworthy that prior to the abandonment of AMA, the European Banking Authority (EBA) proscribed the use of Gaussian copula for modelling dependence between operational risks in bank operational risk models (EBA, 2015).

Therefore, some insurers instead use a T-copula based on a multivariate T-distribution which has a positive co-efficient of tail dependence and will give rise to higher conditional probabilities of an extreme event for risk A given an equally extreme event for risk B compared to a Gaussian copula with the same correlation matrix. A T-copula is somewhat more complex to implement and also requires a degree of freedom assumption in addition to the matrix of correlation assumptions, with the lower the degree of freedom parameter, the greater the likelihood of extreme events co-occurring.

Gaussian- and T-copulas are two of the most common copulas used, but there is a wide range of alternative copulas including the Archimedean family of copulas, which can model particularly heavy tail dependence. Archimedean copulas are not based on a multivariate distribution, nor require a correlation matrix, but are driven instead by a parameter which drives tail dependency. A downside is that they may prove more complex to implement for increasing numbers of risks aggregated.

In terms of the choice of copula, the Working Party believes that the limitations of Gaussian copula and its zero co-efficient of tail dependency can be overstated. Depending on correlation assumptions used, it can model combinations of extreme events co-occurring and may ascribe a higher probability of such co-occurrence than other copulas with weaker correlation and dependency assumptions. Correlation and dependency assumptions may be highly subjective. It may be that using more complex copulas may be spurious given the subjectivity of the assumptions.

Whatever copula and assumptions are chosen, it is important to examine the resulting simulations generated to see whether the likelihood of extreme events under different risks co-occurring, and conditional expectations given an extreme loss in one category of losses under other categories, is reasonable.

4.3. Bayesian Networks

Bayesian Network modelling seeks to derive a combined probability distribution of operational losses from all types, having regard to underlying causal variables (e.g. staff turnover affecting processing errors and internal fraud losses). It thus addresses the modelling dependencies explicitly without the need to consider correlation assumptions.

It may also address the problem of asymmetry. For instance, a Bayesian Network approach could capture the impact of flu pandemics on business continuity losses, or equity market falls on mis-selling, while ensuring that the crystallisation of these operational losses does not affect the occurrence of pandemics or stock market crashes.

Bayesian Networks will be underpinned by assumptions of probability (e.g. of a rise in the staff turnover rate) and conditional probability (probability of process error given a rise in staff

turnover). Many of these probabilities can be determined from empirical data, but others may be based on expert judgement or a combination of two. The process for identifying causal factors and deriving unconditional and conditional probabilities linking these and operational risks is likely to require significant effort. However, it can yield useful insights into linkages between operational risks, and between operational and non-operational risks, which may prove useful in BAU operational risk management.

For a fuller description of Bayesian Networks and other advanced operational risk modelling techniques, the Working Party would refer to Corrigan *et al.* (2013) on operational risk modelling and the Canadian Institute of Actuaries' November 2014 research paper on operational risk.

5. Simulation Study of Operational Risk Dependencies

To gain further insight into operational risk diversification benefits, the Working Party carried out a study of these using a relatively simple dependency structure involving up to seven operational risk types (which may be assumed to correspond to Basel Level 1 categories) with uniform correlations between types and modelled using a Gaussian copula.

Each risk type has a binary probability of a material loss occurrence under each type (i.e. Bernoulli frequency distribution) and a Lognormal severity distribution based on typical and severity loss estimates corresponding to the median and 90th percentile of the distribution. 10 runs of 100,000 simulations were generated to minimise simulation error.

The base run assumed a 25% probability of occurrence for each risk type; typical and severe case loss estimates of £2 and £8 m, respectively, for all types; and 25% correlation between all types. Based on this, the diversification benefit was 52% of undiversified requirements.

Next, we explored the impact of more skewed severity distributions on diversification, with the severe case loss estimate (90th percentile) now assumed to be £16 m for all risk types. As one would expect the marginal requirements at the 99.5th percentile were much higher, but the crucial point to note is that the diversified benefit was much lower at 44% of undiversified requirements, highlighting that the more skewed the marginal distributions are, the lower the likely diversification benefit.

The Working Party then looked at the impact on the base case of different frequency parameters for the individual risk types of 50%, 10% and 2.5% for each. While there was not much difference in diversification benefits for the first two frequency assumptions, the 2.5% frequency assumption resulted in a lower diversification benefit of 48%, highlighting the potential sensitivity of diversification benefits with frequency, particularly at lower levels.

In practice, marginal distributions will not be uniform. Typically, more losses may be assumed to arise under the Basel high Level 1 categories of Clients, Products and Business Practices (CPBP, broadly corresponding to conduct risk losses) and Execution, Delivery and Process Management (EDPM, broadly relating to processing and reporting risks). Based on banking loss figures for 2012−17 from the Operational Riskdata eXchange Association (ORX, 2018), a leading operational loss data-sharing consortium, 61% of losses arose under the CPBP category, with 22% under EDPM.

To gauge the impact of this, rather than assuming £2 m typical loss for each category, the total typical loss of £14 m was weighted in proportion to losses under each high-level category from the ORX survey above, with the severe case equal to four times consistent with the base run skew. As one may expect given the high weighting to CPBP, the diversification benefit reduced to 31% of undiversified requirements.

Diversification benefits will also vary with the number of risks modelled: if only four risks were modelled instead of the seven in the base run, the diversification benefit would be −44% as opposed to −52%. In practice, marginal operational risk distributions will be based on more granular categories of risk, so there may be 20+ risk categories aggregated, with consequent impact on diversification benefits.

6. Setting Correlation Assumptions

The setting of correlation assumptions was covered by the Working Party's paper on inputs to operational risk models (Kelliher *et al.*, 2016). In essence, correlations can be derived from empirical data and/or expert judgement.

6.1. Empirical Data

Correlation assumptions could be derived for internal and external loss data, for example, by considering correlations between quarterly loss totals for each category (as in Cope & Antonini (2008)).

However, loss data and hence empirical correlations may be driven mainly by low-impact, high-frequency losses. These may give a misleading picture of correlations at the tail (see section 3.4 above).

There is also an issue as to how far data go back. A dataset going back to 2010, for example, will not capture the interaction of operational and other risks during the financial crisis of 2007/09 and so may miss key dependencies.

Another issue with empirical correlations is that they may systematically understate correlations between low-frequency events. To illustrate this, as part of our paper on inputs to operational risk models, the Working Party simulated five operational risks, each distributed binomially with $p = 0.1$ probability of a loss and assuming a Gaussian copula with a medium 50% correlation between variables. The empirical correlation between the number of losses was circa 25%.

On the other hand, random coincidence can give rise to significant yet spurious estimates of correlation when other evidence and reasoning do not support a significant correlation between conduct and business continuity losses.

Finally, there is the question of relevance. For instance, pensions and mortgage endowment mis-selling losses may form a large part of insurers' historic loss data, and from above, there is a link between these and market levels. Going forward, however, the combination of policies already reviewed and time bars on complaints from the rest will limit exposure to these sources of mis-selling. Exposure may arise in respect of other products which are not market-related.

6.2. Expert Judgement

Given the limitations of correlations derived from data, the Working Party believes that expert judgement is essential to determine correlation assumptions. However, it would probably be impractical to ask subject matter experts to identify correlations for each pair of risks. If one was seeking to model 20 risks – in line with Basel II Level 2 categories[7] say – this would require 190 separate correlation assumptions which would be too much to ask for and difficult to validate. The resulting correlation matrix is also unlikely to satisfy the positive semi-definite property required to be valid.

To address this, one approach may be to group risks and assume a common correlation between groups of risks. For instance, splitting 20 Level 2 risks into four groups of five, we would need 10 correlation assumptions within each group (40 in total) plus 6 correlation assumptions between groups, which may be more manageable. If one assumed a uniform correlation within groups the task of setting correlations becomes easier still.

Risks could be grouped by some common factors, for instance by

---

[7]Under the Basel II taxonomy, there are seven High Level 1 categories – Internal Fraud, External Fraud, Employment Practices and Workplace Safety; Clients Products and Business Practices (regulatory compliance, mis-selling, etc.); Damage to Physical Assets; Business Disruption and Systems Failure; and Execution, Delivery and Process Management. Sitting underneath these are 20 more granular Level 2 categories. See Annex 9 of Basel II at https://www.bis.org/publ/bcbs128d.pdf

- high-level risk type, for example, Basel Level 1 categories;
- type of risk, for example, people, process, system or external event; or
- function, for example, conduct risks mapped to sales; processing risks to operations, people-related risks to HR, etc.

Given the heterogeneity of operational risk categories, however, it is likely that there will be a loss of granularity, for example, two sub-types of risks in two otherwise uncorrelated groups could be strongly correlated. (It should be noted that this applies not just to groups but also within Level 2 categories given the broad range of sub-risks in each category.)

Another approach to determining correlation may be to consider the results of broader stress and scenario testing work, for example, flu pandemic scenario testing could highlight common dependencies between processing risks (due to backlogs arising) and mis-selling (due to falling markets giving rise to customer losses). This could also help with setting correlations between operational risks and market and other non-operational risks.

An extension of this would be a causal driver approach, which involves seeking to identify underlying factors which may drive losses under categories. Correlations for different operational risks could then be set having regard to the extent that common factors are identified for each risk pair.

Potential causal drivers are discussed in the next section.

Whichever approach is adopted, expert judgements on correlation assumptions should be subject to rigorous review and challenge given their subjectivity. Key correlation assumptions should be identified through sensitivity analysis, which should be subject to particular scrutiny. This review should be independent and performed by those with an understanding of operational risks and how these interact.

7. Generic Operational Risk Dependencies

To assist in the identification of dependencies and the setting of correlation and other dependency assumptions, the Working Party has identified a number of generic dependencies both between operational risks and between operational and non-operational risks, which is set out in detail in Appendix A. This is not a definitive list of possible dependencies, and many may not be relevant for a firm, but it is hoped that this could be a useful basis for assessing and validating dependency assumptions.

7.1. Intra-Operational Risk Dependencies

In summary, disparate operational risks could be affected by the following:

- people – weaknesses in recruitment, training and retention;
- system development and implementation (see below);
- model governance – leading to flaws in product pricing and financial reporting;
- treating customers fairly (TCF) and compliance – a weak culture could lead to compliance breaches across different operational risk categories; and
- governance – weak governance contributing *inter alia* to fraud, conduct failings and other

  operational failings.

Even where prima facie two operational risks might appear independent, there may be underlying drivers which lead to the two being linked. An example might be weaknesses in system development and implementation where flawed design, project management and/or inadequate
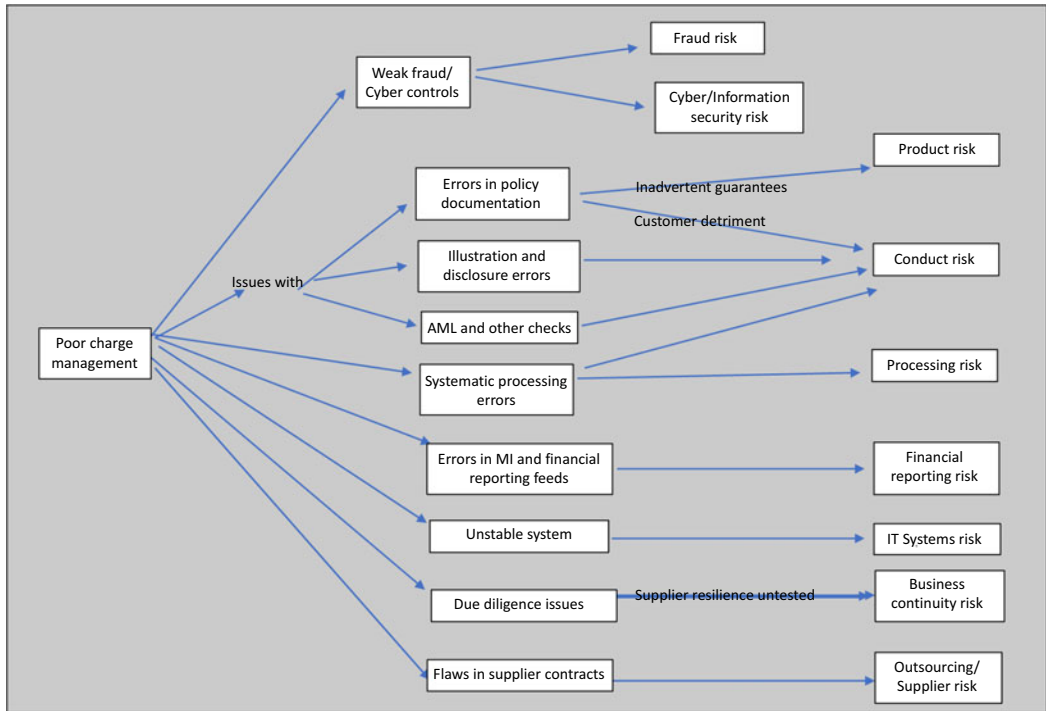
Figure 1. Consequences of flawed system development and implementation.

testing of changes could contribute to a wide range of operational risks as the following diagram illustrates.

7.2. Dependencies with Non-Operational Risks

In terms of dependencies between operational risk and other risks, the Working Party would note in particular that reputational damage as a result of operational failings could feed through into expense and lapse experience. Higher lapses could in turn lead to liquidity strains. Thus, reputational damage may be considered a "vector of transmission" from operational risk to insurance and liquidity risk.

As noted in section 3.6 above, underwriting and claim processing errors as well as fraud can also affect claims experience, though this will be implicitly reflected in insurance risk capital requirements based on this experience. Adverse claims experience can also cause operational failures to crystallise (e.g. an error in an excess of loss reinsurance treaty might only become apparent after claims exceed the loss limit); or exacerbate their severity (e.g. the Sphere Drake fraud cited in section 3.3). Catastrophic claims can also put a strain on claims controls and lead to higher levels of claim processing error.

In terms of market and credit risk dependencies, adverse macroeconomic conditions could lead to increased levels of attempted fraud as well as market falls and higher defaults, while market levels can affect the crystallisation and severity of mis-selling of products linked to markets. The severity of dealing errors will also depend on market movements, though gains may be as likely as losses.

These linkages are summarised in the following diagram.

Finally, issues with business models could trigger a wide range of operational losses as well as market, credit and insurance losses. An example of this is the "originate and distribute" business
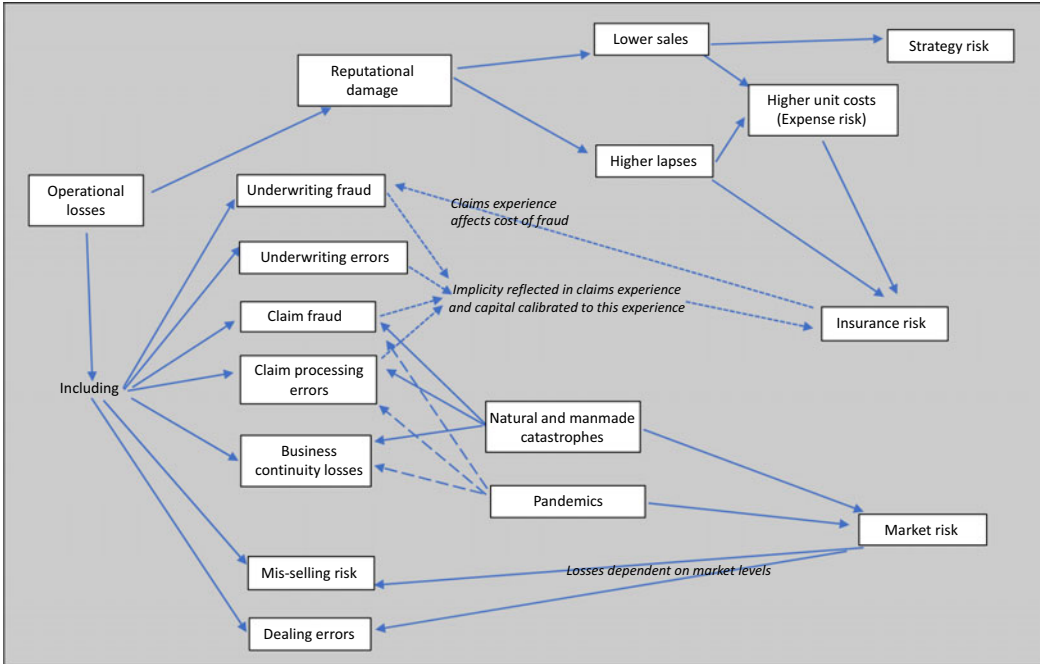
Figure 2. Operational and non-operational risk dependencies.

model adopted by US banks in respect of sub-prime mortgage lending in the run up to the financial crisis of 2007/09. This is considered further in Appendix B, but note that the operational losses associated with this business model arose some years after the market and credit losses, highlighting the point made in section 3.7 above about how operational losses may not be linked with market and credit losses over a 1-year time frame even if over the long term there is a linkage.

8. Review of Literature Review on Operational Risk Dependencies

The Working Party struggled to find literature on operational risk dependencies and how these may be modelled. Such literature as was identified can be split into (a) studies of correlations based on empirical loss data and (b) benchmarking surveys of modelling practices and assumptions.

8.1. Empirical Studies of Correlations

The Working Party has identified two studies of correlations between bank operational losses. The first was Cope & Antonini (2008) on observed correlations and dependencies based on ORX data between 2002 and 2007, with ca. 90,000 loss data points from 41 organisations.

Correlations between seven high Level 1 event types and between 10 business line categories under Basel II were calculated based on quarterly loss data, with a focus on the Kendal tau measure of rank correlation.

Key conclusions of this paper:

- With a few exceptions, Kendall rank correlations by business line or event type level are low, usually not exceeding 20%.
- Homogeneity was observed among correlations measured at different banks and the correlation averages across banks.

- There was slight evidence that extreme losses in one unit of measure are much more likely to occur when extreme losses are observed in other units of measure.
- Based on the available data, there are some indications of diversification benefits at high quantiles of the quarterly loss distribution, although no accurate estimates of this benefit could be drawn at the 99.9[th] percentile level on which bank regulatory capital is based.

The conclusions of the Cope and Antonini paper were challenged by Abdymomunov & Ergen (2017), a paper on tail dependence and systemic risk in the operational losses of the US banking industry. This was based on operational loss data from regulatory returns, with over 277,000 individual loss events across 31 bank holding companies for 43 quarters between 2004 and 2014. Again, data were analysed based on the seven Basel Level 1 event types.

Their analysis starts by establishing tail dependence between operational risks by looking at the ranks of losses and the conditional probability of risk pairs at different percentiles based on the number of observations where the rank of losses for both risks exceeded a certain percentile. Next, Pearson correlation estimates are derived. Generally, these are less than 10% – broadly consistent with Cope and Antonini – but with wide variations between banks.

However, correlations were then derived by applying maximum likelihood estimation techniques to estimate parameters for a T-copula based on empirical loss data. This gave rise to significantly higher correlation estimates with a median correlation parameter for the key operational loss types around 30% and exceeds 50% for some banks in our sample. This is significantly higher than Cope and Antonini and other studies.

The correlation estimates vary between banks, with higher correlations observed in larger banks. The paper also considers correlations between bank operational losses and estimates correlation parameters between losses of large banks in our sample to be 42% on average and suggests the presence of systemic risk from the simultaneous occurrence of operational tail losses in different large banks. It should be noted, however, that the period considered for this study included many industry wide scandals such as LIBOR-fixing which gave rise to heavy fines, and this may affect the degree of correlation observed between banks.

8.2. Benchmarking Surveys of Modelling Practices and Assumptions

A number of benchmarking surveys of modelling practices have covered operational risk dependency modelling and correlations.

ORIC International carried out a benchmarking survey of operational risk correlations across 22 of its member firms (ORIC International, 2016). This survey provides a useful summary of best practices for setting correlations. Key findings in relation to dependencies between operational risks are as follows:

- Most firms allowing for dependencies between operational risks were internal model firms.
- Correlations between operational risk ranged between 0% and 100%, but on average positive correlation was being allowed for between all operational risk categories.
- Half of respondents used causal analysis to set correlations.
- The reduction in operational risk capital after allowing for diversification between operational risks was between 16% and 85%, with a mean of 55% and a median reduction of 36.5%.

In terms of dependencies between operational and non-operational risks, key findings of this survey are as follows:

- Most firms allow for this, with 94%, 88% and 82% of respondents allowing for dependencies between operational and insurance, market and credit risk, respectively.

- No 0% correlations were observed, that is, allowance is made for some level of dependency between operational and non-operational risk.
- The reduction in stand-alone operational risk capital after allowing for diversification with non-operational risks was between 20% and 75%, with mean and median reductions of 45%.

ORIC also contributed to the IRM's 2015 paper on insurer operational risk modelling. This survey covered a mix of internal model (68% of or 19 out of 28 respondents) and standard formula firms.

In terms of operational dependency methodology, this survey found that Gaussian copula aggregation was the most common approach used to aggregate operational risks (30% of respondents), while 78% of respondents used Monte Carlo simulation techniques in some form for aggregation, with T-copula also popular.

There was less consistency around the setting of correlation assumptions, with practices ranging from a common correlation for all operational risks to correlations by operational risk pair, with some opting for a hybrid approach with a common correlation for most risk pairs but with a bespoke assessment for key operational risk. Correlations were set by either statistical analysis of internal and external data or by expert judgement.

A more recent benchmarking survey was produced by KPMG in 2018, the results of which were presented at the 2018 Life Conference. Again, Gaussian copula was the most popular approach to aggregation with 41% of respondents, 12% using T-copula, 29% using correlation matrix aggregation and 18% using other approaches. 82% of firms use pure expert judgement to set correlations between operational risks. KPMG suggest that good practice would be to use a causal driver approach to provide a better structure to the expert judgement process.

KPMG's annual Technical Practices Survey also regularly surveys operational risk modelling practices and includes benchmarking of operational risk correlations against non-operational risks which may be useful in validating correlation assumptions (see 36–37 of the 2018 Technical Practices Survey).

Other actuarial benchmarking surveys which have relevance to modelling operational risk include

- PriceWaterhouseCoopers (PwC's) Life Insurance Capital Modelling Survey noted that the majority of participants use a copula to aggregate operational risk stresses, with most of these opting for the Gaussian copula. The dependencies between operational risks are most commonly based on either causal rationalisation or expert judgement.
- Ernst and Young's UK Solvency II Pillar 1 Survey noted that the main method of aggregate operational risks was the Gaussian copula, with over 80% of respondents setting correlation assumptions by expert judgement as a lack of data makes derivation of correlations from internal data difficult or unstable. The average diversification benefit between operational risks was 46%.

9. Conclusion

For the purposes of economic capital assessment, and for internal models of operational risk under Solvency II, the Working Party believes that it is appropriate to model diversification benefits both between operational risks, and between operational and non-operational risks. Modelling dependencies can also shed insights into how operational and other risks are linked. There are, however, a number of complications to this caused *inter alia* by a lack of data, asymmetry between risks, implicit allowance for operational risks in non-operational risk capital and lags in the emergence of operational losses.

In terms of methodology, benchmarking surveys suggest that copula approaches are the most popular approach to modelling dependencies, with Gaussian copula the most common choice of copula. While this copula has theoretical limitations in terms of tail dependency, we believe that these are moot when there is so much uncertainty around correlation assumptions.

In setting correlation assumptions, empirical studies generally suggest that correlations between operational risks are low (<25%), though a recent paper on US bank losses suggest they could be higher (30–50%). The Working Party would note issues with using empirical data to assess correlations and would recommend that this is supplemented by expert judgement. We have set out some generic sources of dependence which we hope will help this process, noting that even where operational risks may appear independent of each other, there may be underlying drivers linking these.

Overall, we hope actuaries and other risk professionals will find this paper of use in modelling operational dependencies and setting-related assumptions.

Disclaimer

The views expressed in this publication are those of invited contributors and not necessarily those of the Institute and Faculty of Actuaries. The Institute and Faculty of Actuaries do not endorse any of the views stated, nor any claims or representations made in this publication and accept no responsibility or liability to any person for loss or damage suffered as a consequence of their placing reliance upon any view, claim or representation made in this publication. The information and expressions of opinion contained in this publication are not intended to be a comprehensive study nor to provide actuarial advice or advice of any nature and should not be treated as a substitute for specific advice concerning individual situations. On no account may any part of this publication be reproduced without the written permission of the Institute and Faculty of Actuaries.

References

Abdymomunov, A. & Ergen, I. (2017). *Tail Dependence and Systemic Risk in Operational Losses of the US Banking Industry*, International Review of Finance, February 2017.

Basel Committee on Banking Supervision (2006). *Basel II: International Convergence of Capital Measurement and Capital Standards: A Revised Framework – Comprehensive Version*, June 2006, available online from the Bank of International Settlements (BIS) website: https://www.bis.org/publ/bcbs128.htm (accessed 19 October 2019)

Basel Committee on Banking Supervision (2016). *Consultative Document: Standardised Measurement Approach for operational risk*, March 2016, available online from the Bank of International Settlements (BIS) website: https://www.bis.org/bcbs/publ/d355.pdf (accessed 19 October 2019)

Basel Committee on Banking Supervision (2017). *Basel III: Finalising post-crisis reforms*, December 2017, available online from the Bank of International Settlements (BIS) website: https://www.bis.org/bcbs/publ/d424.pdf (accessed 19 October 2019)

Canadian Institute of Actuaries (2014). *Research Paper on Operational Ris*", produced in conjunction with KPMG and available on the Canadian Institute's website: http://www.cia-ica.ca/docs/default-source/2014/214118e.pdf (accessed 19 October 2019)

Committee of European Insurance and Occupational Pensions Supervisors (2010). *Solvency II Calibration Paper*, April 2010, available online at the European Insurance and Occupational Pensions Authority (EIOPA) website: https://eiopa.europa.eu/Publications/QIS/CEIOPS-Calibration-paper-Solvency-II.pdf (accessed 19 October 2019)

Commission Delegated Regulation (EU) 2015/35 (2014) *supplementing Directive 2009/138/EC of the European Parliament and of the Council on the taking-up and pursuit of the business of Insurance and Reinsurance (Solvency II)*, 10 October 2014. Available from the EU Commission website at https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=OJ:L:2015:012:FULL&from=EN (accessed 19 October 2019)

Cope, E. & Antonini, G. (2008), *Observed Correlations and Dependencies Among Operational Losses in the ORX Consortium Database*, November 2008.

Corrigan J., Luraschi P. & Cantle N, (2013). "*Operational risk modelling framework*" produced by Milliman and available at: http://uk.milliman.com/uploadedFiles/insight/life-published/operational-risk-modelling-framework.pdf (accessed 19 October 2019)

Ernst & Young (2018), *UK Solvency II Pillar 1 Survey*, October 2018. While not publicly available, E&Y kindly provided the Working Party with a copy of the relevant sections on operational risk and risk aggregation.

European Banking Authority (2015), *Final Draft Regulatory Technical Standards on the specification of the assessment methodology under which competent authorities permit institutions to use Advanced Measurement Approaches (AMA) for operational risk in accordance with Article 312 of Regulation (EU) No 575/2013*, 3 June 2015.

Institute of Risk Management (2015). *Operational risk modelling: common practices and future developments* produced in 2015 by the IRM's Internal Model Industry Forum in conjunction with ORIC International. Available online from the IRM website: https://www.theirm.org/media/6809/irm_operational-risks_booklet_hi-res_web-2.pdf (accessed 19 October 2019)

Kelliher P., et al. (2016). *Good practice guide to setting inputs for operational risk models.* Produced by the Institute and Faculty of Actuaries Operational Risk Working Party and available from the profession's website: https://www.actuaries.org.uk/documents/good-practice-guide-setting-inputs-operational-risk-models (accessed 19 October 2019)

KPMG (2018), *Operational Risk Modelling Market Survey.* This was presented by Nicole Pang and Eamon McGinnity of KPMG of the Institute and Faculty of Actuariesat the November 2018 Life Conference, available at https://www.actuaries.org.uk/documents/f02-operational-risk-modelling-insurance (accessed 19 October 2019)

KPMG (2018). *Technical Practices Survey*, November 2018, available from KPMG's website: https://www.kpmg.ie/documents/technical-practices-survey-2018.pdf (accessed 19 October 2019)

Operational Riskdata eXchange Association (2018). *Annual Banking Loss Report: Operational risk loss data for banks submitted between 2012 and 2017*". June 2018, available on the ORX website: https://managingrisktogether.orx.org/sites/default/files/downloads/2018/09/annualbankinglossreport2018-printversion.pdf (accessed 19 October 2019)

ORIC International (2016). *ORIC International Benchmarking Series – Correlation Study.*

PriceWaterhouseCoopers (2018). *PwC Solvency II Life Insurers' Capital Model Survey Summary Report*, November 2018, available from PwC's website: https://www.pwc.co.uk/audit-assurance/assets/pdf/pwc-solvency-ii-life-insurers-capital-model-survey-2018.pdf (accessed 19 October 2019)

Shaw R. A., Spivak A. D. & Smith G. S. (2010). *Measurement And Modelling Of Dependencies In Economic Capital,* May 2010, available online from the Institute and Faculty of Actuaries website: https://www.actuaries.org.uk/system/files/documents/pdf/sm20100510.pdf (accessed 19 October 2019)

Appendix A: Generic operational risk dependencies

Type of Dependency	Description	Examples
Between operational risks		
People	Risk that weaknesses in recruitment and retention lead to losses across categories	• For example, poor vetting may lead to increased internal fraud, while poor quality recruits may be more prone to making processing errors. • High staff turnover may have a similar effect in terms of processing errors and the risk of dishonest staff being taken on. • Loss of key Actuarial/Finance staff may lead to product pricing and/or financial reporting errors, while loss of key IT staff could affect systems stability and project delivery (see below). However, these may be less connected with say recruitment of customer service staff above.
System development and implementation	Risk that weaknesses in system development and implementation lead to losses across categories.	Poor project governance, design, implementation and testing may lead to: (a) processing errors both from manual "work-arounds" for uncompleted functionality and from system errors; (b) flawed client documentation (e.g. errors in policy schedules or account statements) exposing a firm to product-related losses; (c) linked to (b), disclosure and other conduct risk failings; (d) unstable IT systems prone to failure; (e) financial reporting errors to the extent there are weaknesses in system feeds to accounting and valuation systems;

(Continued)

Appendix A: (*Continued*)

		(f) migration of data and functionality between systems can be a rich source of most of the above
Model governance	Risk that weak model governance leads to losses across categories	Specifically, financial reporting and product pricing categories. If a pricing model is incorrect, any loss resulting might crystallise though the financial reporting process, but if reporting models and assumptions are also flawed, correcting for these might lead to an adverse impact on own funds over the coming year
TCF/compliance culture	Risk that poor embedding of TCF, FCA/Prudential Regulatory Authority rules and legislative responsibilities leads to breaches across different categories	As well as compliance risks covered under the CPBP high-level category, breaches could arise under financial reporting (e.g. market transaction reporting not in line with FCA requirements) and other categories
Governance	Risk that weak corporate governance could lead to multiple losses across categories	Poor oversight could lead to rogue trading and other internal fraud events and may also lead to conduct risk failings not being picked up and dealt with in a timely manner. Even if no adverse incident occurred, a firm may still be fined by regulators for having weak governance. An example of weak governance may be Co-operative Bank where notable weaknesses in governance helped contribute to PPI mis-selling losses (admittedly an industry issue); the £300 m+ failure of an IT systems programme; and large-scale loan write-downs[8].
Type of dependency description examples		
Between operational and non-operational risk types		
Reputation	Risk that reputational damage as a result of operational failings impacts on insurance and other non-operational risks Reputation may be viewed as a "vector of transmission" between operational and other risks	• Reputational damage is likely to lead to higher lapses. • Similarly, it will lead to lower sales. While the value of such sales is generally excluded from own funds etc., there is still an economic loss associated with lower sales of profitable new business. • Expense risk: over time lower sales volumes combined with higher lapses will cause portfolios to shrink, which will have an impact on unit costs as fixed expenses will be spread over a smaller portfolio. • Reputational damage could impair market access, making it more difficult to hedge risks and could trigger liquidity strains, for example, downgrades lead to collateral calls, which in extremis could trigger failure[9].
Markets	Risk that falling and/or more volatile markets May expose control weaknesses and lead to	• More volatile markets will increase the impact of dealing errors, both in-house and by external fund managers. However, gains could just as easily arise as losses, for example, an inadvertent short position could result in gains in falling markets as well as

(*Continued*)

---

[8]See "Failings in management and governance – Report of the independent review into the events leading to the Co-operative Bank's capital shortfall" by Sir Christopher Kelly, 30 April 2014 at https://assets.ctfassets.net/5ywmq66472jr/3LpckmtCnuWiuuuEM2qAsw/9bc99b1cd941261bca5d674724873deb/kelly-review.pdf

[9]An example of such a failure would be General American Life Insurance Company which in August 1999 went into administration following a credit rating downgrade.

Appendix A: (*Continued*)

	multiple losses across categories	losses when markets rise, so on balance dealing error losses may be uncorrelated.
		• There is a history of falling/volatile markets exposing rogue trading (e.g. barings following the Kobe earthquake, SocGen and UBS during the financial crisis of 2007/09). This does not imply a causal linkage, however (though there could be a link if traders cut corners to recoup losses in falling markets).
		• Mis-selling: Falling markets may expose mis-selling and product defects (e.g. precipice bonds). Even if markets do not trigger their occurrence, the loss may be market dependent, that is, even if the frequency is uncorrelated, severity may be. While there may be lower losses in rising markets (e.g. mortgage endowment losses may have been mitigated by rising markets in the run up to 2007), there will still be asymmetry as often mis-selling effectively gives a put option to consumers at the firm's expense. Note however that while the cost of past mis-selling events such as pensions and mortgage endowments may have been market linked, the cost of PPI was not, so caution should be exercised in extrapolating historic linkages with future operational and market events.

Type of Dependency	Description	Examples
Macroeconomic conditions	Risk that economic conditions lead to increase in operational losses across categories	• Recessions will often lead to higher fraud attempts, both internally and externally • Recession may lead to cost-cutting and a weakening of controls, both by the firm itself and by its trade counterparties and suppliers, increasing the errors to which we may be exposed • In some cases, the recession may cause the failure of trade counterparties and outsourcing and other suppliers • Higher default levels in a recession may expose failures in loan underwriting practices and collateral management. As for mis-selling, the severity may be dependent on economic conditions even if the underlying rate of incidence is not affected. • Note that it may be that underwriting standards weaken in rising markets as lenders become more sanguine about the risks – the widespread deficiencies in US sub-prime underwriting in the run up to 2007 would be an example of this
Pandemics	Risk that flu and other pandemics lead to losses across operational risk categories and with mortality claims and financial risks	• Pandemics may incapacitate staff, weakening controls. In particular, the surge in death claims may increase the risk that claim controls (e.g. to pick up on non-disclosure) fail, exacerbating losses • Note that while these operational losses will be positively correlated with higher mortality rates and losses under assurance contracts, they may also be associated with annuity and other longevity-related profits

(*Continued*)

Appendix A: (*Continued*)

		• Pandemics may trigger market falls (e.g. SARS epidemic of 2002/04) which may point to a correlation at the tail between pandemic related operational losses and market risk
Catastrophes	Risk that natural or man-made catastrophe trigger losses both across operational risk categories and with non-operational risks	• Even if they do not impact on a firm's own physical assets and systems, natural or man-made disaster may impact suppliers and trade counterparties or the functioning of essential infrastructure/services • Like pandemics, they may prevent staff from getting to work leading to backlogs and possibly higher processing errors and control failures • For a general insurer, the catastrophe may also trigger claims on its insured portfolio, but the connection is not automatic, for example, if the catastrophe affects an offshore function, it will not affect domestic claims experience • Again, catastrophes may trigger market falls (9/11) pointing to a correlation between that subset of operational risks giving rise to catastrophe-related operational losses and market risk. • Errors in policy wording or reinsurance treaties may not become apparent until catastrophe strikes. A surge in claims may also lead to claims process errors. • There is a case for making some assumption for tail dependency between general insurance underwriting risk and operational risk to allow for errors exacerbating the impact of catastrophic claim experience.
Type of Dependency	Description	Examples
General insurance underwriting experience	Risk that adverse general insurance underwriting experience may trigger or exacerbate operational losses and vice versa	• The impact of operational errors in writing business such as errors in pricing or underwriting will be linked to general claim experience – even if business is not within appetite or the premium is lower than the firm would have wished to charge, it is still possible that the business could be profitable (i.e. result in a gain as opposed to a loss), if experience is benign • Underwriting errors may be due to errors in manual processes or may be system driven (e.g. systematically failing to exclude or load business) • Fraudulent acceptance of business (such as occurred with Sphere Drake) is more likely to result in losses on contracts, though again the loss may be dependent on underwriting experience • Non-disclosure – either inadvertent or deliberate – may be viewed as an operational risk which would expose a firm to higher claims if this is not detected • Typically, reinsurers will refuse to accept business where there have been errors in underwriting, leading to a larger gross exposure to claims
Life insurance underwriting experience	Risk that adverse mortality or morbidity experience may trigger or exacerbate operational losses and vice versa	• Similar comments apply to life insurance claims experience as for general insurance

Appendix B: Case study of how flawed business models can lead to losses under different categories: the "originate and distribute" model of sub-prime lending in the USA.

This business model involved lenders (/originators) selling on loans through securitisation, hiving off loans to a special purpose vehicle which then issued asset-backed securities (ABSs) on the back of loans made, with the originators earning an origination fee. This business model gave rise to the following operational risks and losses.

- Unlike covered bonds, the ABSs and the underlying loans did not stay on their balance sheet, so lenders did not have the same incentive to underwrite loans properly with the result that loan decisions were frequently unsuitable (processing risk). By 2006 and early 2007, barely half of loans advanced met banks own criteria.[10]
- Being remunerated by origination fees, lenders were incentivised to lend as much as possible and with strong investor demand for ABSs, they lent aggressively and often did not properly explain loan obligations to borrowers. In particular, many loans were adjustable rate mortgages where repayments would rise significantly after an initial period and this was not properly explained (mis-selling risk).
- Investment banks, often part of the same group as the lender, often did not properly explain the risks of the ABSs and Collateralised Debt Obligations (CDOs) linked to these to investors (mis-selling risk).
- In many cases, investment banks were conflicted as they wished to dispose of ABSs and CDOs they held. In the case of Goldman Sachs and its ABACUS 2007-AC1 CDO, they sold this to investors while working for a hedge fund which wanted to short the underlying portfolio. These conflicts of interest, and failure to manage these, gave rise to conduct risk.[11]
- When sub-prime defaults escalated in 2007, ABS and CDO investors suffered severe losses on securities they thought relatively safe. Many successfully sued investment banks on the grounds of mis-selling and/or conflict of interest, with regulatory conduct fines exacerbating the losses.
- Also, while ABS investors bore default losses in the first instance, lenders often gave warranties as part of securitisations and when defaults rose, investors in ABSs sued for damages, transferring losses for flawed underwriting back to lenders.
- Regulators also sued lenders for mis-selling loans to sub-prime borrowers, forcing lenders to pay restitution as well as levying conduct fines.

These operational losses were generated by a flawed business model which also triggered the global financial crisis of 2007/09 with severe market falls, bond defaults and downgrades and economic recession.

It should be noted, however, that while the market and credit impacts were more immediate, there has been a lag in the emergence of losses with regulatory action on reckless lending practices settled for US$26bn in 2012,[12] while regulatory action on mis-selling sub-prime securities continues to this day for some banks such as RBS. The longer timeframe for the emergence of operational losses from a common cause compared to market and credit risk can sometimes give a spurious picture that these are unconnected. Conversely, when looking at a 1-year time horizon, there may be a disconnect between legacy losses emerging and market and credit experience.

---

[10]Based on testimony by Clayton Holdings, a leading provider of due diligence of mortgage lending to the US Financial Crisis Inquiry Commission (FCIC), of over 900,000 mortgages reviewed in the 18 months to 30 June 2007, only 54% fully met guidelines. (See page 166 of the February 2011 FCIC report.)

[11]When the conflicts of interest came to light, investors sued and the US Securities and Exchange Commission (US SEC) began investigating Goldman Sachs for investor fraud. In 2010, the US SEC announced that Goldman Sachs would pay US $550 m, split US$250 m in compensation to investors and US$300 m in a fine – see https://www.sec.gov/news/press/2010/2010-123.htm

[12]See, for example, "*Mortgage Plan Gives Billions to Homeowners, but With Exceptions*", New York Times, 12February 2012 at =http://www.nytimes.com/2012/02/10/business/states-negotiate-26-billion-agreement-for-homeowners.html?hp&_r=1