prevailing market environment. Unlike developed economies, emerging economies do not employ complex derivative transactions or financial products; thus, the nature of their operational losses differs significantly.

Compared to developed economies, emerging economies face significant research gaps in operational risk management, mainly due to structural differences and methodological limitations compared to developed economies. Operational risk profiles in emerging economies fluctuate dramatically in time. Nevertheless, most frameworks apply a uniform and homogenous approach. Therefore, personalized risk measurement methodologies accounting for structural differences with developed economies are needed.

When it comes to emerging economies, there is a sharp sensitivity to overestimation or underestimation of operational risk capital requirements due to structural and regulatory challenges. These issues emerge from differences in risk profiles and economic conditions compared to developed markets. On one hand, standardized approaches developed for developed markets habitually fail to capture the unique operational risk dynamics of developing economies due to higher fraud rates, weaker governance, and less mature infrastructure. On the other hand, operational losses in developing markets exhibit stronger interdependencies between fraud and system failures for example, which are not fully captured by standardized models. Ignoring these dependencies can lead to overestimation. In addition, a decline in real GDP during a crisis may lead to an underestimate of capital required when risks are actually high. Also, operational risk in developing economies is more influenced by sectoral factors (agriculture and manufacturing) and governance quality that are not adequately included in standardized models.

To differentiate between developed and emerging economies , this study employs both the International Monetary Fund's (IMF) World Economic Outlook and classifications by the United Nations. The IMF World Economic Outlook classifies the global economy into two major groups: advanced and emerging, and developing economies. However, this classification is not based on strict criteria; rather, it has been developed over time with a focus on simplifying the data analysis to provide data that are both reasonable and meaningful. Countries including Anguilla, Cuba, Montserrat, and the Democratic People's Republic of Korea, which are not IMF members, are excluded because they are not monitored by the IMF. Moreover, Somalia is not included as an emerging or developing economy owing to data limitations. The United Nations uses the World Economic Situation and Prospects (WESP) dataset, which classifies the global economy into three groups: developed, transition, and developing economies. First, the dataset distinguishes between fuel-importing and fuel-exporting economies within transition and developing economies. Second, countries are categorized into high-, upper-middle-, lower-middle-, and low-income groups based on their gross national income (GNI).

Uniform approaches for modeling operational risks overlook significant tail loss dependencies. Discarding the advanced measurement approach (AMA) and adopting a standardized methodology would lead to the mismeasurement of the required operational risk capital.

This study aims to demonstrate that using a standardized model for all banks worldwide does not lead to precise capital calculations. This can lead to an overestimation or underestimation of the required capital, tying up funds that could otherwise generate income or be reallocated to hedge against other risk types. The modeling of operational risk capital depends on loss data and distribution selection. An error in the input or distribution can lead to a radical change in required capital. This is reflected in Basel's choice to oblige all banks in both developed and emerging economies to use the same modeling technique, despite the major differences in the nature of operational risk losses between economies.

The contribution of this study is to demonstrate that applying AMA in emerging and developed economies by testing a set of statistical models or specifying the distribution of losses leads to different capital requirements owing to differences in the prevailing markets. Our results are consistent with and support those of Peters et al. [ ], who present similar conclusions using an approach tested to measure the operational risk regulatory capital. They demonstrate significant problems in operational risk modeling using any uniform approach, including risk insensitivity, capital superadditivity, and instability. Therefore, they advocate for the AMA and its standardization to avoid heterogeneity problems across banks rather than a complete shift to any uniform approach that would eliminate the AMA entirely. Eliminating AMA could lead to biased results, benefiting only large banks in developed economies with significant operational risk losses, while allowing banks in emerging economies to decrease their required capital for operational risks.

The remainder of this chapter is organized as follows. Section 2 presents a literature review, Section 3 analyzes the data, and Section 4 explores an empirical investigation. Section 5 summarizes the results and Section 6 presents the findings, concluding the article.

2. Literature review

The Basel Committee primarily aims to improve both the soundness and stability of the global banking system by strengthening risk management practices and instituting risk-sensitive capital requirements to avoid catastrophic losses that previously occurred. According to Nystrom and Skoglund [ ], Barings's insolvency and the Allied Irish Bank's loss of $750 million were due to rogue trading, and the Lloyd Banking Group and Barclays were involved in fraudulent actions that led to losses of €5.9 billion and €4 billion, respectively. Such losses occurred because of weak ORM, thus presenting an opportunity for fraudulent action [ ].

Ames et al. [ ] posit that unlike other risks, operational risk tends to exhibit heavy tails, and the available datasets are neither as comprehensive nor as accessible as those for other risks. Therefore, the models are insufficiently robust to explain why minor changes in the data can have a significant impact on the model's results, leading to instability in the operational risk capital requirement.

Operational risk models are broadly classified into top-down and bottom-up approaches [ ]. Chernobai et al. [ ] state that top-down approaches quantify operational risk without identifying events or causes of loss. However, bottom-up approaches quantify operational risk at a micro-level by identifying internal events, which are then incorporated into the overall capital charge calculation.

According to Jednak and Jednak [ ], the advantage of bottom-up approaches over top-down ones lies in their ability to explain the mechanisms behind the reform of operational risk within an institution. The implementation of these models is hindered by limited historical operational loss data. However, banks can adopt bottom-up models if they have robust databases [ ].

According to Ames et al. [ ], the Basel II Accord has three main approaches to calculating operational risk regulatory capital. The first is the basic indicator approach (BIA), the second is the standardized approach (TSA) and the third is the AMA. BIA and TSA are top-down modeling approaches, whereas AMA is a bottom-up modeling approach [ ]. BIA is simple and uses only one factor, which is 15% of the average annual gross income. Under TSA, each standard business line has a different gross income percentage. The AMA is the most advanced and complex approach, generating a more accurate calculation of operational risk faced by banks. Banks using the AMA can employ their internal models, provided they meet the accuracy standards of the Basel II eight business lines based on the seven relevant event types [ ].

Subject to regulatory approval and following the AMA approach, banks can quantify their operational risk using an internally developed model that incorporates the four data elements (tools/sources) specified in the BCBS [ ]: internal loss data, relevant external data, scenario analysis, and factors reflecting the business environment and internal control factors (BEICFs) [, ,]. Loss data (internal and external), key risk indicators (KRIs), risk and control self-assessment (RCSA), and scenarios are extensively used in risk identification and management processes. External data can also be used as direct inputs for capital calculations, but only after extensive development [ ].

Basel II requires banks to categorize their loss data based on a risk matrix of 56 cell combinations (i.e., eight business lines by the seven event types) [ ]. The number of cell combinations can be increased by expanding the business line and loss event type classification from a one-level to a three-level hierarchical tree structure, where each business line node has a branch of event types attached. For simplicity and because of a lack of data, banks tend to quantify their operational risks at different levels and exclude risk cells that are irrelevant to their business [ ].

According to Prokopenko and Bondarenko [ ], collecting data is challenging. They propose several solutions, including team-building events, automation, bonus and penalty systems, data verification, and periodic revision. Banks face several issues, such as a small internal data sample, the need for rescaling when integrating external and internal data samples into a single model, the requirement for the operational risk losses to fit the correct statistical distribution, and the underreporting of internal losses [ ].

Brechmann et al. [ ] suggest that the Basel BIA does not reflect real operational loss capital because it generates 38% less capital than a realistic dependence model. This incentivizes banks to use realistic and advanced models. However, banks under BIA and TSA use simple models to estimate their capital requirements. Because of the modeling complexity and inability to compare AMA models across different banks, the BCBS decided to revert to the simplest approach by removing all internal models and using a uniform approach model [ ].

In March 2016, Basel introduced a fourth approach that was finalized in December 2017, recognizing a uniform approach aimed at reducing the direct link between modeling activity and required capital. Regulators argue that models are fragile and that the lack of AMA standardization across banks makes it difficult to compare the end results. In 2020, all three approaches were phased out, and only a uniform approach was in effect, which is the standardized measurement approach (SMA) [ ].

According to the Basel Committee (2016), the SMA is a uniform approach that combines bank-specific operational loss data with business indicators (BIs), which are a basic financial statement proxy for operational risk exposure. BIs comprise the same components as profits and losses found in the gross income (GI) composition. In October 2014, Basel revised the BIs to avoid penalizing certain business models, such as those based on high interest margins and those based on the distribution of products bought from third parties. The Basel analysis revealed that operational loss exposure increased (more than proportionally) with the BIs. Consequently, the Committee revised the marginal coefficients for the BIs and increased them under any uniform approach. Basel emphasizes that, to have an accurate SMA model, banks must have an internal database loss that follows policies and procedures.

Furthermore, the primary reason for replacing AMA with the Basel Committee's model, SMA, in 2016 was to implement a "one size fits all" model across all banks and avoid complex modeling techniques. Migueis [ ] highlights key weaknesses that led to the replacement of the AMA with the SMA, also referred to as the new standardized approach (NSA), as reported by Basel in January 2019: Many practitioners perceive AMA as a complex and unnecessary approach that lacks value in real business decisions and comparability across banks. Consequently, in March 2016, the Basel Committee issued a consultative document replacing the AMA with the SMA or NSA, a system that would base capital calculation on a fully standardized formula.

According to Migueis [ ], AMA estimates the 99.9th percentile of the annual distribution of operational losses. However, Basel does not specify how this should be accomplished, allowing each bank flexibility in calculating this using a combination of main data elements such as external loss data, internal loss data, scenario analysis, and BEICFs. Six aspects are considered for replacing AMA with SMA: robustness, comparability, risk sensitivity, stability, simplicity, usefulness in risk management, and advancement of quantification techniques.

Robustness and comparability are enhanced by using a standardized approach with a given formula for estimating the required capital, which decreases the potential of model manipulation and minimizes decisions left to the practitioner's judgment. Consequently, the SMA is more robust than the AMA because the AMA does not specify how data elements should be combined or how to use the correct family distribution to estimate the operational loss distribution at the 99.9th percentile. This leads to significant differences in capital estimations between banks. Conversely, the SMA is robust because it applies a standardized formula to historical internal losses and financial statement metrics. Additionally, the standard formula of the SMA is easily compared, unlike AMA, which is difficult to compare across banks. However, if differences in data collection under the SMA are not accounted for, comparability will be difficult for both the SMA and AMA [ ].

Risk sensitivity: The AMA did not specify how banks should model the 99.9th percentile of the operational risk annual loss distribution, allowing banks to tailor the model to be more risk sensitive to a specific data element, potentially decreasing their capital requirement. A similar problem exists in the SMA, as relying on historical internal losses and financial statement metrics does not reflect a bank's risk profile. In addition, the removal of major data elements that existed under the AMA, such as BEICFs and scenario analysis from capital calculations, has curtailed the forward-looking perspective in capital calculations [ ].

Stability and simplicity: Because AMA primarily relies on internal losses, any significant loss can impact capital estimates, particularly the estimation of the 99.9th percentile of loss. Moreover, using external data can cause significant variations in the risk sensitivity of the estimated capital. Consequently, AMA is not a stable approach. In addition, AMA involves numerous data elements and complex modeling techniques. Under the SMA, stability is ensured using a 10-year historical data loss to calculate the required capital. This eliminates variances and guarantees stability. The SMA is a simple approach that uses a standard formula [ ].

Usefulness for risk management and advancement of quantification: Bankers argue that AMA is of limited use beyond regulatory capital estimation because its estimation is based on the 99.9th percentile of past losses. Reliance on past losses eliminates the need for dynamic forward-looking models. Moreover, the 99.9th percentile is an extreme tail percentile useful for pricing and other day-to-day risk decisions. However, because SMA is a top-down approach, it lacks the option of studying risk at a granular level, which produces no motive for risk management to develop advanced quantification techniques [ ].

This shift from the AMA to the SMA adopts a top-down approach that decreases operational risk losses to one unit of measurement. Assuming that losses that are heterogeneous in nature and can all be aggregated simply eliminates the concept of risk sensitivity analysis. Therefore, the BCBS SMA does not achieve its primary objective of measuring the sensitivity of operational risk capital. This is because the capital estimated under any uniform approach is neither stable nor related to the bank's risk profile, potentially encouraging risk-taking behaviors that may cause financial instability [ ].

Under the Basel AMA, significant emphasis is placed on the use of the four main loss data types when calculating capital. These loss data types include the external loss data, internal loss data, BEICF, and scenario analyses. However, the shift to a new SMA excludes three types of data and uses only the internal loss data. For example, standardization must be considered by requiring statistical robustness, using the loss distribution approach (involving all four types of data loss), and detailed reports on the modeling assumptions and techniques [ ].

Compared to the simpler approaches, the capital reserves under the AMA approach are expected to be more relevant to the bank's actual risk profile (i.e., capital is held in proportion to the amount of operational risk involved in its activities). Consequently, capital requirements are typically lower under any uniform approach, thereby incentivizing banks to invest in robust operational practices and risk management [, , ,].

According to a PWC report [ ], the banking industry has criticized the Basel models that measure operational risks. The elimination of the concept of business lines made it more difficult for banks to achieve better risk management by assessing the risk-based performance of each business line. The shift to the new SMA uses five different categories, ranging from 10–30%, based on the BI approach [ ]; however, it does not show how to capture massive variations in banks' business models. By contrast, the BCBS [ ] reports that SMA 5 employed three categories. Notably, it does not explain how a uniform approach can differentiate between banks that have improved their control environments and those that have high-quality ORM practices.

According to Sands et al. [ ], risk-weighted asset (RWA) is one of the three major components of a bank's risk-based capital ratio. RWA is the denominator of the Common Equity Tier 1 (CET1) capital ratio . According to BCBS [ ], "CET1 is the highest quality of regulatory capital, as it absorbs losses immediately when they occur." The RWA of operational risk represents 15.6% of the 30 Globally Systemically Important Banks (GSIB) [ ].

Sands et al. [ ] mention that the BCBS's latest update on the estimation of operational RWA shifts from reliance on complex internal models to standardized modeling. Under the uniform approach, a significant increase in operational risk losses leads to an increase in RWA. Consequently, management cannot reduce the operational risk RWA except by decreasing the RWA of the market or credit risk. Therefore, a uniform approach causes a negative loss of absorbency for banks, leading to further challenges for those operating under such a uniform approach. Specifically, it does not provide the bank with an incentive to improve ORM. Moreover, the ability to compare risk-based capital ratios across banks will not improve because of variability and a lack of consistency in the derivation of the operational RWA under both the uniform approach and AMA. A uniform approach may provide comparability by appearance rather than real comparability across banks. This is because under the uniform approach, two banks could have equivalent operational RWA while facing different levels of risk and vice versa.

Mignola et al. [ ] examine the impact of the shift from AMA to SMA through a case study simulation. They state that this shift undermines the accurate measurement of the operational risk in banks, as SMA fails to capture different risk profiles, resulting in inaccurate capital calculation. Cohen [ ] mentions that the SMA cannot capture granular risk levels. SMA is a "one- size-fits-all type of model," which means one equation applies to all banks with different risk profiles. This completely ignores idiosyncratic characteristics such as lines of business, asset classification, and other individual bank characteristics. The only details captured by the SMA are the bank's profits and operational losses. Cohen [ ] supports the view that SMA fits all banks and makes comparability applicable; however, AMA should not be eliminated. The modeling data can be improved by focusing on fewer details, reducing the noise in the modeling results, generating one overall dominating trend, and adjusting the confidence level from the 99.9th percentile.

Mignola et al. [ ] reveal three main points that highlight the weakness of SMA over AMA, apart from the fact that SMA is easier to compare across banks. First, the SMA is risk insensitive, does not change with the bank risk profile, and cannot differentiate between different risk profiles across banks. This is because SMA does not grow in proportion to the operational losses; therefore, it is said to be risk insensitive, unlike AMA. Second, the SMA is directly linked to bank income, which is imperfectly correlated with historical losses. According to a recent survey, there are wide variations between the income level generated by banks and operational loss data. Because SMA banks with similar risk profiles can have different capital levels, the SMA loses its main advantage, which is comparability. Third, SMA can lead to over-or underestimation of operational risk capital since it is not linked to any risk measure, unlike AMA, which is linked to the 99.9th percentile value at risk (VaR) of the annual operational loss distribution. The SMA can be linked to various confidence levels, beginning from the 99th to 99.9999th percentiles. This proves that the SMA does not differentiate between different risk profiles.

Because operational losses are typically presented by a heavy-tailed loss distribution, the SMA is expected to have the following characteristics: First, assuming that two banks have the same expected loss (EL), a bank with a low frequency-high intensity loss profile should have more capital than a bank with a high-frequency and low-intensity loss profile. Second, if the two banks have risk factors, the bank with high EL should hold more capital than the one with low EL. After conducting a case-study simulation, the SMA failed to follow these two characteristics. The main component of the SMA is the business size rather than the loss profile. Increasing the loss component (LC) by 100% does not exceed the increase in the final SMA figure by 33% (assuming no change in the BI). Therefore, if neither BI nor the risk factors remain unchanged, any change in LC would be directly linked to a change in EL. This indicates that as EL increases, SMA decreases, which is contrary to the first characteristic mentioned above [ ].

Mignola et al. [ ] conclude that SMA is considered a deterioration in two aspects. First, it measures risk sensitivity. Second, it fails to establish a link between capital requirements and managerial actions. For instance, assume two banks with similar loss profile and size: One bank invests in improving the existing legal environment, controls, and resources, while the other makes no such improvements. Under the SMA, both banks have the same capital requirements. However, under AMA, the first bank is likely to have a reduced risk profile through improvements and lower required capital.

This study aims to estimate the capital required for operational risk using several models for both developed and emerging economies. There are two key components: loss frequency and loss severity distributions of the historic operational loss data. Actuarial models can differ based on the type of loss distribution with respect to empirical loss distribution models and parametric loss distribution models. Operational risk capital is measured by the VaR of the aggregated one-year losses.

For example, three actuarial models can be used simultaneously to measure a bank's operational risks [ ]. Alternatively, an autoregressive moving average/generalized autoregressive conditional heteroskedasticity (ARMA/GARCH) model can be applied to the losses below a high threshold, while the generalized Pareto distribution can fit the data exceeding it [ ]. This is the approach adopted in our model, which employs both the bottom-up and top-down approaches. These models show that using a standardized model for all banks in emerging and developed economies leads to an under-or overestimation of required capital, highlighting the main objective of this study.

3. Data

In this study, we use the "SAS Operational Risk Global Data" related to the operational risk losses in banks in developed and emerging economies. There are eight business lines and seven event types that constitute 56 risk categories, as shown in .

Business lines	Event types
Corporate Finance	Internal Fraud
Trading & Sales	External Fraud
Retail Banking	Employment Practices and Workplace Safety
Commercial Banking	Clients, Products & Business Practices
Payment and Settlements	Damage to Physical Assets

Business lines	Event types
Agency Services & Custody	Business disruption and system failures
Asset Management	Execution, Delivery & Process Management
Retail Brokerage	

Table 1.
Operational risk matrix (Basel classification).

As shown in , under the Basel II and subsequent frameworks banks are mandated to categorize their activities into eight distinct business lines and seven event types. Each business line echoes a different area of banking operations related to the exposure to operational risk. The goal of this classification is to ensure that operational risk capital requirements are sensitive to the specific risks inherent in each type of banking activity.

We used the global SAS data on operational risk from 1971 to 2017. The total number of reported events are 16,468, of which 15,471 and 997 are from developed and emerging economies, respectively. The items with significant and recent data for both developed and emerging economies include the business line "Trading & Sales" and the event types "Clients, Products & Business Practices" and "Damage to Physical Assets" which account for 57% of the total number of events in emerging economies. Business lines and event types are selected based on the number of events declared and available in the SAS system. demonstrates that business line "Trading & Sales" and the event types "Clients, Products & Business Practices" and "Damage to Physical Assets" have the highest number of events in developing countries. In addition, to preserve the efficiency of the model's parameter estimates, we restrict our analysis to these types of events. Economic data on developing countries are recognized by their scarcity, specifically, in the banking sector.Clients, Products and Business Practices" and "Damage to Physical Assets" account for 41.98% and 17.43%, respectively, contributing to 59.41% of the total number of events in developed countries. Emerging economies account for 28.77 and 11%, respectively, amounting to 39.77% of the total number of events.

Count of events	Event category							
Business line	Internal Fraud	External Fraud	Employment Practices	Clients, Products	Damage to Physical Assets	Business Disruption	Execution	Total
Corporate finance	73	42	1	27	2	0	0	145
Trading and sales	75	33	15	287	105	10	2	527

Count of events	Event category							
Business line	**Internal Fraud**	**External Fraud**	**Employment Practices**	**Clients, Products**	**Damage to Physical Assets**	**Business Disruption**	**Execution**	**Total**
Retail Banking	6	0	0	9	0	0	0	15
Commercial banking	1	2	0	8	0	0	1	12
Payment and settlement	16	0	0	7	0	1	0	24
Agency Services & Custody	5	2	0	0	1	0	0	8
Retail Brokerage	80	55	0	44	6	0	0	185
Asset Management	3	0	2	6	0	0	0	11
Total	259	134	18	388	114	11	3	927

Table 2.
Count of events for developing countries.

We select the marginal distributions of operational severities and frequencies for every intersection of event types and business lines, as well as their joint distribution (copula) using the Vuong test. We utilize the Akaike information criterion and the Anderson-Darling test for the same purpose. Subsequently, we approximate the total loss distribution using Monte Carlo simulations, through which we estimate the global VaR with a 99.9% confidence level.

4. Modeling methodology

We refer to Pretorius [ ], “The superiority of one frequency function over another depends rather on the success with which that function can be applied to graduate data than on the manner in which it originated.”

This insight highlights that a model with good properties should not be complicated or sophisticated. Specifically, it should be flexible, enabling practitioners to generate stylized data. Therefore, a model must be more flexible while containing a finite number of good interpretable parameters while remaining tractable and simple for estimating and predicting the variables or key indicators such as the risk of exceeding a certain threshold value. We pursue these desirable properties to model the severity and frequency of operational risk losses.

Operational risk is a compound process because it depends on two random variables: the size or severity of the risk and the number or frequency of events. Severity is a continuous variable, and frequency is a discrete variable.

The loss distribution approach is a common model used to measure operational risk losses. It assumes that the number of events (frequency) of internal operational losses and the severity (s) of a single loss are independent random variables and that the individual losses are independent and identically distributed. The total loss is given by $L = \sum_{i=1}^{f} Si$, and the total loss distribution on function (H) is given by

$$H(l) = pr(L < l) = \sum_{n=0}^{+\infty} Pr(f = n) F_n(S). \qquad E1$$

where F_n is the n-fold convolution of the severity distribution F. As our loss data are heavily tailed (subexponential), a simple closed-form approximation of the upper quantile of the total loss (L) derived by Böcker and Kluppelberg [ ] exists:

$$H(1) \approx 1 - E(f)(1 - F(s)) \cdot \qquad E2$$

In this case, the quantile of (L) is given by

$$q_a \approx F^{-1}\left(1 - \frac{1-\alpha}{E(f)}\right) \cdot \qquad E3$$

VaR is equal to the quantile (q_a) when α is close to 1. In the subsequent subsections, we present the different distributions of severity (s) and frequency (f) used to estimate the operational risk capital required for developed and emerging economies.

4.1 Severity modeling

To model the severity of operational risks, we use univariate distributions to capture the heavy-tailed distribution of operational risk losses: We consider the following distributions: Exponential, Weibull, Gamma, Log-normal, Exponentiated-Exponential, Exponentiated-Weibull, and Pareto. presents the density for each distribution and the derived VaR.

Distribution	Density	VaR
Exponential	$f(s.\mu) = \frac{1}{\lambda}\exp\left(-\frac{s}{\lambda}\right). s \geq 0. \text{and } \lambda > 0.$	$VaR_\alpha(S) = Q(\alpha.\mu) = \mu(-\ln(1-\alpha)). 0 < \alpha < 1. \text{and } \lambda > 0.$

Distribution	Density	VaR
Weibull	$f(s.\lambda.k) = \frac{k}{\lambda}\left(\frac{s}{\lambda}\right)^{k-1}\exp\left(-\left(\frac{s}{\lambda}\right)^{k}\right).s \geq 0.\lambda > 0 \text{ and } k > 0.$	$VaR_{\alpha}(S) = Q(\alpha.\lambda.k) = \lambda(-\ln(1-\alpha))^{\frac{1}{k}}.0 < \alpha < 1.\lambda > 0 \text{ and } k > 0.$
Gamma	$f(s.\lambda.k) = \frac{1}{\lambda^{k}\Gamma(k)}s^{k-1}\exp\left(-\frac{s}{\lambda}\right).s \geq 0.\lambda > 0 \text{ and } k > 0.$	$VaR_{\alpha}(S) = Q(\alpha.\lambda.k) = \gamma^{-1}(\alpha.\lambda.k).0 < \alpha < 1.\lambda > 0 \text{ and } k > 0.$ $\Gamma(a) = \int_{0}^{+\infty} t^{a-1}\exp(-t)\,dt.\gamma(\lambda.k.x) = \int_0^x \frac{\exp\left(-\frac{s}{\lambda}\right)s^{k-1}}{\lambda^{k}\Gamma(k)}ds$
Log-normal	$f(s.\lambda.\mu) = \frac{1}{\sqrt{2\pi}\lambda s}\exp\left(-\frac{1}{2}\frac{(\ln(s)-\theta)^2}{\lambda^2}\right.s > 0.\lambda > 0 \text{ and } \theta$	$VaR_{\alpha}(S) = Q(\alpha.\lambda.k) = \exp\left(\lambda\Phi^{-1}(\alpha)+\theta\right).0 < \alpha < 1.\lambda > 0 \text{ and } \theta$
Exponentiated-Exponential	$f(s.\lambda.k) = \frac{k\left[1-\exp\left(-\frac{s}{\lambda}\right)\right]^{k-1}\exp\left(-\frac{s}{\lambda}\right)}{\lambda}.s \geq 0.\lambda > 0 \text{ and } k > 0$	$VaR_{\alpha}(S) = Q(\alpha.\lambda.k) = \lambda\left(-\ln\left(1-\alpha^{\frac{1}{k}}\right)\right).0 < \alpha < 1.\lambda > 0 \text{ and } k > 0$
Exponentiated-Weibull	$f(s.\lambda.k) = \frac{k\theta\left[1-\exp\left(-\left(\frac{s}{\lambda}\right)^{k}\right]^{\theta-1}\exp\left(-\left(\frac{s}{\lambda}\right)^{k}\right)s^{k-1}}{\lambda^{k}}.s \geq 0.\lambda > 0.\theta > 0 \text{ and } k > 0$	$VaR_{\alpha}(s) = Q(\alpha.\lambda.k) = \lambda\left(-\ln\left(1-\alpha^{\frac{1}{\theta}}\right)\right)^{\frac{1}{k}}.0 < \alpha < 1.\lambda > 0.\theta > 0 \text{ and } k > 0$
Pareto	$f(s.s_m.\lambda.k) = \frac{ks_m^k\left(\frac{s}{\lambda}\right)^{-k-1}}{\lambda}.s \geq s_m > 0.\lambda > 0 \text{ and } k > 0$	$VaR_{\alpha}(S) = Q(\alpha.\lambda.k) = \lambda s_m\left(1-\alpha\right)^{\frac{1}{k}}.0 < \alpha < 1.s_m > 0.\lambda > 0 \text{ and } k > 0$

Table 3.

Density for each distribution and derived VaR.

4.2 Frequency modeling

The frequency data of the operational risk is a type of count data. The standard framework for modeling the outcome variable includes the Poisson and negative binomial models.

The Poisson model is expressed as follows:

$$\Pr(F = f) = \frac{\exp(-\mu)\mu^{f}}{\Gamma(f+1)}.\mu > 0.f = 0.1.2\cdots \qquad \text{E4}$$

where F represents the frequency, and μ denotes the mean. The variance in this model is equal to the mean ($\sigma^2 = \mu$). The basic Poisson model assumes that the variance in an outcome is equal to the mean, which is of limited use in empirical analyses. However, count data are often over-dispersed relative to the Poisson distribution. One frequent manifestation of overdispersion is that the data may originate from different sources (e.g., different populations). This is the case with the frequency of operational risk data. Another alternative is the negative binomial model. This model complements more conventional models for overdispersion that concentrate on modeling the variance-mean relationship correctly.

The negative binomial model is expressed as follows:

$$\Pr(F = f) = \frac{\Gamma(\eta+f)}{f!\Gamma(\eta)}(1-\pi)^{\eta}\,\pi^{f}.\ \eta > 0.0 < \pi < 1.\ f = 0.1.2.\cdots \qquad E5$$

If a distribution is used for regression, it is more appropriate to express the probability mass in terms of the mean. Therefore, if we substitute $\mu/(\eta + \mu)$ for π, the probability mass becomes

$$\Pr(F = f) = \frac{\Gamma(\eta+f)}{f!\Gamma(\eta)}\left(\frac{\eta}{\eta+\mu}\right)^{\eta}\left(\frac{\mu}{\eta+\mu}\right)^{f}\ \eta > 0.\ \mu > 0.\ f = 0.1.2\cdots \qquad E6$$

The negative binomial distribution is particularly appropriate for modeling operational risk event frequency in banks owing to its ability to handle overdispersion, which is a common feature of real-world loss data where variance exceeds the mean. Banks in emerging economies may lack extensive historical loss data. In such a situation, the negative binomial performs better than Poisson as it accounts for periods of low losses and abrupt spikes. Another advantage is that, in Basel frameworks banks are required to model tail risks accurately in which case the negative binomial can do better in capturing the tail behavior and rare but severe events (large frauds, etc.). In addition, the negative binomial distribution enhances stress testing by allowing simulation of extreme but plausible loss frequencies linked to systemic risks (cyberattacks, geopolitical disruptions, etc.).

4.3 Dependence modeling: Copula

To model the dependence between different types of losses, we use the Gumbel and Clayton copulas. The Gumbel copula captures upper-tail dependence, whereas the Clayton copula models lower-tail dependence. If small losses occur more often than larger ones, the Clayton copula is appropriate. If large losses occur more frequently than small losses, then the Gumbel copula is preferred.

4.4 Model selection and estimation

We use the maximum-likelihood estimator to estimate our models of severity and frequency processes. Specifically, the inference function for the margin (IFM) method is used to estimate the parameters. The IFM approach follows a two-step approach introduced by Shih and Louis [ ]. In the first step, the marginal parameters are estimated separately, and in the second step, the dependence parameters are estimated.

We utilize the Vuong test to select an appropriate model for frequency, severity, and copula. The Vuong test is a likelihood-ratio-based test used for model selection. This statistic compares the likelihoods of two models. These models can be nested, non-nested, or overlapping. The statistic verifies the null hypothesis that two competing models are equally close to the true data-generating process, against the alternative that only one model is closer (see Vuong [ ] for further details). Furthermore, we use the Akaike information criterion to classify the models based on their loss of information, with the preferred model being the one with the lowest value for this criterion. Additionally, we conduct a nonparametric test to determine whether the data come from the proposed distribution. Specifically, we use the Anderson-Darling test to assess the specification for the considered distributions.

5. Results

To measure the dependence among losses, we use the Pearson, Spearman's rank, and Kendall's rank correlation coefficients. While the first correlation captures linear dependence, the last two correlations capture nonlinear dependence. For the two marginal operational losses, reports the three types of dependency measures and their corresponding p-values (in parentheses).

Correlation	Linear	Spearman	Kendall
Developed	0.4467 (0.0195)	0.7106 (0.0000)	0.5328 (0.0001)
Emerging	0.0033 (0.9868)	0.4768 (0.0119)	0.3908 (0.0073)

Table 4.
Correlations.

Furthermore, demonstrates that the linear correlation for emerging economies is −0.33%. For developed economies, it is 44.67% and significant. These results suggest that the linear independence hypothesis can be a valid assumption for banks in emerging economies, implying that using any uniform approach, as recently introduced by Basel, could lead to an increase in required regulatory capital. However, Spearman's and Kendall's rank correlation coefficients for emerging economies are 47.68 and 39.08%, respectively. These correlation coefficients for developed economies are statistically significant at 71.06 and 53.28%, respectively. This indicates that using a uniform approach instead of the AMA for developed economies would generate lower regulatory capital for banks. These results emphasize that the dependence on the operational losses is nonlinear, thereby rejecting the independence hypothesis.

We also test the assumption that the correlation is equal to unity, and this hypothesis is strongly rejected by the data for all types of correlations. Thus, the complete dependence assumption, as suggested by Basel in the AMA, is inadequate for modeling the relationship between different types of losses. Thus, the assumption that different risks are positively dependent is inaccurate. This demonstrates that copulas provide a more representative framework for dependence modeling and that the independence assumption is inaccurate.

– present the Vuong test results for specifying the marginal distributions of the two different operational losses. The results indicate that the Exponentiated-Weibull is the best candidate for modeling severity losses in developed economies, whereas the Log-Normal is preferred for emerging economies.

	Exponential	**Weibull**	**Gamma**	**Log-Normal**	**Pareto**	**Exponentiated-Exponential**	**Exponentiated-Weibull**
Exponential	—	Weibull	Gamma	Log-Normal	Exponential	Exponentiated-Exponential	Exponentiated-Weibull
Weibull	—	—	Weibull	Log-Normal	Weibull	Weibull	Exponentiated-Weibull
Gamma	—	—	—	Log-Normal	Gamma	Gamma	Exponentiated-Weibull
Log-Normal	—	—	—	—	Log-Normal	Log-Normal	Exponentiated-Weibull
Pareto	—	—	—	—	—	**Exponentiated-Exponential**	Exponentiated-Weibull
Exponentiated-Exponential	—	—	—	—	—	**—**	**Exponentiated- Exponential**
Exponentiated-Weibull	—	—	—	—	—	—	—

Table 5.
Developed: business line: trading & sales/event type: clients, products & business practices.

	Exponential	**Weibull**	**Gamma**	**Log-normal**	**Pareto**	**Exponentiated-exponential**	**Exponentiated-Weibull**
Exponential	—	Weibull	Gamma	Log-Normal	Exponential	Exponentiated-Exponential	Exponentiated-Weibull
Weibull	—	—	Weibull	Log-Normal	Weibull	Weibull	Exponentiated-Weibull
Gamma	—	—	—	Log-Normal	Gamma	Gamma	Exponentiated-Weibull
Log-Normal	—	—	—	—	Log-Normal	Log-Normal	Exponentiated-Weibull
Pareto	—	—	—	—	—	**Exponentiated-Exponential**	Exponentiated-Weibull
Exponentiated-Exponential	—	—	—	—	—	—	**Exponentiated-Exponential**
Exponentiated-Weibull	—	—	—	—	—	—	—

Table 6.
Developed: business line: trading & sales/event type: damage to physical assets practices.

	Exponential	Weibull	Gamma	Log-Normal	Pareto	Exponentiated-Exponential	Exponentiated-Weibull
Exponential	—	Weibull	Gamma	**Log-Normal**	Pareto	Exponentiated-Exponential	Exponentiated-Weibull
Weibull	—	—	Weibull	**Log-Normal**	Weibull	Weibull	Exponentiated-Weibull
Gamma	—	—	—	**Log-Normal**	Gamma	Gamma	Exponentiated-Weibull
Log-Normal	—	—	—	—	**Log-Normal**	**Log-Normal**	**Log-Normal**
Pareto	—	—	—	—	—	Exponentiated-Exponential	Exponentiated-Weibull
Exponentiated-Exponential	—	—	—	—	—	—	Exponentiated-Weibull
Exponentiated-Weibull	—	—	—	—	—	—	—

Table 7.

Emerging: business line: trading & sales/event type: clients, products & business practice.

	Exponential	Weibull	Gamma	Log-Normal	Pareto	Exponentiated-Exponential	Exponentiated-Weibull
Exponential	—	Weibull	Gamma	**Log-Normal**	Pareto	Exponentiated-Exponential	Exponentiated-Weibull
Weibull	—	—	Weibull	**Log-Normal**	Weibull	Weibull	Exponentiated-Weibull
Gamma	—	—	—	**Log-Normal**	Gamma	Gamma	Exponentiated-Weibull
Log-Normal	—	—	—	—	**Log-Normal**	**Log-Normal**	**Log-Normal**
Pareto	—	—	—	—	—	Exponentiated-Exponential	Exponentiated-Weibull
Exponentiated-Exponential	—	—	—	—	—	—	Exponentiated-Weibull
Exponentiated-Weibull	—	—	—	—	—	—	—

Table 8.

Emerging: business line: trading & sales/event type: damage to physical assets.

This is consistent with the results of the Akaike criterion and the Anderson-Darling test presented in – .

	Anderson-Darling Statistic	Akaike
Exponential	135.6565	12205.91
Weibull	2.311741	11786.49
Gamma	8.572192	11833.36
Log-Normal	1.018559	11759.7
Pareto	29.26322	11911.95
Exponentiated-Exponential	9.886807	11839.75
Exponentiated-Weibull	1.034691	11762.53

Table 9.
Marginal: Anderson-Darling test and Akaike criterion, Emerging economies.

(Business line: Trading and sales/event type: Damage to physical assets).

	Anderson-Darling Statistic	Akaike
Exponential	1526.534	270977.6
Weibull	121.9547	266741.4
Gamma	255.7549	267644.2
Log-Normal	20.3355	265633.4
Pareto	1210.815	273541.5
Exponentiated-Exponential	285.5045	267781.9
Exponentiated-Weibull	11.76942	265590.4

Table 10.
Marginal: Anderson-Darling test and Akaike criterion, developed economies.

(Business line: Trading and sales/event type: Damage to physical assets).

	Anderson-Darling Statistic	Akaike
Exponential	63.9200	4815.225
Weibull	3.1750	4653.13
Gamma	6.1698	4672.619
Log-Normal	1.2922	4634.195
Pareto	12.15908	4690.947
Exponentiated-Exponential	6.513094	4674.169
Exponentiated-Weibull	1.945219	4634.623

Table 11.

Marginal: Anderson-Darling test and Akaike criterion, Emerging economies.

(Business lines: trading and sales/event type: clients, products, and business practices).

	Anderson-Darling Statistic	Akaike
Exponential	327.5706	32900.93
Weibull	32.1438	32101.34
Gamma	58.6899	32269.43
Log-Normal	11.8317	31887.47
Pareto	121.8443	32549.48
Exponentiated-Exponential	63.5005	32290.31
Exponentiated-Weibull	5.5957	31849.09

Table 12.

Marginal: Anderson-Darling test and Akaike criterion, Developed economies.

(Business lines: trading and sales/event type: clients, products, and business practices).

and present that, using the Vuong test, the Gumbel copula is the best fit for capturing dependence in developed economies, and the Clayton copula is the best choice for emerging economies.

	Normal	Clayton	Gumbel
Normal	—	Clayton	Gumbel
Clayton	—	—	Gumbel
Gumbel	—	—	—

Table 13.
Copula-developed market.

	Normal	Clayton	Gumbel
Normal	—	**Clayton**	Gumbel
Clayton	—	—	**Clayton**
Gumbel	—	—	—

Table 14.
Copula-emerging market.

These results corroborate the results of the Akaike criterion and Anderson-Darling test presented in and .

	Anderson-Darling Statistic	Akaike
Gaussian Copula	1.2018	106.1774
Clayton copula	0.6455	−8.133466
Gumbel Copula	0.8922	−7.152300

Table 15.
Copula: Anderson-Darling test and Akaike criterion emerging.

	Anderson-Darling Statistic	Akaike
Gaussian Copula	26.5543	95.29025
Clayton copula	0.9312	−17.09323
Gumbel Copula	0.7524	−17.56574

Table 16.

Copula: Anderson-Darling test and Akaike criterion developed.

For the frequency distribution, for both emerging and developed countries, the Akaike criterion and the Anderson-Darling test select a negative binomial, as presented in – .

	Anderson-Darling statistic	Akaike
Poisson	0.0242	145.556
Negative-Binomial	0.0064	104.2360

Table 17.

Frequency: Anderson-Darling test and Akaike criterion, emerging economies.

(Business line: Trading and sales/event type: Damage to physical assets).

	Anderson-Darling Statistic	Akaike
Poisson	0.2598	8512.0446
Negative-Binomial	0.0003	477.2543

Table 18.

Frequency: Anderson-Darling test and Akaike criterion, developed economies.

(Business line: Trading and sales/event type: Damage to physical assets).

	Anderson-Darling Statistic	Akaike
Poisson	0.0321	624.6632
Negative-Binomial	0.0101	146.4304

Table 19.

Frequency: Anderson-Darling test and Akaike criterion, emerging economies.

(Business lines: trading and sales/event type: clients, products, and business practices).

	nderson-Darling Statistic	Akaike
Poisson	0.259807	801.1519
Negative-Binomial	0.000322	255.8277

Table 20.

Frequency: Anderson-Darling test and Akaike criterion, Developed economies.

(Business lines: trading and sales/event type: clients, products, and business practices).

Significant difference exists between the two copulas: The Clayton copula exhibits lower tail dependence, and the Gumbel copula captures upper tail dependence. In emerging economies, losses show a high degree of dependence for small losses and exhibit independence when there are large losses, whereas the opposite is true for developed economies. This supports our research hypothesis that banks in different markets cannot apply the same methodology to measure operational risks because of the differences in the nature of the data. However, this may result in differences between the level of capital and money markets in both economies. Therefore, using a standardized model proposed by Basel would result in an inaccurate capital calculation, overestimating the operational risk capital in emerging economies while underestimating the operational risk capital in developed economies.

We define the relative percentage error (underestimation or overestimation) in the VaR forecast as:

$$\mathrm{RPE} = \frac{\mathrm{AM}-\mathrm{OM}}{\mathrm{OM}} \times 100 \qquad \text{E7}$$

where AM represents the actual model, and OM represents the optimal model. If the RPE is negative, the actual model underestimates the VaR by the given percentage. Moreover, if the RPE is positive, the actual model overestimates the VaR. indicates the VaR results for the different models, where columns 2 and 3 report the results for developed and emerging economies, respectively. As shown in , the last two rows show the results of the perfect dependence and independence models included in Basel's AMA.

	Developed	Emerging
Gaussian	59.45%	6.00%
Clayton	62.64%	0
Gumbel	0	12.31%
Complete Dependence	3.97%	17.67%
Independence	26.45%	0.63%

Table 21.
VaR Results.

These results indicate that the independence model underestimates VaR and the complete dependence model overestimates VaR. Nonetheless, the complete dependence model overestimates VaR by 3.97% for developed economies, compared with 17.67% for emerging economies. Conversely, the independence model underestimates VaR by 26.45% for developed economies and 0.63% for emerging economies. This is consistent with the correlation results in , where the correlations are significantly higher for developed economies compared with emerging economies.

Given the above results, the study looked at different ways to estimate how much capital a bank could lose in a worst-case scenario due to operational problems like fraud, system failures, or human error. Assuming that different types of risk are unrelated is not realistic in the real world. On the other side, assuming that all risks occur together leads to an approach that is overly cautious. There is no single model that provides a perfect estimate for every situation. Some models are too optimistic, while others are too pessimistic, and the best model may depend on the country and its specific circumstances. This means banks, especially in developing countries, need to be careful about which models they use to measure operational risk.

From the contour plot in and given our empirical results, it is revealed that the Gumbel copula is suitable to capture the upper tail dependence which is critical to better capturing the clustering of extreme losses. On the other side, the figure shows that the Clayton copula is more adapted to capture the clustering of small losses happening in the lower tail. That is, Clayton copula is more adapted to situations where small losses are realized jointly and simultaneously while the Gumbel copula is relevant in modeling joint spikes (joint extreme losses). Therefore, using the Gumbel copula in the case of emerging economies, where the big losses are rare, leads to an overestimation of capital at risk while adopting Clayton copula in the case of developed economies, where big losses are realized jointly and frequently leads to underestimation of capital at risk.

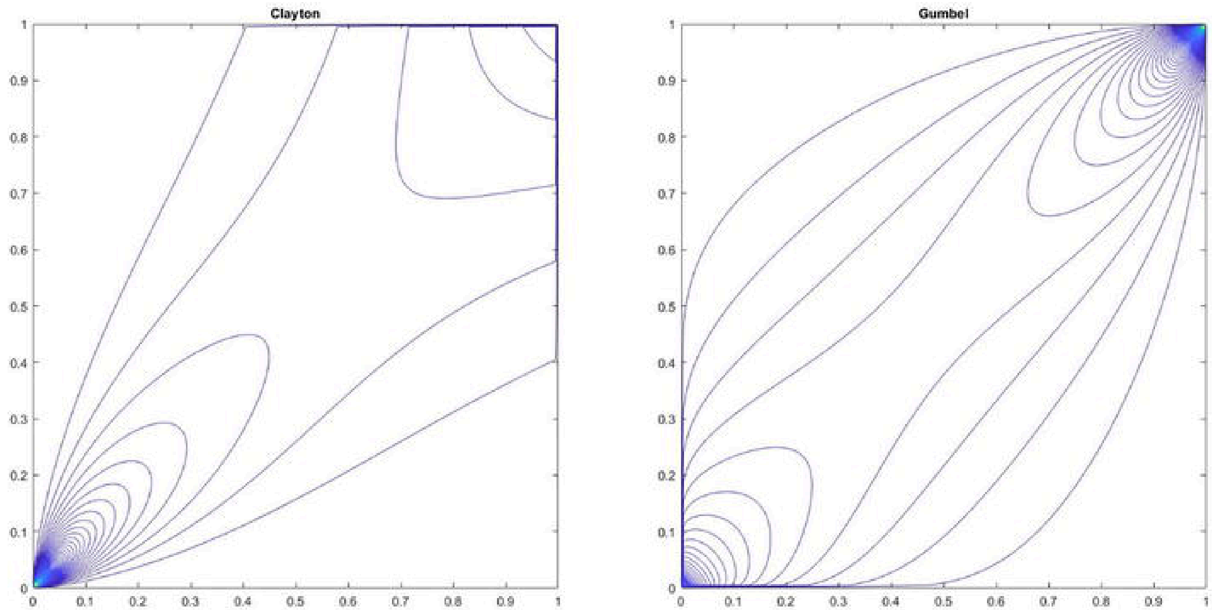

Figure 1.

Contour plot of Clayton and Gumbel copulas (Kendall's Tau correlation of 0.5).

5.1 Limitations and further improvements

In the absence of available of detailed panel data on operational risk available for research, we used SAS database that includes publicly reported operational losses above a certain threshold (typically USD 100,000) leading to underrepresentation of smaller losses and incidents typical to small-sized banks. This translates into a skewed dataset. Another limitation of our study is related to scale bias, a consequence of data aggregation of losses from institutions of varying sizes and regions. This can twist operational risk estimates when applying a given model to banks of a different size. The SAS data may also suffer from homogeneity in internal control and risk management practices across different banks. The data may also suffer from a scarcity of severe events that were not reported.

5.2 Possible improvements

As an extension and improvement of our findings, it will be very important to include qualitative and quantitative factors, both macro and specific. It will also be essential to develop methods to fine-tune the differences in internal control and risk culture among reporting institutions where qualitative indicators are central.

6. Conclusion

From , Column 2, Rows 2 and 3 show that adopting the Gaussian or Clayton copula instead of the Gumbel copula underestimates VaR by 59.45 and 62.64%, respectively, for developed economies. Conversely, if we use the Gaussian or Gumbel instead of the Clayton copula, the VaR is overestimated by 6 and 12.31%, respectively, for emerging economies. This is possibly due to differences in the risk profiles of banks in different economies.

This study highlights that the estimation of operational risk capital cannot be uniformly applied across all banks under the new Basel regulation. The main finding of our study is that a uniform approach, such as the one based on Basel's complete dependence model, may lead to an overestimation or underestimation of capital. Our results also suggest that adopting the same approach for all banks across emerging and developed economies is not recommended because of the differences in the nature of operational risk losses in each economy.

Our results are consistent with and support those of Peters et al. [ ], who present similar conclusions using an approach tested to measure operational risk regulatory capital. They demonstrate that significant problems result in operational risk modeling using any uniform approach, such as risk insensitivity, capital superadditivity, and instability. Therefore, they advocate AMA and its standardization to avoid heterogeneity problems across banks rather than a complete shift to any uniform approach that would eliminate the AMA entirely. Eliminating AMA could lead to biased results, benefiting only large banks in developed economies that experience large operational risk losses.

The proposal to shift to a uniform approach does not address the primary issues of operational risk owing to its qualitative nature and business lines. It is further recommended that the standardized approach needs only a revisit and consultation process to have a homogeneous standard to compare and assess reliability across different banks in different markets. Sands et al. [ ] state that no uniform approach can successfully protect the economy from the negative externalities created by operational risk losses. In recent years, banks have faced significant losses due to operational risks. The externalities resulting from bank losses, such as decreased trust in the financial system and credit risk provisions, have been significant. No uniform approach has addressed the concerns raised under the AMA. In fact, it has only marginally improved some aspects that the standardized approach did not address, neglecting other aspects such as risk sensitivity. Three main aspects must be considered when attempting to correctly estimate operational risk capital, as no uniform approach properly addresses. In the first aspect, capital should be deployed against operational RWA. The second aspect must concern the scale of losses from operational risk, and the third should focus on the future risks facing the banking system.