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A SIMULATION-BASED APPROACH TO CALIBRATING TARGET FUND LEVELS FOR INVESTOR COMPENSATION SCHEMES

Abstract

Purpose: Investor compensation schemes (ICSs) provide a safety net for retail investors when investment firms fail. However, the optimal level of ex-ante funding remains largely undefined. This paper proposes a quantitative framework to calibrate target fund size, based on operational risk logic.

Methodology: The study applies a Monte Carlo model incorporating firm-level exposure data, supervisory risk classifications (SREP), and stochastic loss distribution (Beta-distributed loss given default). The simulation estimates expected ICS liabilities across 100,000 simulations, capturing low-frequency, high-severity loss patterns.

Results: The model confirms a highly skewed distribution of losses. Based on data from the Croatian market, while most simulations result in no payout, the 99th percentile loss reaches EUR 18.7 million, with a maximum payout exceeding EUR 96 million. The results validate the use of risk-sensitive approaches over fixed-percentage benchmarks and highlight the importance of confidence intervals in reserve planning.

Conclusion: This paper contributes a novel, adaptable methodology to size ICS funds based on probabilistic modelling. It supports regulators in transitioning from static to evidence-based reserve targets. Future refinements could involve dynamic monitoring, enhanced estimation of loss given default, and integration of SREP scores into contribution mechanisms.

Keywords: Investor compensation scheme, target fund level, SREP

1. Introduction

Investor compensation schemes (ICSs) are a core component of the regulatory architecture that governs capital markets and protects retail investors (Burke, 2009). While often compared to deposit guarantee schemes (DGSs), ICSs differ in both purpose and systemic significance. DGSs are designed not only to safeguard depositors but also to preserve financial stability and prevent bank runs. By contrast, ICSs are aimed primarily at investor protection and market integrity rather than systemic risk mitigation.

Modern financial regulation employs a layered framework to manage investor risk. This includes disclosure obligations, conduct-of-business rules, prudential requirements, and ultimately compensation schemes. ICSs serve a critical function within this framework by providing coverage for retail investors unable to recover assets from failed investment service providers. They are underpinned by both microeconomic and macroeconomic rationales: at the micro level, ICSs mitigate agency problems between investors and intermediaries, particularly given the informational disadvantages retail clients face (Llewellyn, 1999); at the macro level, they support confidence in market infrastructure and institutional trust (Garcia & Prast, 2004). Importantly, ICSs only activate when mechanisms such as asset segregation or compliance oversight fail, making them a residual but essential element of investor protection (Moloney, 1999, p. 455).

Despite their practical importance, ICSs remain underexplored in the academic literature, particularly with respect to the calibration of ex-ante funding models. While a rich body of work addresses target fund levels for DGSs, there is a noticeable absence of comparable analysis for ICSs. This is especially relevant given that Directive 97/9/EC (Investor Compensation Schemes Directive, or ICSD) requires EU Member States to establish such schemes but provides no guidance on how to determine appropriate funding levels. As a result, national ICSs vary widely in terms of funding structures, reserve accumulation strategies, and governance models.

This paper seeks to fill that gap by proposing a novel methodology for determining the target level of an ICS fund. Drawing on frameworks used in operational risk modelling—well-established in banking supervision under the Basel framework—we conceptualise ICS losses as operational risk events. These are typically low-frequency but high-impact failures arising from mismanagement, fraud, or administrative breakdowns in investment service providers. This framing allows us to leverage established quantitative techniques from risk management to estimate loss distributions, set reserve levels at specific confidence intervals (e.g., 95% or 99%), and simulate payout scenarios under stressed conditions.

Our contribution to the literature is threefold. First, we bring an analytical structure to an area that has largely relied on qualitative judgment or political negotiation. Second, the proposed model is flexible and adaptable to different jurisdictional settings: it can incorporate variation in investment service types (e.g., execution of orders, portfolio management, safekeeping of assets), local market practices, and regulatory frameworks. Third, the approach supports evidence-based supervision by linking target fund levels to measurable inputs, improving both transparency and policy defensibility.

The central hypothesis of this study is that ICSs can—and should—adopt risk-sensitive approaches to ex-ante fund sizing. Relying on static contributions or arbitrary targets does not sufficiently reflect the underlying risk distribution of potential compensation events. A data-driven, probabilistic model, grounded in operational risk logic, offers a more effective and credible approach to reserve planning.

Accordingly, the research goals of the paper are:

(1) to advance a conceptual rationale for treating ICS exposures as operational risks;

(2) to develop a simulation-based methodology that uses Monte Carlo techniques to estimate potential ICS liabilities at various confidence thresholds; and

(3) to demonstrate how this methodology can be tailored using service-level and firm-level parameters, making it both scalable and jurisdiction-specific.

Methodologically, the paper introduces a Monte Carlo simulation framework that integrates firm-level failure probabilities, service-specific exposure data, and loss given default distributions to estimate aggregate ICS liabilities. The use of stochastic modelling allows for the incorporation of volatility in retail trading activity and client asset profiles, particularly for services like order execution, where exposure is more variable. Unlike credit risk-based models or fixed multiplier approaches, the proposed method reflects the heterogeneous risk landscape of investment service providers and their clients.

The paper is structured as follows. After this introductory section, the next section sets out the theoretical and conceptual background of ICSs, distinguishing them from DGSs and explaining their place in the regulatory ecosystem. The methodology section follows, detailing the simulation framework and key modelling assumptions. The subsequent empirical section presents the simulation results and discusses their implications for ICS target levels. Finally, the paper concludes with observations on limitations, policy relevance, and areas for future research.

2. Theoretical and conceptual framework

The academic literature addressing the optimal sizing of ICSs remains strikingly limited. Shkolnyk et al. (2017) attempt to approach this challenge by applying a modified Markowitz portfolio model to determine the ICS fund size. However, their model avoids quantifying potential compensation levels, citing the difficulty of predicting loss events and defining plausible boundaries. Saad and Elsayed (2016), in turn, evaluate the capital adequacy of the Egyptian Investor Protection Fund using historical indicators such as premiums collected, market capitalisation, and the number of investors, traders, and listed companies, but without proposing a generalisable or risk-based methodology.

Other contributions focus on the structural characteristics of national ICSs. Bogna (2009) and Kazandzhieva and Mladenov (2008) conduct comparative assessments of the Polish and Bulgarian schemes, respectively, against broader European standards. A more recent study by Kazandzhieva and Ralinska (2024) highlights the low public awareness of the ICS in Bulgaria, contrasting it with the DGS.

From a regulatory standpoint, efforts have been made to bring more structure to ICS funding. In its 2011 proposal to the ICSD, the European Parliament recommended that ICSs adopt mandatory ex ante funding with a target level equal to 0.5% of the value of monies and financial instruments held, administered or managed by investment firms, to be reached within ten years (Lamandini et al., 2011, p. 9). This approach closely resembles deposit guarantee funding models in several Member States (Oxera, 2005, p. 83). However, this paper argues that such fixed-percentage models are suboptimal for ICSs. They do not reflect the probability of asset loss following a firm failure, nor do they rely on jurisdiction-specific data or empirical claims experience. Moreover, they are particularly ill-suited for small jurisdictions with limited numbers of investment service providers.

By contrast, deposit guarantee has inspired a broader body of academic work. Some of this literature focuses on pricing mechanisms (Chan et al., 1992; Bernet & Walter, 2009), others examine how insurance levels affect social welfare (Dávila & Goldstein, 2023), and several papers explore the behavioural responses of market participants (Manz, 2009). Studies also address how to determine the optimal capital size of a deposit insurance fund. This is usually conceptualised as a trade-off between financial safety and moral hazard: higher protection levels improve depositor confidence but may disincentivise prudent risk management by banks and depositors (Bernet & Walter, 2009, p. 48). Three groups of models can be found.

In more sophisticated models, the optimal fund size is a function of risk exposure, typically determined by the probability of failure, volume of covered deposits, and loss given default (Bernet & Walter, 2009; O'Keefe & Ufier, 2017). Some frameworks also account for contagion effects and the DGS diversification potential. These models express expected losses (EL) for the DGS as the sum of products of all exposures at default (EAD), probabilities of default (PD), and losses given default (LGD) (Ognjenovic, 2017, p. 166):

$$EL = \Sigma EADi \times PDi \times LGDi \tag{1}$$

EADi is the amount of covered deposits in a member bank "i" which has a probability of failure PDi. LGDi is the share of losses the DGS will suffer in case a particular bank fails (the amount that is not recovered). While default probability estimates may be informed by ratings, CDS spreads, or option prices, these models are limited by a lack of past statistical and empirical data, and assumptions of loss independence, which are unlikely to hold during systemic crises. Furthermore, statistical calculations are made difficult by the presupposed skewed distribution function of losses, where long periods of low losses contrast with short periods of high losses (Bernet & Walter, 2009, pp. 48–50).

A second group of models is based on historical experience. Given sufficient data on failure costs, it is possible to determine the level of losses that the DGS should be able to absorb. However, countries with limited experience in closing failed banks will lack sufficient data to develop an accurate empirical loss distribution and may have difficulty estimating the likelihood of low-probability, high-loss events.

From this perspective, models based on credit risk appear better suited as they are forward-looking and more adaptable to jurisdictions with limited empirical data. They also allow stress-testing of assumptions and adapt to current economic or institutional realities (O'Keefe & Ufier, 2017, p. 5)

Finally, a third methodological category for determining the target fund size is expert opinion. This approach is inherently discretionary, relying on judgment or regulatory "feeling" rather than a formalised methodology. In practice, many DGSs adopt this approach by setting the target level arbitrarily, typically using a bottom-up cumulative method. Under this method, the fund is sized to cover the potential failure of a given number of the smallest credit institutions, or in some cases, a few medium-sized ones. In contrast, banks considered "systemic" for DGSs and financial resolution are generally excluded from this calculation, as their potential failures are expected to be managed through broader safety-net mechanisms involving multiple authorities (Ognjenovic, 2017, pp. 160–162).

The same logic applies to ICSs. However, although deposit guarantee models can inform ICS design, there are crucial differences. Deposits are direct liabilities of credit institutions and typically lack legal safeguards such as segregation from the credit institutions' own assets. In contrast, client assets held by investment firms often benefit from protective mechanisms, including segregation and custodian arrangements, that reduce the LGD in case of the investment firm's default. Still, these mechanisms are not fail-proof. Failures can result from operational lapses, misappropriation, or regulatory loopholes, thus justifying the need for ICSs as a residual safety net.

Furthermore, ICS-eligible entities span a wider spectrum, including investment firms, credit institutions, and fund managers authorised to provide MiFID services. In this paper, we call them collectively investment service providers. Business models vary considerably, as do risks stemming from service types such as order execution, safekeeping, portfolio management, and underwriting of financial instruments. The European regulatory framework, particularly Directive 2014/65/EU (MiFID II), requires "adequate arrangements" to protect client assets (Art. 16, paras. 6, 8–10) but leaves specifics to national implementation. This regulatory ambiguity generates cross-country variation in risk exposure and practices. For example, some jurisdictions require client assets to be held with third-party custodians, while others permit internal segregation, creating divergent failure pathways (Oxera, 2005, pp. 112–113).

Given this complexity, the use of standard deposit guarantee methodologies to size ICS funds is questionable. Importantly, although the default of an investment service provider may result from credit or market risk, loss of client assets originates from operational risks. Hence, this paper proposes to reconceptualise ICS fund sizing within an operational risk framework.

The proposed methodology draws theoretical support from the well-established field of operational risk modelling, particularly as developed under the Basel II and Basel III regulatory frameworks for banking supervision. Under these frameworks, operational risk is defined as the risk of loss resulting from inadequate or failed internal processes, people, systems, or external events. This includes losses from fraud, mismanagement, legal uncertainty, or system failures —risk categories that closely align with the potential failure modes covered by ICSs.

Although ICSs operate outside the core banking prudential framework, their loss characteristics exhibit features comparable to operational risk. Specifically, ICS-related losses arise not from market or credit failures, but from events such as fraud, improper asset segregation, or failure of client protection protocols. These events are typically low-frequency but potentially high-severity, with outcomes dependent on legal enforceability and operational resilience. The nature of these risks makes them poorly suited to traditional credit risk models but amenable to loss distribution approaches, which form the backbone of advanced measurement approaches under the Basel framework.

Incorporating this conceptual lens enhances the methodological robustness of ICS fund sizing. By applying a Monte Carlo simulation based on distributions of exposure and LGD, the paper mirrors the loss distribution approach used by banks to model extreme operational events. This theoretical mapping supports the use of skewed, bounded distributions (such as the Beta distribution) for estimating potential losses, while also justifying the application of high confidence intervals (e.g., 99th percentile) in fund adequacy assessments. Embedding ICS modelling within this framework strengthens the rationale for moving away from static or purely heuristic fund targets toward a more risk-sensitive and forward-looking methodology.

To our knowledge, this is the first academic effort to apply operational risk theory to ICSs. This perspective allows for a stronger assumption of independence between loss events (compared to correlated bank failures) and enables the use of simulation tools to model tail risks and low-frequency, high-severity losses. Monte Carlo simulations, informed by firm-level failure probabilities, client exposure distributions, and ICS payout caps, can offer more precise and defensible estimates of target fund size.

Recent advances in operational risk modelling have introduced more sophisticated estimation techniques, including Bayesian inference, extreme-value theory, and copula-based dependence structures to capture tail correlations between loss events (see e.g. Shevchenko, 2011; Chernobai et al., 2007; Chernobai & Rachev, 2007). Although these methods have not yet been applied to ICSs, they provide a conceptual foundation for future extensions of the framework proposed in this paper.

3. Methodology

This section presents the methodological framework used to estimate the optimal target fund size for ICSs. It combines a conceptual mapping of ICS losses to operational risk events with a quantitative Monte Carlo simulation. The framework consists of two main components. Section 3.1 describes the data sources and assumptions underlying the estimation of exposures, while Section 3.2 outlines the modelling approach, including the derivation of default probabilities, the specification of loss distributions, and the structure of the simulation.

3.1 Data collection

Publicly available data on exposures relevant to ICS is extremely limited, making empirical modelling and simulation exercises inherently challenging. Despite its age, Oxera (2005) remains the most comprehensive publicly available source on ICSs. The report notes that most schemes do not maintain records of protected client monies or securities held by participating firms. Furthermore, it finds that only a small number of ICSs have conducted rigorous assessments of their funding adequacy, with the majority relying instead on simplistic heuristics to determine their target fund size.

For this study, we constructed a representative dataset using limited publicly available information on Croatian investment service providers and a series of approximations. While these approximations are necessarily crude, their limitations do not undermine the theoretical validity of the proposed methodology. In practical application, financial regulators would have access to more granular firm-level data and could tailor the model accordingly. We focus on the Croatian market for two reasons: first, the authors possess detailed knowledge of its institutional contexts, allowing for effective application of reality checks; second, the 2024 amendments to the Croatian Capital Market Act introduced a legal obligation for the national regulator to determine a target fund size for the ICS (Article 280, paragraph 8), making this a timely and policy-relevant case study.

The modelling framework requires service-specific estimates of ICS exposure, which we define as the potential loss of eligible client assets. In this study, we focus on three core services: (1) reception, transmission, and execution of orders, (2) portfolio management, and (3) safekeeping and administration of financial instruments. We exclude the service of underwriting and placing of financial instruments despite its theoretical relevance, as it is infrequently offered in the Croatian market. Notably, this service also lacks detailed asset segregation requirements, introducing additional risk. As with other services, the critical risk driver is not merely the failure of the investment firm, but the effectiveness of legal safeguards designed to protect client assets, and the probability of those safeguards failing due to operational errors or fraud.

To contextualise our data approximations, it is useful to summarise the Croatian regulatory framework governing client asset protection. Article 80 of the Capital Market Act sets out core obligations: investment service providers must implement safeguards to preserve clients' property rights, prevent proprietary use of client financial instruments without explicit consent, and—for non-bank investment service providers—ensure that client money is not used for proprietary purposes. Segregation is typically implemented through internal record-keeping rather than third-party custodianship. Crucially, client assets are legally separate from the firm's estate and are excluded from liquidation or bankruptcy proceedings. Moreover, client cash held in deposit accounts at credit institutions is protected from creditor claims in the event of the bank's failure. These rules enhance asset protection but could benefit from more detailed secondary legislation to eliminate interpretative ambiguity—particularly regarding cross-border custodianship, securities lending, margin accounts, etc.

Our study includes 19 investment service providers covering the entire Croatian market: five investment firms, ten credit institutions, and four fund management companies authorised to provide portfolio management services.

To approximate exposure from the service of reception, transmission, and execution of orders, we used publicly available data on market share (measured by the number of transactions), assumed an average trade size of EUR 3,200 per eligible investor, and estimated that 470 eligible investors were active daily on the Zagreb Stock Exchange. With an average of 21 trading days per month, this yields an annual retail turnover of approximately EUR 379 million, closely aligned with retail trading figures provided by the Zagreb Stock Exchange (EUR 390 million in 2024). Assuming a settlement period of T+2, we estimate exposure over a three-day horizon. Furthermore, based on audited accounts from two leading firms, we assume that Croatian investors trade 1.27 times more frequently on foreign exchanges than on the Zagreb Stock Exchange. While these are rough estimates, they align with market data and do not compromise the conceptual integrity of the model. One limitation is the simplifying assumption that each day's cohort of eligible clients is unique, potentially overstating exposure. Individual investment service provider figures are detailed in Table 1.

Table 1 Total eligible client assets per relevant service (in EUR)

Investment service provider	Order transmission and execution	Portfolio management	Safekeeping of financial instruments	Total
IF1	1,583,641	2,307,329	176,779,957	180,670,927
IF2	86,244	80,619	1,749,623	1,916,486
IF3	1,370,230	0	186,109,561	187,479,791
IF4	883,484	3,624,918	79,549,374	84,057,776
IF5	1,768,177	2,447,134	1,092,364	5,307,675
CI1	1,459,969	0	140,808,954	142,268,923
CI2	213,695	5,763,768	5,997,806	11,975,269
CI3	150,978	3,984,334	65,348,187	69,483,499
CI4	0	0	2,440,968	2,440,968
CI5	298,797	0	56,769,930	57,068,727
CI6	322,122	12,271,753	70,788,058	83,381,933
CI7	0	0	19,388,256	19,388,256
CI8	1,008,303	0	125,256,504	126,264,807
CI9	0	0	5,230,645	5,230,645
CI10	1,103,094	0	175,470,693	176,573,787
FM1	0	44,110,448	0	44,110,448
FM2	0	46,563,782	0	46,563,782
FM3	0	58,650,551	0	58,650,551
FM4	0	48,545,219	0	48,545,219
TOTAL	10,248,759	228,349,855	1,112,780,878	1,351,379,469

Note: IF = investment firms, CI = credit institutions, FM = fund managers
Source: Authors' own calculations

Exposure from portfolio management services was modelled using available public data and firm-level disclosures. Asset volumes per provider category were drawn from official sources, while detailed figures for the three largest managers (representing 75% of total assets) were extracted from their audited statements. Portfolio sizes for investment firms and banks were estimated at EUR 20,000 or EUR 50,000, depending on provider size, while average portfolios at the three largest fund managers ranged from EUR 250,000 to EUR 350,000. Because fund managers are not authorised to safeguard financial instruments directly, they use third-party custodians. Details are provided in Table 1. For modelling purposes, we assume 2,572 eligible clients, each above the EUR 20,000 compensation cap.

For safekeeping services, total exposure was estimated using public figures by provider type, supplemented by audited reports where available. We assumed that 3% of assets under custody at credit institutions and 75% at investment firms were held on behalf of eligible clients. This translates to roughly 5% of total custodial assets. As with portfolio management, it is assumed that all clients exceed the EUR 20,000 coverage limit. While these estimates are imprecise, their purpose is to illustrate the model's structure rather than provide precise risk measures. As shown in Table 1, safekeeping poses the largest risk in terms of eligible client assets, followed by portfolio management. Order execution services contribute the least, which is consistent with the relatively low liquidity of the local market and limited retail trading activity. Table 1 also highlights variation in per-client exposure based on firms' business models, with firm IF1 standing out due to its significant custody-related risk. It is important to note that the figures presented in Table 1 reflect gross exposures of eligible clients. The actual exposure of the ICS fund is significantly lower in practice due to the EUR 20,000 per-client compensation cap established by the scheme.

3.2 Modelling

To estimate expected losses for the ICS, this paper develops a modelling framework inspired by the credit risk model presented in Section 2, adapted specifically to the operational realities of the investment services industry. Like credit risk models, it uses exposure at default (EAD), probability of default (PD), and loss given default (LGD). However, instead of relying on a static formula, the proposed approach employs Monte Carlo simulations to model stochastic elements of exposure and loss.

Exposure at default (EAD) is determined at the level of each relevant investment service, as outlined in Section 3.1. Because exposures from order transmission and execution services are inherently volatile, the model does not use the static averages presented in Table 1. Instead, a nested Monte Carlo simulation is employed to simulate fluctuations in retail trading volumes, assuming that eligible clients exhibit highly correlated behaviour in response to market conditions. This simplification is defensible, given that retail investor flows are often driven by common external factors. It also allows us to assume that the standard deviation of trading volume of any single investor is equal to the standard deviation of trading volume of the retail market divided by the number of clients. The standard deviation of daily orders is approximated by dividing the monthly retail turnover estimate by the square root of the number of trading days, applying the standard square-root-of-time rule under the assumption of independent daily fluctuations. To model this volatility, a lognormal distribution is applied to capture the nonnegative, skewed nature of trading volumes. The distribution parameters (μ and σ) are derived from the mean and standard deviation of the underlying data.

In contrast, exposures related to portfolio management and safekeeping services are relatively stable and are therefore treated as static inputs in the model. At the firm level, exposure is generated by combining the number of eligible clients, the volume of assets per client, and the ICS coverage cap of EUR 20,000. A simplifying assumption is made that clients across services are distinct and all exposed at the average volume of assets, which likely overstates total exposure but simplifies modelling in the absence of client-level data.

We propose to derive the probability of failure for each investment service provider using the supervisory review and evaluation process (SREP) classification and scores, which offer a structured regulatory assessment of firm risk. Traditional proxies such as credit ratings or CDS spreads are often unavailable for small firms, making SREP scores a more suitable alternative. These scores are widely applied by regulators under harmonised EU guidance (EBA & ESMA, 2022) and can be reliably used in regulatory simulations. SREP scores are not publicly available. They are ratings from 1 to 4 that reflect an entity's risk profile, with 1 indicating low risk and 4 indicating high risk. For this paper, they were assigned by the authors based on informed judgment, using observable firm characteristics such as size, business model, and service complexity. These assumptions serve solely to demonstrate the structure and functioning of the proposed model rather than to reproduce actual supervisory assessments. In applied settings, financial market regulators would substitute these illustrative inputs with official SREP data.

Firm-specific probabilities of default (PD_i) are calculated using the following equation:

$$PDi = Base\_PD_i \times (1+AdjSREP\_os_i + AdjSREP\_gs_i \times AdjServices_i), \quad (2)$$

where:

- Base_PDi represents the baseline probability of default corresponding to the firm's supervisory class, as shown in Table 2.
- AdjSREP_osi is an adjustment reflecting the firm's overall SREP score, capturing its general risk profile across business, capital, and liquidity dimensions.
- AdjSREP_gsi is an adjustment derived from the SREP internal governance score, serving as a proxy for operational risk and internal control quality.
- AdjServicesi represents an adjustment for the number of MiFID II services and activities the firm provides, as a measure of operational complexity.

The model adjusts the base probability of default using a set of additive modifiers representing risk factors. Each risk factor (the overall SREP score, the internal governance SREP score, and the number of services provided) adjusts the base probability by a given amount, reflecting increased or reduced risk. This approach allows for proportional yet bounded variation in firm-level default probabilities.

Table 2 presents the assumed base probabilities of default by SREP classification. These are based on the firm's systemic importance, business model, and size. While these estimates are based on judgment rather than historical data, they are consistent with public disclosures by ICSs such as EdW (Germany) or FGDR (France), which report annual failure rates of less than 1% for small investment firms. The rationale behind base probabilities of default is that larger investment service providers involved in riskier activities are subject to stricter supervision and capital requirements, resulting in lower base probabilities of default. In addition, these entities are more likely to benefit from resolution procedures in case they fail or are likely to fail.

In the next step, idiosyncratic adjustments are applied to reflect each firm's individual risk characteristics. These include the SREP overall score ($SREP\_os_i$), the SREP internal governance score ($SREP\_gs_i$), and the number of services provided ($Services_i$).

Table 2 SREP category and base probabilities of default

Category	Description	Base probability of default
Class 1	Credit institutions and systemically important investment firms	0.001
Class 2	Investment firms exceeding the threshold for not being classified as small and non-interconnected but not treated as Class 1	
Class 2, Category 1	Total assets and off-balance sheet exposures > EUR 1 bln; or > EUR 250 mln and engages in dealing on own account and underwriting/placing on a firm commitment basis	0.003
Class 2, Category 2	Total assets and off-balance sheet exposures < EUR 1 bln and > EUR 250 mln, and engages in neither dealing on own account or underwriting/placing on a firm commitment basis	0.004
Class 2, Category 3	Total assets and off-balance sheet exposures < EUR 250 mln and do not meet the conditions for Class 3	0.005
Class 3	Small and non-interconnected firms as defined in Article 12 of the Regulation (EU) 2019/2033	0.005

Source: EBA & ESMA (2022), authors' estimates

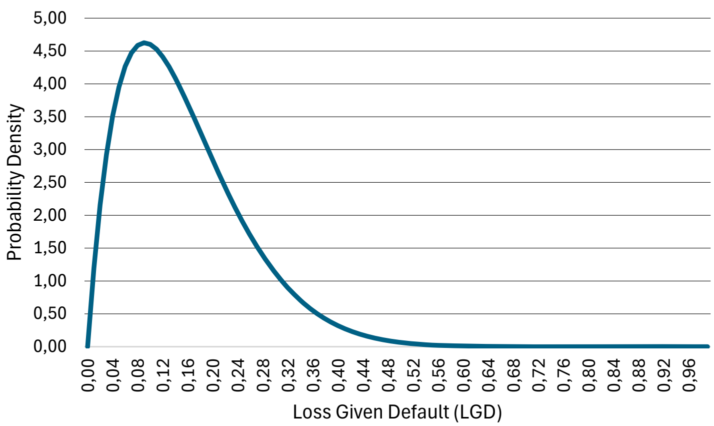
The base probability of default is adjusted by 0 for SREP score 1 (the lowest risk), 0.25 for SREP score 2, 0.5 for SREP score 3, and 2 for SREP score 4 (the highest risk). The SREP internal governance score is treated as a proxy for operational risk, given that failures in internal controls are the primary channel through which client assets may be compromised despite legal protection.

Operational complexity is proxied by the number of MiFID II services and activities a firm is authorised to provide. Each additional service implies new operational systems and regulatory obligations, increasing potential points of failure. This modular approach allows the model to reflect varying firm profiles with minimal data input. The base probability of default is decreased by 0.25 for firms offering only one service and increased by 0.25 for firms offering four or five services.

Loss given default (LGD) is modelled as a random draw from a Beta(2,11) distribution. The Beta distribution is particularly suitable for LGD because it is confined to the (0,1) interval and allows flexible skewness depending on its parameters. It is also widely used in credit and operational risk literature to model low probabilities of high losses (e.g., Arias-Serna et al, 2024; Bruche & Gonzalez-Aguado, 2010; Gupton & Stein, 2002; Peters & Sisson, 2006; Huang & Osterlee, 2011; Gelman et al., 2013). The specific parameters α=2 and β=11 were selected to reflect the authors' informed belief that extreme losses of client assets are very rare, consistent with the presence of robust segregation and custody safeguards. This configuration produces a right-skewed distribution with a mean loss of approximately 15.4% and a modal loss of approximately 9.1%, implying that most losses are small, but severe events remain possible. In Bayesian terms, this corresponds roughly to a prior of one extreme event and ten non-extreme events. While the parameters are not empirically estimated, the resulting distribution captures the qualitative expectation that ICS losses are infrequent yet potentially material, and it can be readily recalibrated as supervisory or claims data become available.

Chart 1 presents the Beta(2,11) probability density function, highlighting the concentration of values near zero and the tapering tail representing more severe loss scenarios.

Chart 1 Beta(2,11) probability density function



Source: Authors' own calculations

The full simulation model is implemented in Python. The Monte Carlo Simulation runs 100,000 iterations, in which each investment firm may default based on its PD. A failure is marked as 1; no failure is marked as 0. In each simulated failure event, ICS exposure at the client and investment service level is calculated by applying the respective LGD and EUR 20,000 cap. In the next step, ICS exposure for each service provider is calculated by multiplying the number of clients by capped average client assets. The total ICS exposure is obtained by aggregating losses for each defaulted service provider and the respective service. Table 3 shows the simulation inputs.

Table 3 Monte Carlo simulation inputs

Firm_ID	Service	PD	Eligible_Clients	Avg_Client_Assets	μ	σ
IF1	Execution	0.011250	495	3,200	7.883075	0.61292
IF1	Portfolio	0.011250	115	20,000		
IF1	Safekeeping	0.011250	3,536	50,000		
IF2	Execution	0.026250	27	3,200	7.883075	0.61292
IF2	Portfolio	0.026250	4	20,000		
IF2	Safekeeping	0.026250	87	2,000		
IF3	Execution	0.003750	428	3,200	7.883075	0.61292
IF3	Portfolio	0.003750	0	0		
IF3	Safekeeping	0.003750	1,241	150,000		
IF4	Execution	0.008750	276	3,200	7.883075	0.61292
IF4	Portfolio	0.008750	181	20,000		
IF4	Safekeeping	0.008750	530	150,000		
IF5	Execution	0.011250	553	3,200	7.883075	0.61292
IF5	Portfolio	0.011250	122	20,000		
IF5	Safekeeping	0.011250	55	20,000		
CI1	Execution	0.001750	456	3,200	7.883075	0.61292
CI1	Portfolio	0.001750	0	0		
CI1	Safekeeping	0.001750	535	263,007		
CI2	Execution	0.001250	67	3,200	7.883075	0.61292
CI2	Portfolio	0.001250	288	20,000		
CI2	Safekeeping	0.001250	120	50,000		
CI3	Execution	0.001500	47	3,200	7.883075	0.61292
CI3	Portfolio	0.001500	199	20,000		
CI3	Safekeeping	0.001500	436	150,000		
CI4	Execution	0.002000	0	0	0	0
CI4	Portfolio	0.002000	0	0		
CI4	Safekeeping	0.002000	49	50,000		
CI5	Execution	0.001750	93	3,200	7.883075	0.61292
CI5	Portfolio	0.001750	0	0		
CI5	Safekeeping	0.001750	194	292,068		
CI6	Execution	0.001500	101	3,200	7.883075	0.61292
CI6	Portfolio	0.001500	245	50,000		
CI6	Safekeeping	0.001500	242	3,200		
CI7	Execution	0.001250	0	0	0	0
CI7	Portfolio	0.001250	0	0		
CI7	Safekeeping	0.001250	129	150,000		

Firm_ID	Service	PD	Eligible_Clients	Avg_Client_Assets	μ	σ
CI8	Execution	0.001750	315	3,200	7.883075	0.61292
CI8	Portfolio	0.001750	0	0		
CI8	Safekeeping	0.001750	429	292,068		
CI9	Execution	0.005000	0	0	0	0
CI9	Portfolio	0.005000	0	0		
CI9	Safekeeping	0.005000	105	50,000		
CI10	Execution	0.001750	345	3,200	7.883075	0.61292
CI10	Portfolio	0.001750	0	0		
CI10	Safekeeping	0.001750	546	321,130		
FM1	Execution	0.006250	0	0	0	0
FM1	Portfolio	0.006250	882	50,000		
FM1	Safekeeping	0.006250	0	0		
FM2	Execution	0.005000	0	0	0	0
FM2	Portfolio	0.005000	145	321,130		
FM2	Safekeeping	0.005000	0	0		
FM3	Execution	0.005000	0	0	0	0
FM3	Portfolio	0.005000	223	263,007		
FM3	Safekeeping	0.005000	0	0		
FM4	Execution	0.005000	0	0	0	0
FM4	Portfolio	0.005000	166	292,068		
FM4	Safekeeping	0.005000	0	0		

Note: IF = investment firms, CI = credit institutions, FM = fund managers
Source: Authors' estimates

The aggregated losses across simulations form a probability distribution of ICS liabilities, which is then used to estimate the target fund level at various confidence intervals.

4. Results

The Monte Carlo simulation results provide three main insights: (i) the frequency of failures, (ii) the distribution and magnitude of potential payouts, and (iii) the implications for determining a target fund level for the ICS.

First, the simulation generated 10,272 instances of investment service provider failures across 100,000 iterations. Failures occurred in 9,808 of the 100,000 runs, or 9.81% of the total, reflecting the low baseline probabilities of default assigned to individual firms. Among these, 95.37% involved a single failure, 4.53% involved two simultaneous failures, and only 0.10% involved three. No simulation resulted in more than three concurrent failures. This supports the underlying assumption of independence across defaults and reflects the policy rationale that ICSs are not designed to absorb losses arising from systemic market crises. This is further reinforced by the legal framework of most ICSs, which presumes that simultaneous firm failures and widespread fraud or operational breakdowns are highly unlikely in regulated markets with robust asset protection mechanisms. To reflect this assumption, loss given default was modelled using a Beta(2,11) distribution.

Second, the simulation output reveals a highly skewed distribution of potential ICS payouts. As shown in Table 4, the mean payout across all iterations was EUR 656,204, while the median payout was EUR 0, underscoring that the majority of simulations resulted in no default. The standard deviation of EUR 3,943,291 indicates significant dispersion around the mean. At the tail of the distribution, the 95th percentile reached EUR 2.9 million, and the 99th percentile EUR 18.66 million. The maximum simulated payout was EUR 96.04 million. Among the 9.81% of simulations with non-zero outcomes, the average payout rose to EUR 6.69 million, demonstrating a heavy concentration of losses in the tail. The calculated skewness of 9.68 confirms the pronounced right-skewed shape of the distribution, consistent with the low-frequency, high-severity nature of compensation events in ICSs.

Table 4 Distribution of losses

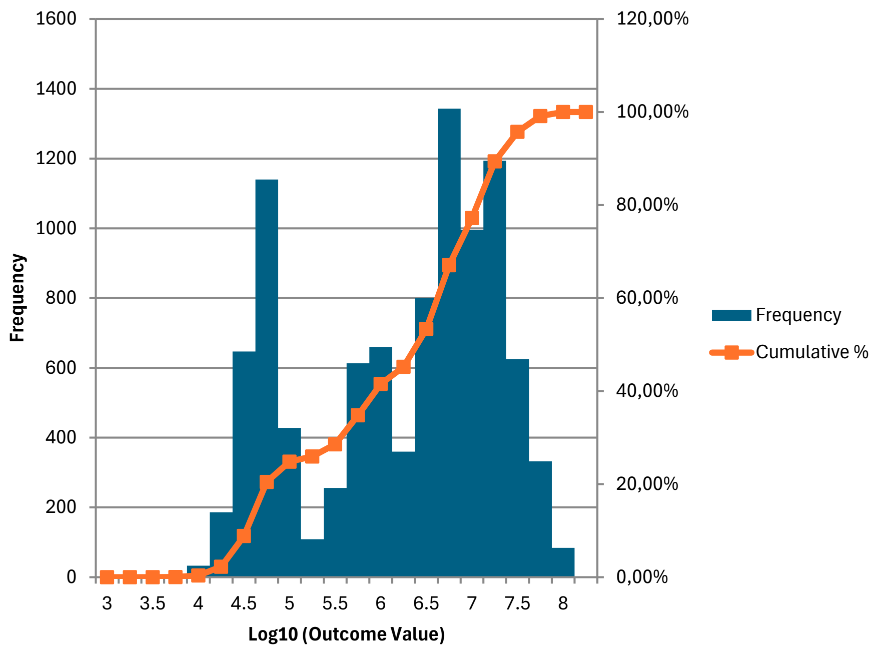
Statistic	Value
Mean	656,204
Mean of non-zero payouts	6,690,494
Median	0
Standard deviation	3,943,291
95th percentile	2,900,000
99th percentile	18,664,321
Maximum payout observed	96,043,863
Number of observations with payout >0	9.81%
Skewness	9.68

Source: Authors' calculations

These results support the rationale for employing risk-sensitive methodologies—such as Monte Carlo simulations—over static or heuristics-based fund-sizing approaches. The model illustrates that while most events result in low or zero payouts, the ICS must remain capable of addressing rare but severe events involving large exposures or multiple failures.

As illustrated in Chart 2, a log10 transformation was applied to non-zero simulation outcomes to visualise the tail more clearly. Of the 100,000 total simulations, 90.19% yielded zero payout, while the remaining 9,808 ranged from log10 values of approximately 3.52 to 7.98, corresponding to payouts between EUR 3,351 and EUR 96 million.

Chart 2 Distribution of non-zero simulation outcomes (log10 scale)



Source: Authors' own calculations

The resulting loss distribution can be used in three ways. First, it allows policymakers to determine the level of ex-ante funding required to meet specific confidence thresholds, for instance, by setting the target fund size at the 99th percentile. Second, it provides a basis for evaluating the adequacy of current ICS reserves against the spectrum of modelled liabilities. Third, it enables stress testing of the ICS under extreme but plausible scenarios.

5. Discussion

The primary objective of modelling ICS losses is to inform a robust and transparent framework for setting the target fund level. While the final choice of confidence interval (e.g., 95th vs. 99th percentile) remains a policy decision, this framework provides a data-driven foundation for that choice. It is essential to recognise that ICSs are not intended to cover systemic market-wide failures. Such failures would require not only the simultaneous default of numerous investment service providers but also the widespread collapse of asset protection mechanisms—an extremely rare scenario in jurisdictions with mature regulatory frameworks.

Indeed, the most plausible systemic risk to ICSs may arise not from coordinated fraud but from judicial decisions that undermine segregation rules, e.g., court rulings requiring client assets to be pooled with bankruptcy estates. This underscores the critical importance of ensuring that asset segregation frameworks are both legally sound and practically enforceable. Risk may arise, in particular, in cross-border operations.

The simulation results also highlight model sensitivity to the assumed probabilities of default. A marginal increase in PDs raises the likelihood of multiple failures, thereby increasing the estimated payout distributions. This sensitivity reinforces the importance of carefully calibrating default probabilities, whether derived from SREP scores or historical data.

As a complementary perspective, the loss distribution can be used to assess the fund's ability to withstand actual defaults. For instance, a fund sized at the 99th percentile (EUR 18.66 million) would be sufficient to fully cover liabilities—assuming a 100% LGD—for any investment service provider but the one with the single largest exposure to eligible clients (IF1). From a cumulative standpoint, the same fund could fully cover simultaneous defaults of the seven smallest providers. This aligns with the "bottom-up" approach used in some deposit guarantee schemes (Ognjenovic, 2017, p. 119), where fund levels are calibrated to cover a specified number of small or medium-sized entities.

It is also important to consider the nature of client exposures. The EUR 20,000 compensation cap appears relatively modest, especially for portfolio management and safekeeping services, where average client holdings may far exceed this limit. As a result, the ICS may only partially compensate affected investors in the event of failure, particularly where larger firms are involved. Alternative investor protection mechanisms, such as robust disclosure rules and effective asset segregation, remain the primary defence.

Finally, ICSs must maintain access to supplementary funding sources in cases where ex-ante reserves are insufficient. In Croatia, for example, the ICS may borrow (Capital Market Act, Art. 283) but cannot levy extraordinary contributions, contrary to standard practice across the EU (Oxera, 2005, p. 34). Thus, while a well-sized ex-ante fund is essential, it should be viewed as part of a broader financial safety net that includes contingent resources and robust regulatory safeguards.

6. Conclusion

This paper proposes a novel, risk-sensitive methodology for determining the optimal target fund size for ICSs. Drawing from operational risk modelling and Monte Carlo simulations, the framework departs from static or politically negotiated funding benchmarks and offers a data-driven alternative grounded in firm-level exposures and failure probabilities.

The findings confirm the hypothesis that ICSs should adopt risk-sensitive approaches to ex-ante fund sizing. ICS exposures exhibit low-frequency, high-severity characteristics. Most simulations result in no payout, yet rare defaults can generate significant liabilities. The resulting loss distribution is highly skewed, supporting the case for sizing ICS funds based on defined confidence intervals—such as the 95th or 99th percentile—rather than fixed-percentage heuristics.

Key contributions of the paper include: (i) conceptualising ICS exposures through an operational risk lens; (ii) applying SREP scores as proxies for default probabilities; and (iii) integrating service-specific data to simulate aggregate ICS liabilities.

This paper offers a practical, risk-based methodology for determining ICS fund targets. The proposed framework represents a clear methodological advance over static or heuristically derived approaches. Its transparent structure and modular design make it particularly suitable for smaller jurisdictions, where data limitations often preclude complex empirical modelling. As supervisory and regulatory information progressively expands, the model can be refined to deliver increasingly accurate and risk-sensitive assessments of the required fund size, thereby strengthening the contribution of ICSs to overall market stability. In addition, it encourages coordination between ICS managers and supervisors and could serve as a template for EU-wide best practices in the absence of harmonised funding standards.

Nevertheless, the model is not without limitations. Key assumptions, particularly regarding default probabilities, client asset concentration, and loss given default distributions, are based on approximations due to limited public data. These can be improved through access to regulatory datasets and expanded empirical calibration.

Future research should address several areas. First, further refinement of the loss given default assumptions could be achieved through approaches such as extreme value theory, allowing better characterisation of the tail behaviour of losses. Second, developing a dynamic model to adjust the target level over time would improve the framework's responsiveness to changing market and risk conditions. Third, leveraging SREP scores for risk-based pricing of ICS contributions could align funding requirements more closely with firm-specific risk.

In addition, several open questions remain. The current model assumes independence of defaults. Although arguments in favour of this assumption are presented throughout the paper, in reality, the failure of investment service providers may be correlated through macro-financial shocks or common operational vulnerabilities. Exploring dependency structures between defaults—possibly through copula or network models—would enhance realism and allow stress-testing of systemic scenarios. Moreover, reliance on expert judgment in parameter estimation, especially for default probabilities and loss given default, introduces subjectivity; future work should examine data-driven calibration techniques based on supervisory and claims experience. Finally, further research could analyse systemic risk transmission between ICSs, DGSs, and broader market safety nets to understand how cross-sectoral linkages might affect the resilience of investor protection systems.

In future applications, the assumed Beta(2,11) distribution for loss given default could be further refined through a Bayesian updating process as supervisory or historical data on actual ICS losses become available. In Bayesian terms, the Beta distribution is a "conjugate prior" to the binomial likelihood—meaning that as new evidence (e.g., observed recovery rates or loss frequencies) is incorporated, the posterior distribution remains Beta-shaped but with updated parameters. This allows the model to progressively "learn" from experience while retaining analytical simplicity.

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