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Evaluating event risks in a securitisation transaction

by Harshit Rathi and Pavan Kumar, Northern Arc Capital

Northern Arc Capital (previously known as IFMR Capital) acts as a structurer, arranger and investor of securitisation transactions in different sectors like microfinance, housing finance, vehicle finance, consumer finance and small business loans. It has done over 700 securitisation transactions in the last 10 years and helped different originators raise more than US$5bn capital through these transactions. To date, the losses to the investors in the securitisation transactions are below 0.28%; for senior investors, the losses are below 0.06%. As knowledge leader in the sectors it operates in, Northern Arc brings onboard a deep understanding of risk and best practices in risk management. It has a unique approach of combining high-touch field monitoring with advanced data-backed risk analytics which helps in maintaining a high-quality portfolio and provide ongoing input to its clients and investors.

During the last 10 years, we have witnessed many event-based shocks which had a significant impact on the economy, livelihoods of people and businesses. On November 8, 2016, the Government of India announced the demonetisation of all INR500 and INR1,000 banknotes. Because of the sudden nature of the announcement, it caused prolonged cash shortage in the following weeks accompanied with a significant disruption in the economy and stress in the portfolio of financial institutions. Due to the stress, many originators in the microfinance sector had faced losses in the range of 4% to 6%. The investors in Northern Arc transactions faced a loss of only 0.88% (at that time), which is significantly lower than the losses faced by the overall sector.

Further, there have been numerous natural disasters and socio-economic events which have occurred in India over the last decade. There have been no losses to the investors in our securitisation transactions. This can be attributed to (i) Northern Arc's underwriting guidelines, pool selection criteria, loss estimation, credit enhancement optimisation models; and (ii) healthy recovery rates in the collection efficiencies seen post these events.

Pool loss estimation and optimum credit enhancement

Risk models which are used to estimate losses in a securitisation pool incorporate factors like the performance of pools, correlations and concentration risks based on which a loss distribution is generated as an output. The originator's past delinquency patterns in its portfolio provide some pointers to the possible performance of the pool being securitised. Further, a benchmarking of pool characteristics is done with overall portfolio to identify positive or negative deviation in pool quality from portfolio quality.

A detailed methodology for estimation of loss distribution for securitisation transactions was discussed in *The Securitisation & Structured Finance Handbook 2018*, "Estimating loss distribution for a securitisation transaction". Once losses are estimated, the next logical step is to estimate the optimum credit enhancement required for the transaction in order to safeguard the investors. Optimum credit enhancement is computed using Gradient Descent Algorithms and was discussed in *The Securitisation & Structured Finance Handbook 2019*, "Credit Enhancement Optimisation model in securitisation transactions".

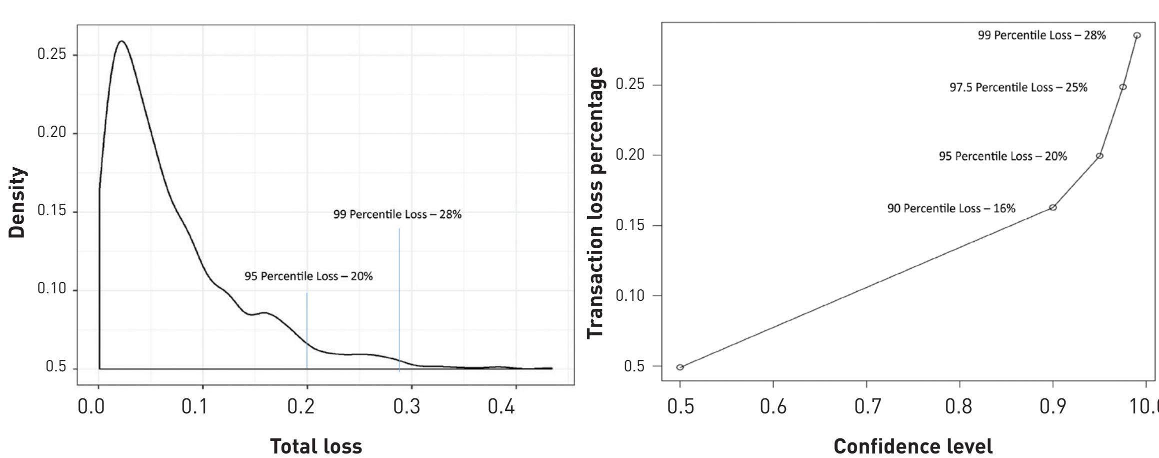
This article discusses adding an event risk premium to the losses estimated at each percentile and using the higher estimated loss (including event risk premium) in the optimum credit enhancement computation algorithm. The same approach can also be used to estimate the capital required for event-based shocks by running the event risk module on the entire portfolio.

Increasing probabilities of tail risk events

According to various climate research articles available in the public domain, a total of two billion out of seven billion global population might be at risk of flooding by the year 2050. In the period 2020-2050, if global sea levels rise by three feet as projected, and droughts, fires, heat waves and floods continue to worsen, we could see around 250 million people displaced from their homes. As derived from the various projections of natural disasters, the number of catastrophic events in the next 30 years (2020-2050) would be more than the number of such events in the last century (1920-2020). Considering only historical tail risk events in the loss estimation model would mean ruling out any possibility of incremental extreme events happening in the future, which is not prudent considering the outlook for such event risks.

It is important to look at all the possible types of risks which might occur during the tenure of a securitisation

Sample output of transaction loss estimation model **Exhibit 1**



Source: Northern Arc Capital

transaction and to understand the nature of underlying risk for correctly estimating the losses. Historical repayment behaviour may provide significant insights to enable reasonable estimation of credit risk. However, the estimates may be limited to losses experienced in the past.

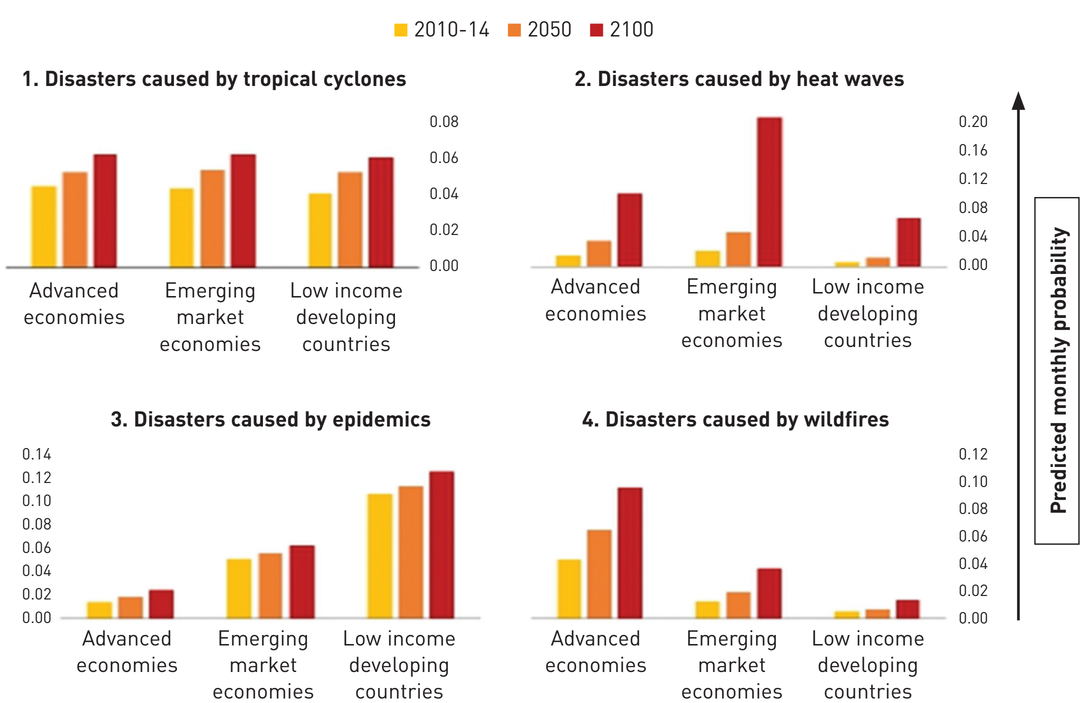
For example, a credit institution based in North-West India might have never experienced losses due to a devastating earthquake in its 10-year vintage. However, it is not prudent to rule out the potential losses due to such an earthquake in the future. Similarly, while a global pandemic (Covid-19) in 2020 has occurred after more than 100 years since the 1918 Spanish Flu, but assuming no such pandemic would occur in the next 100 years till 2120 might not be prudent. The key is to assess the potential risk of events which may have a low probability of occurrence, in fact may not have occurred in the last 20-30-100 years, but have the potential for a high impact.

Based on IMF findings in Exhibit 2, most types of weather-related disasters will become more common by 2050 and further by the end of the century.

Identification of tail risk events for modelling

Extreme events or tail risk events can be identified as those low-probability high-impact events which might result in

Increasing probability of disasters, IMF Blog on climate change 2017 **Exhibit 2**



Note: Panel 1-4 show the predicted monthly probability of a disaster in the years 2050 and 2100 based on the climate change scenario RCP8.5. Most of the predicted probablilities for individual months are not statistically significant; the results should only be interpreted as indicative of the potential increase in the frequency of disasters with climate change.

Source: International Disaster Database (EM-DAT); Climate Research Unit (CRU); NASA Earth Exchange Global Daily Downscaled (NEX-GDDP); and IMF staff calculations.

large-scale disruption in the normal course of business activities. A few such events are listed below (not an exhaustive list by any means):

- Natural disasters – floods, cyclones, droughts, earthquakes *(in the scope)*
- Public health emergencies – SARS, H1N1, MERS, COVID-19 *(in the scope)*
- Socio-economic events – demonetisation, loan waivers, communal riots *(in the scope)*
- Regulatory and technological changes *(out of scope)*
- Man-made disasters like pollution, deforestation, increase in mean sea level, etc. *(out of scope)*

While there can be many such events, the model discussed in the article is only applicable to:

(i) Sudden and uncertain events

(ii) Negative impact events

Assuming the impact of manmade disasters is gradual and is eventually incorporated in the historical delinquency/ other portfolio data, these are kept out of the scope of an event risk module.

While the first four are sudden and uncertain events, regulatory and technological changes can have both positive and negative impacts. As the model only deals with negative impact events, these change events are out of the scope of event risk module.

Thus, events like natural disasters, public health emergencies, socio-economic changes can be modelled using the approach. The remaining parts of the article discuss steps in generating event risk premium using natural disasters with an output of a sample transaction at Northern Arc and how the model can be extended to other events like pandemics, socio-economic changes.

Generating event risk premium for a securitisation transaction

This section explains a broad framework that can be used to calculate event risk premium for securitisation transactions. This is a simulation-based framework and microfinance sector is taken as an example, wherever illustration is required in detail.

Poisson distribution

The Poisson distribution is a discrete probability distribution of the number of events occurring in a given time period, given the average number of times the event occurs over that period.

Let X be the discrete random variable that represents the number of events observed over a given period. Let lambda λ be the expected value (average) of X. If X follows a Poisson distribution, then the probability of observing k events over the period is:

$$P(x=k) = \frac{\lambda^k e^{-\lambda}}{k!}$$

For example, if it is known that there have been three earthquakes during the last 10 years, what is the probability of k no of earthquakes in the next 10 years? The probabilities given by Poisson distribution are shown in Exhibit 3.

Calculation of Lambda (λ)

At Northern Arc, we have a large set of historical data (~100 years) on natural disasters, which are sourced from

Harshit Rathi Pavan Kumar

Harshit Rathi, Associate Director – Risk Analytics & Modelling

Tel: +91 90 2298 9405

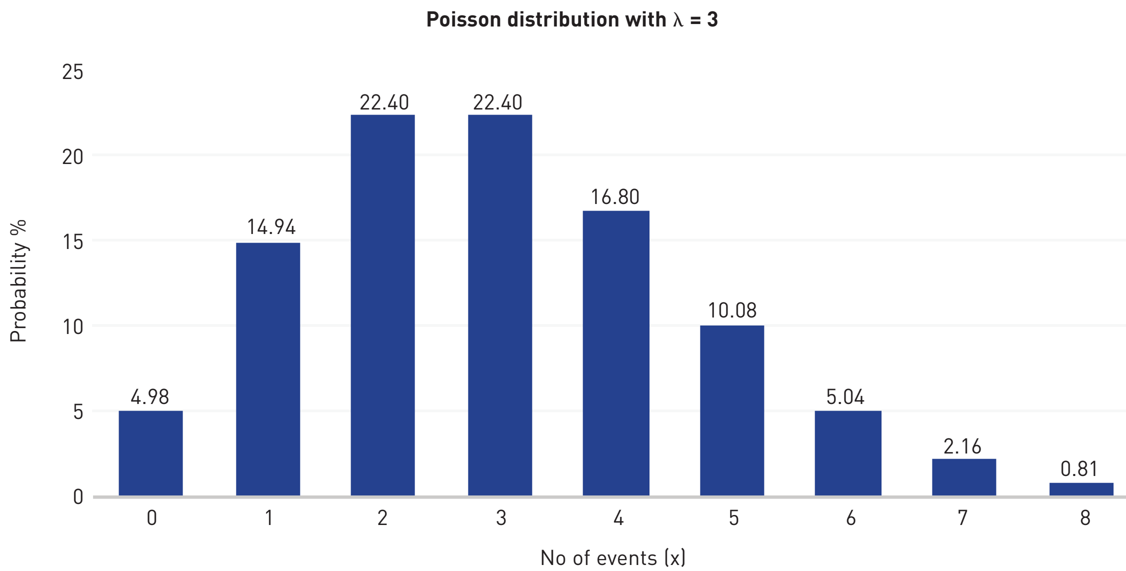
Email: harshit.rathi@northernarc.com

Pavan Kumar, Director – Risk Analytics and Modelling

tel: +91 98 4079 4401

email: pavan.kumar@northernarc.com

Poisson distribution	Exhibit 3



Source: Northern Arc Capital

the Indian Meteorological Department (IMD). Lambda is calculated using a weighted average of the available data for each of these natural disasters.

For socio-economic events, major historical events have been tabulated by researching the news articles available online.

Methodology

The detailed methodology deployed in event risk module is mentioned below:

Inputs required for computation of event risk premium

a. Set of events: Identify a set of events which can affect servicing ability of underlying borrowers in a securitisation transaction. For instance, a set of natural disasters which can impact the livelihoods of borrowers and thus their repaying ability.

   Set of events = {Cyclone, Drought, Earthquake, Flood}

b. Set of lambdas: For all identified events, calculate lambda (λ), which is the expected value (average) of events. The calculation of lambda is discussed in previous section.

   $$\text{Set of Lambdas} = \{\lambda_{\text{cyclone}}, \lambda_{\text{drought}}, \lambda_{\text{earthquake}}, \lambda_{\text{flood}}\}$$

Identify factor of risk for underlying asset class and develop a methodology to choose event affected risk factor values for simulation

For a given pool of loans which need to be securitised, identify single or multiple factors of risk. Please note that more the factors of risk, more is the granular requirement of data. For instance, in microfinance pool of loans, geographic location of underlying borrower (district) is a possible factor of risk.

Once factor(s) of risk is identified, a methodology needs to be developed to choose event affected values of risk factor in each iteration of simulation. This can vary from a simple random to a cluster-based or systematic selection. One of the methodologies is discussed in detail below, on how event affected districts of underlying pool are chosen for each iteration.

For instance, if premium is being calculated for cyclone event for underlying pool of microfinance loans, district can be considered as unit of risk here. Historical data on number of cyclones occurring in each of the districts needs to be compiled. A probability mass function (PMF) for number of cyclones can be constructed as below.

$P_x(x_k) = P(X = x_k)$, for k = 1,2,3 …. where k is number of cyclones

$P(X = x_k) = n_k/n$, where nk is number of districts with k cyclones and n is total number of districts

The calculated PMF is the desired distribution of random variable, through which districts will be selected in each of the simulations. To achieve this objective, inversion method is used where a random variable generated through uniform distribution is mapped to desired distribution through a discrete cumulative distribution function (CDF). CDF for same random variable, number of cyclones, is noted as below.

$F_x(x) = P(X <= x)$, for all x, where x is number of cyclones.

CDF is always a non-decreasing function, starts at 0 and approaches 1 as k becomes a very large value. To draw a random variable from distribution, a uniform random number is generated, and a possible outcome is selected from CDF, in a way that probability of choosing an outcome is outcome's own probability. Below is a simple step wise illustration of the same:

- Generate CDF, F(x), for a given PMF function
- Compute inverse, $F^{-1}(x)$
- Generate a random number between 0 and 1 from uniform distribution, ξ
- Compute $X_k = F^{-1}(\xi)$

When all districts are arranged in ascending order of number of cyclones and in alphabetical order within same frequency of cyclones, rounding off X_k to nearest integer will pin-point to a district. Please note that through this methodology, probability of choosing a district will depend on frequency of cyclones in that district.

Other factors for simulation

a. Timing of event: The timing of event will have an impact on securitisation transaction based on its amortisation schedule. Impact on a transaction will be higher if an event occurs immediately after settlement compared to an event which happens closer to maturity. In each iteration, timing of event can be decided either through a simple random selection from uniform distribution or through a distribution. For instance, seasonality can be considered for timing of events like cyclones or floods.

b. Severity of event: Not all homogeneous events will have a similar impact on portfolio. For instance, in a natural disaster like floods, there are multiple factors like amount of rainfall in a given period of time, proximity of a geography to a water body which is flood prone, topography of a location, that determine severity of an event. For every type of event, it is important to determine different levels of severity and their impact on different geographies from historical data if possible. Purely from an event risk premium perspective, impact can be measured in ultimate loss terms as a percentage of exposure at time of event.

Calculation of event risk premium

Below is the step wise calculation of event risk premium with reference to code snippets in R. Calculation is illustrated through a pool of microfinance loans and for ease of understanding, cyclones are the only event considered.

Step 1: Determine $\lambda_{cyclone}$

Step 2: In the microfinance sector, district is the factor of risk. For all districts in securitisation pool, build probability mass function by considering number of cyclones in each of the districts for a specified period. {cyclone_distict_dataframe <- data_frame(cyclones_count$_{district1,}$ cyclones_count$_{district2,}$ ….)}

Create PMF data frame for different number of cyclones as below.

{cyclone_pmf_dataframe <- data_frame($p_1, p_2, p_3,$ ....)}
where $p_k = n_k/n$,
n_k is number of districts with k cyclones
n is total number of districts

Create CDF data frame for this discrete random variable.
{cyclone_cmf_dataframe <- cumsum(cyclone_pmf_dataframe)}

Using $\lambda_{cyclone}$ as overall number of cyclones hitting districts of analysis, assuming period for λ and period of analysis are same, corresponding number of random numbers and thus districts affected due to cyclone are generated through CDF and inversion method as discussed in point 2 above. For instance, if λ is 3, there will be three affected districts in each simulation.

Step 3: Using past data on impact of cyclones in securitisation transaction or on portfolios in microfinance sector, build a data frame of loss percentages (net of recoveries) for districts of analysis.
{cyclone_loss_dataframe <- data_frame ($loss\%_{dist1}$, $loss\%_{dist2}$, ...)}
Such data frames need to be built for different levels of severity of event

Step 4: Simulate timing of event either through uniform distribution or distribution incorporating seasonality of event. A simple Boolean data frame of size equal to number of periods of servicing in securitisation transaction can be used to code timing of event
{cyclone_timing_dataframe <- data_frame (0,0,1,0,....)}

Step 5: Data frame containing district wise principal exposure fall-off of all districts needs to be constructed. For every iteration, based on district affected and timing of event, corresponding principal exposure will be at risk.
{cyclone_falloff_dataframe <- data_frame (P_{11}, P_{12}, P_{13}, ..., P_{21}, P_{22}, P_{23}, ...)}
where P_{ik} is scheduled principal outstanding for district i in month k after transaction settlement

Step 6: For calculating expected loss due to cyclone in an iteration - list of districts affected, loss% for districts affected for a given severity level, timing of event and district wise principal exposure falloff are required. In these datasets, while list of districts and timing are simulated and vary for each iteration, loss% for districts is obtained through historical data and district wise principal exposure falloff is prepared for a given transaction. For instance, if λ=1, district1 is chosen as affected in an iteration, loss%1 is given and timing of event is first month post settlement, possible loss can be computed as follows.

Estimated loss for iteration 1 (EL_1) = P_{11}*$loss\%_1$

For iterations involving multiple districts, estimated loss can be determined through multiplication of data frames. Please note that for multiple districts iterations, data frames for corresponding districts need to be considered.

Estimated loss for iteration 1 (EL_1) = cyclone_loss_dataframe* cyclone_timing_dataframe* cyclone_falloff_dataframe

Total estimated pool loss due to events (event risk premium) would be sum of estimated losses for all n iterations.

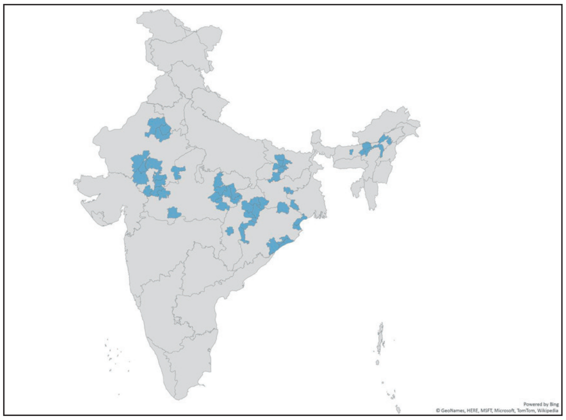
Event_risk_premium = $\sum_{i=1}^{n} EL_i$

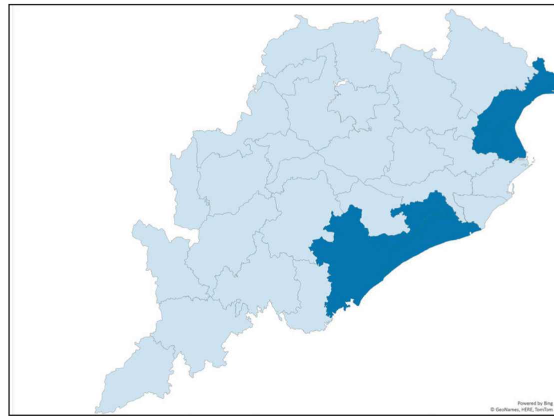
Output of a sample transaction

This is an output of a transaction arranged and co-invested by Northern Arc. The securitisation transaction is a pool of microfinance loans originated across 73 districts of India. Among these, there are five coastal districts which are highly prone to cyclone and 22% of total pool exposure comes from these districts. The maps in Exhibit 4 illustrate exposure to these districts.

Exhibit 5 depicts estimated loss of the transaction at different percentile levels. Both event specific loss and total loss numbers are plotted. Event losses here account

Exposure to five coastal districts **Exhibit 4**





Source: Northern Arc Capital

for cyclone, drought, earthquake, and floods in all districts of pool though cyclone in these five districts contributes maximum to estimated losses.

Extending the event risk model to events like pandemics, socio-economic changes

(i) **Mapping** – Like natural disasters, it is essential to map the geographies prone to these event risks. For pandemics, it is possible to have a nation-wide mapping, however there can be localised pandemics like the SARS, MERS, Ebola, Nipah virus where the impacted districts need to be mapped. In case of socio-economic events like loan waivers, communal riots, civil wars, etc., event risks can be mapped to geography using historical data (Step 1 & Step 2).

(ii) **Impact** – If there is some historical data on such events, the impact on the pool of loans can be calculated using the loss data available. This will depend on the industry type, balance-sheet strength of the originators, AUM / Net-worth ratio, their collection team's abilities etc. If it is a new event like the Covid-19 pandemic, impact can be assumed based on the economic projections and industry-specific impact assessments. However, for similar future pandemics, loss data pertaining to Covid-19 might be used (Step 3).

(iii) **Simulation** – Timing of the event can be simulated, or a uniform distribution can be used. Some factors like higher chances of loan waivers and heightened crime incidents closer to the local elections or central elections can be taken into account in the distribution (Step 4).

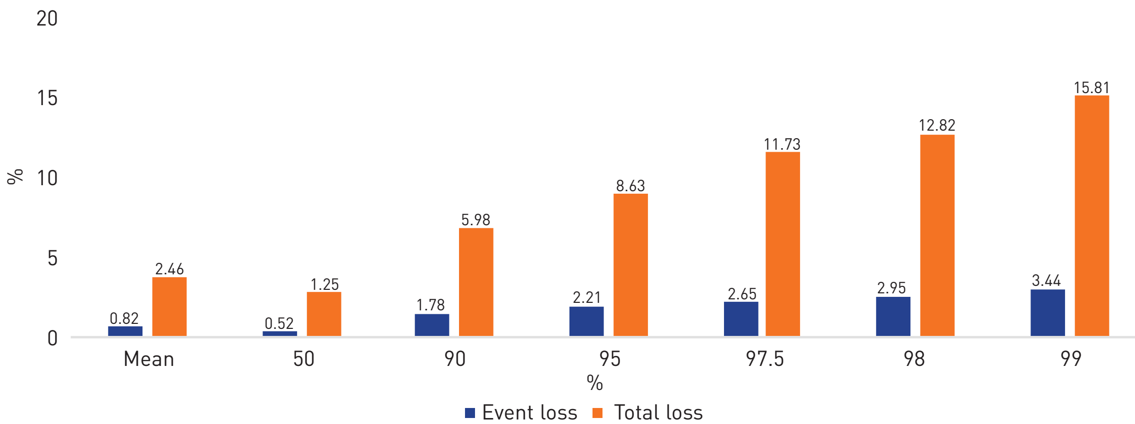
(iv) Step 5 and Step 6 remain the same.

Conclusion

The low probabilities associated with tail risk events means that there are likely to be few historical observations for estimating losses. Moreover, the impact of disasters/ negative events are not always recorded in detail when they do occur. Therefore, computational models are used to simulate potential impacts from hypothetical (but realistic) or historical loss events.

This article has described one such approach using a loss distribution and simulation of the loss events both for timing and severity. Events must be mapped with the risk

Event loss and total pool loss at different percentile levels **Exhibit 5**



Source: Northern Arc Capital

factor underlying the pool in order to accurately estimate pool's event exposure. The impact of the event on a pool is computed using loss data net of recoveries post similar events. The resulting output of the simulations is an event risk premium at various confidence levels. For capital estimation purposes, the entire portfolio of pools needs to be simulated to get economic capital at various confidence levels using the same method.

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Contact us:

Northern Arc Capital

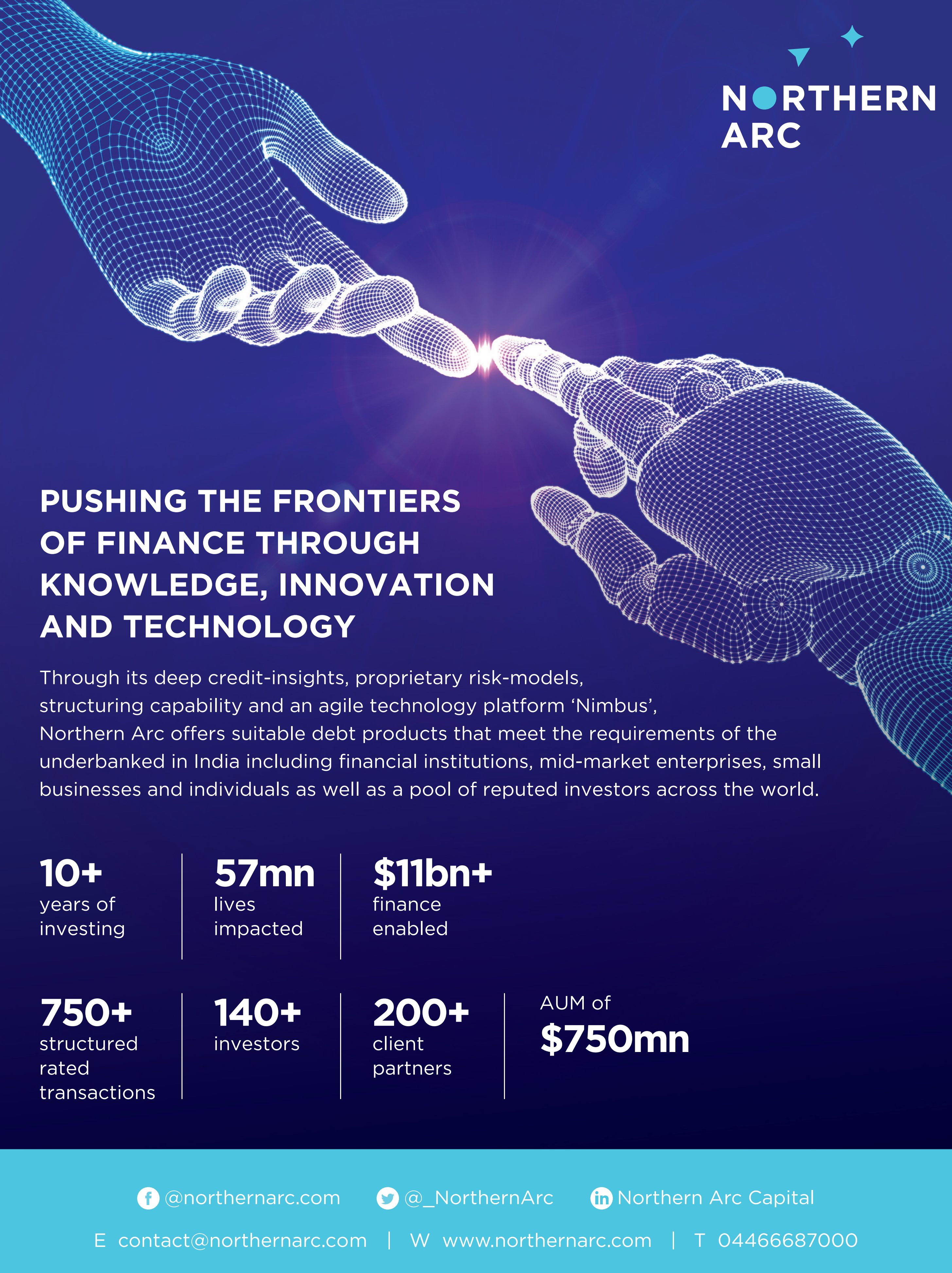
10th Floor-Phase 1, IIT-Madras Research Park

Kanagam Village, Taramani

Chennai 600113, India

tel: +91 44 6668 7000

web: http://northernarc.com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