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CAMBRIDGE GLOBAL RISK INDEX 2018 METHODOLOGY

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Cambridge Global Risk Framework

Cambridge Global Risk Index 2018 Methodology

1	Global Risk Index Methodology Summary	2
2	Baseline City GDP and Population Estimates and Forecasts	4
3	Resilience: Rate of Recovery	6
4	Local Impact Severity: Threat Scenarios	8
5	Expected Loss Calculations	11

1 Global Risk Index Methodology Summary

The Global Risk Index is a measure of expected loss of GDP from events occurring across 22 threat types on 279 cities. The index analyses the exposure to shocks of the global economy against a baseline growth projection. It accounts for potential losses as well as the likelihood of events occurring within a 3-year outlook period.

The resulting measure provides an evidence base for ranking cities' economic exposure to these threats as well as for ranking the threats to the global economy.

This section provides a summary of how the index metric is derived. Section 5 describes the details of the calculation.

The Global Risk Index Metric: Expected Loss

As the Global Risk Index measures the aggregate risk of multiple threats, expected loss is a useful metric to indicate average losses from all threats. The sum of estimated possible losses from a large set of events only tells what the loss might be if all the events were to, quite unrealistically, happen simultaneously. The sum of expected losses meanwhile remains insightful as it measures the amount you expect to lose, on average, given the set of possible events.

An illustrative example is a \$10 loss from an event that has a 50% chance of occurring. This event has an expected loss of \$5, the amount you expect to lose on average. The expected loss metric is probability-weighted and should be distinguished from the potential loss of \$10 if the event does occur.

Economic Outlook

The economic loss measured by the Global Risk Index is the difference between the GDP trajectory if catastrophic events were to occur and the baseline GDP forecast ("the counterfactual"). This is a multi-year loss in economic output, capped at 5 years; economic recovery from some catastrophes can be long-lasting and in some instances, some places never recover fully. In this analysis, an event occurring in 2018 may experience losses stretching out to 2022. The same event could occur in 2019 with losses out

to 2023, or in 2020 with losses out to 2024. The measurement of a city's loss from a given event considers:

(a) **Outlook Period:** The risk outlook for the Cambridge Global Risk Index 2018 is three years, from the start of 2018 through to the end of 2020. This is the period over which we evaluate the risk of events occurring. We do not consider events occurring past 2020.

(b) **City GDP Forecast:** A forecast of the city's baseline GDP (assuming no shocks from the 22 threats). Economic output loss is relative to this baseline GDP.

Scenario Losses

A catastrophic event of each threat type can unfold in various ways. Characteristic scenarios are defined for each threat, representing small, medium and large events of increasing severity. The set of characteristic scenarios are termed **local impact severity (LIS) events**, detailed descriptions of which can be found in Section 4.

For each LIS event, there are two parameters which determine the GDP impact for each city:

(a) **Threat Vulnerability:** Each city is assigned a vulnerability rating for each threat type. This determines how significant the initial shock to the city's economy would be in the case of an event. The threat vulnerability parameter determines the initial percentage shock to GDP.

(b) **Socio-economic Resilience:** Currently, each city is assigned a resilience parameter which is applied across all threats. Resilience determines how much and how quickly the city can recover from the initial shock of the event.

For each city and threat event we first estimate separately the five-year loss of the event assuming the event can begin in any year during the risk outlook. We then take the arithmetic mean of the three estimates to give an average loss of the event. We also refer to this average five-year loss as a Local Impact Severity (LIS).

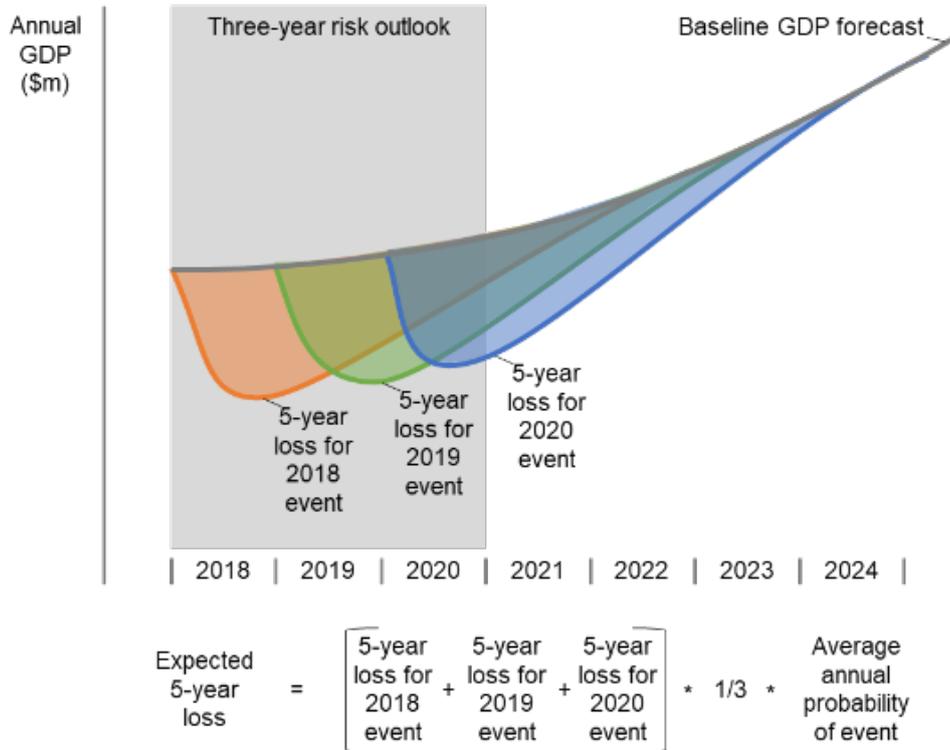


Figure 1: Graphical representation of the expected loss calculation

Expected Losses

The average five-year scenario loss is then multiplied by the average annual probability of the event during the risk outlook to give the expected loss of the event. The annual probability is determined by the:

(a) **Threat Assessment Grade (TAG):** Each city is assigned a threat assessment grade for each threat type. This determines how likely the city is to experience a threat event. The TAG parameter determines the annual probability of the event during the outlook period.

Figure 1 depicts this expected loss calculation graphically.

2 Baseline City GDP and Population Estimates and Forecasts

Overview

The first step in our city risk assessment involves estimating and forecasting baseline GDP for each city. We rely on Oxford Economics' Global Cities service¹ for this baseline data along with corresponding estimates and forecasts of city population. Cities are defined as metropolitan areas: regions of deeply interconnected economic activity, typically consisting of one or more core cities and their surrounding commuter areas.

The availability of consistent GDP and population data also allows us to estimate per capita GDP of each city. We use per capita GDP as a useful proxy indicator of city affluence, which we consider to be a component part of overall city resilience to economic shocks.

Data source: Oxford Economics' Global Cities service

Oxford Economics' Global Cities service has been developed to explore markets trends and opportunities among the world's largest cities. The service provides city annual historic estimates and forecasts to 2035 to support business decision making and strategy, research analysis, urban planning, and client consultation and engagements.

In addition to city GDP and population, the service covers a range of indicators including demographic and sector breakdowns.

The Global Risk Index 2018 is based on city data released by Oxford Economics in November 2017.

Defining metropolitan areas

Oxford Economics define cities according to urban agglomerations and metropolitan areas, which include the built-up area outside the historical or administrative core, with official definitions being used where possible. This broader city definition better reflects self-contained economic entities than narrower historical or administrative

definitions and helps ensure the comparability of cities across the dataset.

Overview of Oxford Economics' approach

Oxford Economics' Global Cities service is consistent with their Global Macroeconomic service. This ensures that city level figures are anchored in industry-standard national level estimates and forecasts.

The process of 'scaling-down' national level figures requires extensive work collecting, checking and cleaning data from myriad national statistical agencies and supranational sources (such as World Bank, OECD, Eurostat, UN, etc.). Established economic principles are used to estimate missing data, including: interpolation and extrapolation to complete timeseries data; city-level estimates based on broader region or country data; city- and national-level estimates based on analysis of similar countries.

City population estimates

The UN's World Population Prospects² and official definitions provide the primary data sources for Oxford Economics' city population estimates. Given the variability of data availability and quality, several approaches are taken: if official estimates are close to UN estimates, then official estimates are used; if official estimates are significantly different to UN estimates, then official estimates are scaled to the UN definition (to ensure consistency in the definition of metropolitan areas and urban agglomerations, although in some case the official estimates are used); and finally, in China larger city prefecture definitions than those used by the UN have been adopted to remain in line with traditionally recognised city regions in that country.

Forecasting city population change requires analysis of birth and death rates and net in-migration. Where official city-level data

¹ Oxford Economics Cities Data (2017). URL: <http://www.oxfordeconomics.com/forecasts-and-models/cities/overview>

² Population Division of the Department of Economic and Social Affairs of the United Nations Secretariat, World Population Prospects: The 2010 Revision and World Urbanization Prospects: The 2011 Revision

is unavailable national level data is scaled according to economic principles. For example, city birth rates are lower than national rates due to various demographic, economic and social factors, while death rates correlate negatively with both per capita GDP (i.e., a city that is richer than its parent country would expect to have a lower death rate) and the working age share of population (i.e., both the elderly and young have higher mortality rates).

City GDP estimates

First it is important to note that city GDP estimates are consistent with the city population boundaries discussed above. Consistent official city GDP estimates are used where available. Missing data is estimated either by scaling up narrower city definition estimates or scaling down national or regional estimates.

Employment estimates by industry within the desired city boundary definition are required to robustly scale GDP estimates. City productivity can then be estimated accounting for any likely differences between economic levels. For example, the productivity of certain industries, such as finance, may be considerably higher in a major city than the national average because of better infrastructure and concentration of highly skilled workers.

3 Resilience: Rate of Recovery

The recovery from catastrophes is defined as the speed and extent to which an affected city's economy can return to normality. This includes reconstruction of factories, homes and damaged infrastructure; regaining consumer confidence; and re-engaging in business activities. The Global Risk Index defines a resilience metric to model the pace of recovery after a shock. The resilience metric is a composite metric of socioeconomic resilience and fiscal resilience.

Socio-economic Resilience

The definition of resilience within the Global Risk Index is largely based off work by the Index for Risk Management INFORM³, a joint initiative of the European Commission, the Inter-Agency Standing Committee Task Team (IASC) for Preparedness and Resilience, and other partners. The INFORM index is a composite index to identify countries at risk of humanitarian crises.

While the Global Risk Index measures risk of catastrophes from an economic perspective rather than humanitarian, there are many overlaps between the two. The capacity of a city or country to recover from a disaster is dependent on similar factors to determine how well human mortality or social disruption are managed.

We include the elements external to the hazard analysis in the INFORM index: vulnerability and lack of coping capacity.

The vulnerability dimension of the INFORM composite index measures the economic, political and social characteristics that can be destabilized. The lack of coping capacity dimension measures the institutional and infrastructure capacity – formal, organised activities in response to disasters. We consider those regions with more vulnerable populations and less coping capacity as less able to recover as they are more susceptible to catastrophic damage and have fewer resources to rebuild.

³ INFORM Index for Risk Management (2017). URL: <http://www.inform-index.org/>

Fiscal Resilience

As the Global Risk Index is an economic indicator, we add an additional fiscal resilience element to account for the economic and financial capacity to recover from disasters. Factors of fiscal resilience include being able to withdraw funds from reserves, to shift fiscal budgets or raise new funds, and to distribute funds efficiently. In this component, fiscal resilience for each city is proxied by its GDP per capita⁴ and the country's non-life insurance penetration⁵.

A Composite Resilience Score

The final composite resilience score is calculated using the two types of socio-economic resilience and fiscal resilience. Each is given an equal weighting.

City Resilience Score = Vulnerability^{1/3} * Coping Capacity^{1/3} * Fiscal Resilience^{1/3}

Figure 2 summarises the elements which comprise the final city resilience score. This score is then translated into five resilience levels to reflect major step changes and group similar cities together. These categories are labelled: 1 Very Strong, 2 Strong, 3 Moderate, 4 Weak, 5 Very Weak.

Resilience Parameter for GDP Recovery

Each city's resilience score category determines the characteristic recovery from a shock in each LIS, i.e. threat event. A matrix of recovery parameter exists for each threat and LIS, modelling the percentage recovery back to baseline GDP levels in the years following the shock.

There is currently one resilience parameter for each city, thus the parameter does not distinguish a city's ability to recover from some threat types more than others. This is a known shortcoming of the model which can be addressed in future iterations.

⁴ Oxford Economics Cities Data (2017). URL: <http://www.oxfordeconomics.com/forecasts-and-models/cities/overview>

⁵ Swiss Re Sigma Non-life Insurance Penetration (2017). URL: http://institute.swissre.com/research/overview/sigma_data/

Vulnerability (INFORM)					Lack of Coping Capacity (INFORM)					Fiscal Resilience	
Socio-Economic			Vulnerable Groups		Institutional		Infrastructure			Wealth	Insurance
Development deprivation	Inequality	Aid dependency	Uprooted people	Other vulnerable groups	DRR	Governance	Communication	Physical Infrastructure	Access to health system	City GDP/Capita (OEM)	Non-Life Insurance Penetration (Sigma)

Figure 2: Dimensions of resilience are defined by ‘Vulnerability’ and ‘Lack of Coping Capacity’, based on INFORM Index for Risk Management analysis and further supplemented by ‘Fiscal Resilience’ using data from Oxford Economics and Swiss Re Sigma

4 Local Impact Severity: Threat Scenarios

For each of the 22 threat types, we defined three local impact severity events representing small, medium and large scenarios of increasing severity. Note that for a handful of threats, characteristic scenarios are defined by fewer than three levels.

Each LIS event definition is presented in the table below. Losses are estimated for each of these scenarios and for each of the 279 cities, according to their GDP growth projections and threat assessments.

	Threat	Code	Description
Finance, Economics and Trade	Commodity Price Shock	CP1	Sudden (i.e. within a single quarter) increase in unit price of crude oil from \$50/bbl to \$100/bbl (100%); pass-through impacts seen in other commodities
	Commodity Price Shock	CP2	Sudden (i.e. within a single quarter) increase in unit price of crude oil from \$50/bbl to \$150/bbl (200%); pass-through impacts seen in other commodities
	Commodity Price Shock	CP3	Sudden (i.e. within a single quarter) increase in unit price of crude oil from \$50/bbl to \$300/bbl (500%); pass-through impacts seen in other commodities
	Market Crash	MC1	Stockmarket Index drops (peak to trough) by 10% in a single quarter (e.g. Asian Crisis 1997)
	Market Crash	MC2	Stockmarket Index drops 50% (peak to trough) in a single year (e.g. SubPrime 2008)
	Market Crash	MC3	Stockmarket Index drops 85% in a single quarter (e.g. Wall Street Crash 1929)
	Sovereign Default	SD1	Country defaults and reschedules its debt, devalues its currency substantially (e.g. 50%). Investors flee; FDI Lost
Geopolitics and Society	Civil Conflict	CC1	N/A
	Civil Conflict	CC2	Incidents of sectarian fighting between armed gangs and private militias in the streets of the city for multiple years
	Civil Conflict	CC3	Violence involves months of street fighting between well-organized and well-equipped armies using heavy weaponry.
	Interstate Conflict	IW1	City mobilized for war, but not attacked; industrial activity switches from commercial to military production; consumer demand and investor confidence drops, some outmigration; conflict impact lasts for 1 year
	Interstate Conflict	IW2	City suffers sporadic attack from occasional missiles or aerial bombardment (and possible damage from cyber attack); city is mobilized for war; consumer demand and investor confidence drops, large outmigration; conflict impact lasts for 2 year
	Interstate Conflict	IW3	City is the target of strategic bombing by enemy forces, destroying industrial and commercial output and military facilities in the city; significant outmigration. Possible rebuilding afterwards by major injection of capital; conflict impact lasts for 3 years
	Social Unrest	SU1	Civil Unrest causes riots and protests in the streets for months; violent confrontations with police
	Terrorism	TR1	Sustained campaign of small-scale terror attacks (e.g. individual and mass-attack shootings, poisonings, food chain sabotage etc.) over a period of 9 months causes fear and distrust in urban population, leading to loss of consumer confidence, demand drop and loss of external investment
	Terrorism	TR2	Coordinated series of simultaneous high profile large terrorist attacks (e.g. major truck bombings, airplanes into buildings or other surprise destructive events) causes horrific loss of life and major destruction to property in and around city centre, leading to several years of depressed economic activity and reduced external investment
	Terrorism	TR3	WMD Terrorist Attack - City is attacked by sophisticated terrorist operation using weapons of mass destruction; (e.g. anthrax, air-dispersed bio-weapons, or chemical or radioactive contaminant, or small yield nuclear detonation) kills large numbers of people and contaminates many buildings in Central Business District, requiring years of recovery

Health and Humanity	Human Pandemic	HE1	Localized epidemic of new emergent disease that has case fatality rate of 10% causes public health emergency and fear in population of catching disease, leads to loss of tourism trade (e.g. SARS)
	Human Pandemic	HE2	Highly infectious moderate virulence pandemic where influenza virus infects 43% of the population, with a case fatality rate of 0.3% (e.g. Sao Paulo Scenario); anti-microbial resistance seen in hospitals in some countries
	Human Pandemic	HE3	Highly virulent pandemic causes high (3%) fatality rate in infected cases
	Plant Epidemic	PE1	Localized Plant Epidemic affects prices of staple foods in city markets
	Plant Epidemic	PE2	National plant epidemic affects price of staple foods in city markets
	Plant Epidemic	PE3	International Plant Epidemic affects price of stable foods in city markets
Natural Catastrophe and Climate	Drought	DR1	D2 'Severe Drought': drought causes water consumption restrictions for that city for 6 months, resulting in water rationing for businesses and residential. Water prioritized for industry, agriculture and emergency provision
	Drought	DR2	D3 'Extreme Drought' Three successive seasons of record levels of below average rainfall results in major water shortages for several years
	Drought	DR3	D4 'Exceptional Drought' sustained for multiple years. Major change in precipitation patterns causes extended drought, which results in severe water consumption restrictions for 5 years
	Earthquake	EQ1	A 'Large Magnitude Earthquake' (Ms6.5) within the city boundaries. Centroid of city experiences VII (PGA 250-400)
	Earthquake	EQ2	A 'Great Earthquake' (Ms7.0) with its epicentre close to the edge of the city, just outside its boundaries. Centroid of city experiences VIII (PGA 400-600)
	Earthquake	EQ3	A 'Great Earthquake' (Ms7.5) occurring at shallow depth with its epicentre close to the centre of the city. Centroid of city experiences IX (PGA 600-1000)
	Flood	FL1	10% of city affected by flooding, reaching 1m depth in parts, low velocity water, 3 months recovery period (e.g. Superstorm Sandy New York)
	Flood	FL2	25% of city area affected by flood waters that reach over 3m depth (more than one storey) in parts; Moderate velocity flowing water moderately contaminated.
	Flood	FL3	Over 50% of city land area affected by flooding, reaching more than two storeys in parts, high velocity destructive water flows and highly polluted waters
	Freeze	FR1	Freeze of up to 5 deg below 0 deg Celsius for 3 weeks (-20-100 Degree-days) with some snow and ice, moderate winds
	Freeze	FR2	Freeze of up to 10 deg below 0 deg Celsius for 8 weeks, combined with deep snow and high winds
	Freeze	FR3	Freeze of up to 20 degrees below 0 deg Celsius for 12 weeks, combined with heavy snow and severe ice loads periodically
	Tropical Windstorm	HU1	Category 1 Hurricane, windspeed 118-153 km/hr
	Tropical Windstorm	HU2	Category 3 Hurricane, windspeed 178-209 km/hr
	Tropical Windstorm	HU3	Category 5 Hurricane, windspeed >250 km/hr
	Heatwave	HW1	Heatwave of 1-5° above 32° C for 4 weeks (20-100 Degree-days)
	Heatwave	HW2	Heatwave of 1-8° above 32° C for 8 weeks (50-500 Degree-days)
	Heatwave	HW3	Heatwave of 1-12° above 32° C for 16 weeks (112-1300 degree-days)
	Tsunami	TS1	Tsunami with 3m run-up
	Tsunami	TS2	Tsunami with 6 m run-up
Tsunami	TS3	Tsunami with 12 m run-up	
Temperate Windstorm	TW1	Wind Storm of Beaufort Scale 10: Storm or Whole Gale (windspeeds of over 89 km/hr)	
Temperate Windstorm	TW2	Wind Storm of Beaufort Scale 11: Violent Storm (windspeeds of over 103 km/hr)	

	Temperate Windstorm	TW3	Wind Storm of Beaufort Scale 12: Hurricane (windspeeds of over 118 km/hr)
	Volcano	VE1	Ashcloud shuts city for extended period, and covers it with several centimetres of ash, preventing air travel, road traffic, port functions, and normal business activity.
	Volcano	VE2	Ashcloud covers city to 1m depth, entailing lengthy recovery process
	Volcano	VE3	Parts of city impacted by direct effects of volcanic eruption (pyroclastic gases, lahar flows etc.). City evacuated and population not allowed to return for some time.
Technology and Space	Cyber Attack	CY1	Cyber attacks and technology failures increase to such a level that it undermines consumer confidence in technology, weakens productivity of tech sector, and reduces e-commerce
	Cyber Attack	CY2	A sustained public cloud outage causes significant downtime to companies' e-commerce platforms and halts access to vital data for continuation of business, resulting in heavy losses to many commercial industries
	Cyber Attack	CY3	Cyber attacks on critical infrastructure destroy the power distribution grid and causes power loss in the city for 6 months
	Nuclear Accident	NP1	City receives radioactive fallout of >0.01Bq/km ² (0.3 Curies of Cs137), similar to within 200km of Chernobyl 1986 or 120km of Fukushima 2011
	Nuclear Accident	NP2	City receives radioactive fallout of >0.1Bq/km ² (3 Curies of Cs137) similar to within 70 km of Chernobyl 1986 or 50km of Fukushima 2011
	Nuclear Accident	NP3	City receives radioactive fallout of >1Bq/km ² (30 Curies of Cs137) similar to within 30km of Chernobyl INES 7 event in 1986
	Power Outage	PO1	One City-Day of Power Loss (100% of city loses power for 1 day or 50% of city loses power for 2 days etc).
	Power Outage	PO2	A 5-City-Day event (100% of city loses power for 5 days, 50% of city loses power for 10 days etc)
	Power Outage	PO3	A 10 City-Day event (100% of city loses power for 10 days)
	Solar Storm	SS1	NOAA Space Weather Scale for radiation storms level S4 and equivalent to a solar flare of X20. Radiation hazard to passengers and crew in commercial jets at high latitudes (approximately 10 chest x-rays). Satellite systems experience memory device problems and noise on imaging systems, GPS navigation systems prone to error, blackout of HF radio communications. Some low level electrical interference and voltage control problems. 3-5 days of disruption caused.
	Solar Storm	SS2	NOAA Space Weather Scale for radiation storms level S5 and equivalent to a solar flare of X40 (Similar to 'Carrington Event'; Radiation hazard to passengers and crew in commercial jets at high latitudes (approximately 10 chest x-rays). Satellite systems experience memory device problems and noise on imaging systems, GPS navigation systems prone to error, blackout of HF radio communications. Some low level electrical interference and voltage control problems. 3-5 days of disruption caused.
	Solar Storm	SS3	NOAA Space Weather Scale for radiation storms level S6+ (Beyond 5-point NOAA Scale). Estimated effects of a solar flare of X60 - also known as a class Z event. High radiation exposure to passengers and crew in commercial jets at high latitudes (approximately 100 chest x-rays). Satellites rendered useless, GPS navigation systems fail, serious noise on imaging systems. Telecommunication systems fail. Widespread voltage control problems and protective system problems can occur, some grid systems may experience complete collapse or blackouts. Transformers may experience damage. Several weeks of disruption caused before systems back online.

5 Expected Loss Calculations

This section describes the calculations behind the expected loss calculations in further detail.

Expected loss is presented as a total GDP loss (*expected_5yr_loss*) and as a percentage GDP loss (*expected_5yr_loss_share*).

Each threat type is represented by up to 3 **local impact severities (LIS)**, which are characteristic events that represent how events of various magnitude can occur, as described in Section 4. The **expected loss** is calculated for each LIS within each of the 22 threat types for each of the 279 cities:

$$\begin{aligned} & \text{Expected_5yr_Loss}_{event,3yr_outlook} \\ &= \text{Average_Loss}_{event,3yr_outlook} \times \text{Annual_Probability}_{event} \end{aligned}$$

$$\begin{aligned} & \text{Expected_5yr_Loss_Share}_{event,3yr_outlook} \\ &= \text{Average_Loss_Share}_{event,3yr_outlook} \times \text{Annual_Probability}_{event} \end{aligned}$$

The probability of an event occurring (*Annual_Probability_{event}*) in any year for each city is determined by its Threat Assessment Grade (*TAG*). There is a matrix of annual probabilities for each threat's tag categories. For each city:

$$\text{Annual_Probability}_{event} = f(\text{TAG})$$

The LIS loss is (*Average_Loss_{event,3yr_outlook}*) the average GDP loss for each LIS severity, if it were to occur any year within the 3-year outlook.

$$\begin{aligned} & \text{Average_Loss}_{event,3yr_outlook} \\ &= \text{Average}(\text{Loss}_{event,yr1start}, \text{Loss}_{event,yr2start}, \text{Loss}_{event,yr3start}) \end{aligned}$$

$$\begin{aligned} & \text{Average_Loss_Share}_{event,3yr_outlook} \\ &= \text{Average}(\text{Loss_Share}_{event,yr1start}, \text{Loss_Share}_{event,yr2start}, \text{Loss_Share}_{event,yr3start}) \end{aligned}$$

For any year, the total GDP loss (*Loss_{event}*) and percentage GDP loss (*Loss_Share_{event}*) for an event is determined by its initial shock or percentage loss to GDP, *Shock_{0,event}*, and its subsequent recovery profile (*Recovery_Parameter_{t,event}*) of GDP back to its baseline projection:

$$\text{Loss}_{0,event} = \text{GDP}_0 \times \text{Shock}_{0,event}$$

$$\text{Loss}_{1-4,event} = \sum_{t=1}^4 \text{Loss}_{0,event} \times (1 - \text{Recovery_Parameter}_{t,event})$$

$$\text{Loss}_{event} = \text{Loss}_{0,event} + \text{Loss}_{1-4,event}$$

$$\text{Loss_Share}_{event} = \frac{\text{Loss}_{0,event} + \text{Loss}_{1-4,event}}{\text{GDP}_{0-4}}$$

The percentage shock (*Shock_{0,event}*) to a city's GDP in the year the modelled event of any threat type occurs is determined by its threat *vulnerability* category. There is a matrix of shocks for each vulnerability level within each threat category. For each city:

$$\text{Shock}_{0,event} = f(\text{vulnerability})$$

The recovery profile (*Recovery_Parameter_{t,event}*) is the rate at which GDP recovers from its initial shock. The recovery parameter is determined for each of the subsequent four years of recovery, as measured in the Global Risk Index. There is a matrix of recovery parameters for each resilience grading within each threat category. For each city:

$$\begin{aligned} & \text{Recovery_Parameter}_{t,event} \text{ for } t_{1,2,3,4} \\ &= f(\text{socioeconomic}_{resilience_grading}) \end{aligned}$$

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