Chapter 21
Structured Expert Judgement in Adversarial Risk Assessment: An Application of the Classical Model for Assessing Geo-Political Risk in the Insurance Underwriting Industry

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Abstract For many decision and risk analysis problems, probabilistic modelling of uncertainties provides key information for decision-makers. A common challenge is lacking relevant historical data to quantify the models used in decision and risk analyses. Therefore, experts are often sought to assess uncertainties in cases of incomplete or non-existing historical data. As experts might be prone to cognitive fallacies, a structured approach to expert judgement elicitation is encouraged with the aim to mitigate such fallacies. Further, it enhances the assessment's transparency. An area, in which the assessment and modelling of uncertainties are particularly challenging due to incomplete or non-existing historical data is adversarial risk analysis (ARA). In contrast to more traditional application areas of decision and risk modelling, in ARA intelligent adversaries add more complexity to assessing uncertainties given that their behaviour and motivations can be versatile so that they adapt and react to decision-makers' actions, including actions based on traditional risk assessments. This often inhibits the availability of historical data. This additional complexity is also shown by the challenges that machine learning methods face when informing adversarial risk assessments. As such, using expert judgements for assessing adversarial risk (at least supplementary) often provides a more robust decision. In this chapter, we discuss the importance of structured expert judgement for ARA and present an application of the *Classical Model* as a structured way for eliciting uncertainty from experts on geo-political adversarial risks. We elicit the frequency of terrorist attacks and strikes, riots and civil commotions (SR & CCs), including insurgencies and civil wars, in various global regions of interest. Assessing such uncertainties is of particular interest for insurance underwriting.

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21.1 Introduction

Probabilistic uncertainty modelling is fundamental for decision and risk analysis. It allows for considering the variability in model inputs and the uncertainty propagation onto its outputs. For decision-makers, this information is often of key importance for understanding the robustness of their decisions and actions. Nevertheless, as modellers and analysts building models that inform decision and risk analyses, we commonly face the challenge of lacking relevant, historical data to quantify our models. In this case, and when (in addition) simplifying assumptions on the uncertainties of interest are not sensible, we should use experts' judgements to assess the uncertainties. This can also be a way of quantifying uncertainties when other forms of data gathering are too costly.

In order to consider assessments elicited from experts as scientific data and at the same time ensure they are defensible in front of and transparent for any stakeholders involved in the decision problem, we require a formal process for obtaining expert judgements. Therefore, an elicitation includes the careful definition of the target variables, formulating and pilot testing the elicitation questions, training the experts, eliciting the uncertainty assessments, and analysing together with documenting the elicited results. Further, we need to choose a defensible way for aggregating various assessments as elicitations typically involve multiple experts to capture diverse backgrounds, knowledge and opinions. Clemen and Winkler (1999, 2007) provide an overview of aggregation methods, commonly classified as either *behavioural*, aiming at obtaining a single consensus distribution through group interaction, or *mathematical*, considering analytic ways for yielding one combined distribution from the experts' assessments, usually without expert interaction. In the elicitation presented in this chapter, we use the *Classical Model* for structured expert judgement (Cooke 1991). It provides a mathematical aggregation method that is based on validating experts' assessment performance against empirical data. For overviews and discussions on elicitation processes and their specific elements, see Dias et al. (2018) and Chap. 1.

The area of decision and risk analysis on which we focus in this chapter is *adversarial risk analysis* (ARA). It considers risks which are due to intentional acts of intelligent adversaries and their impact on uncertain outcomes (Rios and Rios Insua 2012; Chap. 7). Therefore, in ARA a lack of relevant historical data is common, in particular due to the versatile and adaptive nature of the risks to be modelled. A particularity, in contrast to many other research areas in risk analysis, is that the complexity of the risks considered poses specific challenges on the more recent advances in machine learning which is why using or at least including human expert judgement is regarded as more reliable for assessments (Cederman and Weidmann 2017). In other words, while in many fields of decision and risk analysis machine learning-based methods, such as expert systems, are used more and more often to assess risk (see for instance Abdelgawad and Fayek (2010) for construction risk, Hadjimichael (2009) for aviation risk, Fares and Zayed (2010) for water supply risk, or as well Idrus et al. (2011) for project risk), in ARA they face several limitations and challenges that human experts can overcome.

The purpose of adversarial risk models is usually to inform counter-terrorism decisions, such as investments and resource allocations for responding to terrorism risk (Rios and Rios Insua 2012). This often involves geo-political considerations and concerns. Traditionally, counter-terrorism intelligence has been available for and used by governmental decision-makers. However, many industries require and invest in similar information today. As such, the industry of interest for this chapter, that of insurance underwriting, is also more and more often in need of rigorous adversarial risk models on geo-political risks. These inform for instance decisions on global insurance portfolios that are possibly impacted by terrorism threats. Therefore, in the elicitation presented in this chapter, our experts are insurance underwriters with an expertise in terrorism analysis.

The objective of this chapter is to explore how the Classical Model works within ARA by presenting one of its first applications for geo-political adversarial risk, in particular with regard to the availability of suitable seed questions for calibrating experts' performance on terrorism events and the general acceptance of SEJ elicitation by experts and decision-makers in this domain.

The remainder of this chapter is structured as follows. The next Sect. 21.2 provides more background on ARA problems, their foci and the role structured expert judgement can play for improving these. This section also contrasts human experts to machine learning approaches in adversarial contexts. Section 21.3 presents some recent developments in the insurance industry due to large-scale terrorism risk given that this is the industry from which our experts come from and for which the elicitation is done. In Sect. 21.4, we then outline our elicitation protocol together with the seed and target questions, before in Sect. 21.5 we present the elicitation results. Lastly, Sect. 21.6 provides a discussion on alternative seed questions for elicitation in geo-political ARA and their availability before we conclude the chapter in the final Sect. 21.7.

21.2 Adversarial Risk Analysis and Structured Expert Judgement

In recent years, there has been an increased interest in advanced analytical methods and models that consider uncertain events and outcomes triggered or are at least affected by intelligent opponents who intend to cause harm and about whose behaviour, actions, motivations and utilities we have imperfect information. This research area is often referred to as ARA. Structured expert judgement and machine learning methods, both face particular challenges when used for adversarial risk which determine their different opportunities for enhancing models in this area.

21.2.1 Brief Background on Adversarial Risk Analysis

Loosely, ARA combines traditional probabilistic risk analysis (PRA) with game-theoretic methods (Roponen and Salo 2015).

The traditional methods and models evolved from the need to assess risk when uncertain outcomes are due to chance (nature) directly without the inclusion of intelligent adversaries. While they have been proposed to be used directly for assessing adversarial risks, e.g. by Ezell et al. (2010), at the same time their use has also been criticised, for instance, by Brown and Cox (2011) and Cox (2009). One of the main potential issues is that an attacker's decision rule for selecting a target is dynamic and as such might be even informed by the anticipated defender's assessment of targets' likelihoods. In this way, a defender's initial assessment of the most likely to be attacked target(s), which as a result obtains most defence resources, has now zero probability of being attacked given that the defender's PRA informs the attacker's choice. This can also happen if the attacker cannot access the defender's assessment directly but rather anticipates his way of thinking. Therefore, traditional risk analysis tools, such as influence diagrams and probabilistic reasoning, are extended for adversarial problems. Examples are Pinker (2007), who uses influence diagrams for informing the supply of countermeasures to terrorism, Merrick and McLay (2010), applying decision trees for modelling the instalment of sensors for screening cargo containers under threat of terrorists, and Parnell et al. (2010), modelling terrorists' objectives for biological weapon usage with decision trees.

Similar to using traditional PRA methods on their own, considering only game-theoretic approaches can also be problematic. For these, min-max solutions, i.e. ones in which both opponents seek to minimise their expected maximum losses across all actions available to them, might lead to sub-optimal solutions (Roponen and Salo 2015). This is due to the attacker and defender not respecting the min-max rationality principle whereas modelling such rational solutions requires particular strong assumptions on the common knowledge available to both opponents (Kadane and Larkey 1982). For instance, the worst possible outcome can have such a low probability that (in reality) it is not considered at all (Roponen and Salo 2015). ARA does not need such strong assumptions on the knowledge of opponents' aims and resource capabilities (Roponen and Salo 2015) and Banks et al. (2011) provides an overview on how classical game-theoretic approaches compare to ones modified for use in ARA.

21.2.2 Structured Expert Judgement for Adversarial Risks

In order to understand the role of structured expert judgement for assessing adversarial risk and hence for enhancing ARA models, we first note briefly how adversarial aspects have been integrated in some more recent definitions on risk. A main advent of new risk definitions that include adversaries followed the terrorist attacks on the USA in September 11th, 2001 (9/11) (Haimes 2009). For overviews see Aven and

Guikema (2015), Aven and Krohn (2014) or Aven (2012). As such, Garrick (2002), for instance, extends the common, quantitative risk definition by Kaplan and Garrick (1981), based on the triplet $\langle s_i, p_i, x_i \rangle$ of i scenarios, their probabilities and outcomes, by a threat (outcome) likelihood as the conditional probability of a successful attack given that the attack is planned.

When using expert judgement for adversarial risk, this altered definition together with the discussion on ARA models shows that experts face more complex uncertainties. This is why it is often necessary to consider a decomposition of the assessments. For example, Paté-Cornell and Guikema (2002) propose assessing a probability of an attack through modelling an attacker's objective from the viewpoint of a defender first before the attacker's probabilities and utilities are assessed through point estimates. In a similar way, expert judgement is used in the *Probabilistic Terrorism Model* by Risk Management Solutions (RMS[1]) to assess target selection probabilities, capabilities of attack modes and attacks' overall probabilities. Here, experts consider the attackers' motivations, resources and capabilities together with defenders' vulnerabilities for an assessment. This shows how experts need to be able to assess probabilities by taking into account the aims, knowledge and skills of attackers as well as defenders. See Willis et al. (2007) for a more detailed discussion of the model.

Similarly, Chap. 22 suggests that experts should assess the probability of operational success and failure, conditional on terrorists' technical capabilities and their modus operandi. He recommends that thereby enhancing our understanding of terrorists' technical capabilities and the modus operandi is what we should use experts for, while highlighting that some (other) uncertainties of terrorism events cannot be expected to be assessed. He provides an example of a failed terrorist attack on an Algerian gas plant due to an accidental cut of the power supply, which ultimately prevented the plant to explode, a contingency we cannot expect to be reliably assessed.

Such decompositions can comprise a lot of information to elicit and therefore their elicitation needs to be well-structured or otherwise we need to make assumptions on the information that is considered by experts for making an assessment. Further, this underlines the importance of other elements in an elicitation process, such as structuring experts' knowledge and beliefs prior to the quantitative elicitation as well as the training of experts. This is similarly the case for SR & CC events.

21.2.3 Machine Learning Methods for Adversarial Risks

This additional complexity of assessments not only affects human experts but also machine learning approaches which are being developed for assessing uncertainties. This is an important aspect to consider given that in particular the recent focus on the terms "data analytics" and "big data" has resulted in an increased interest

[1]RMS, founded at Stanford University in 1989, provides services in the area of catastrophe modelling for (re-)insurers.

in more applications of machine learning methods to do uncertainty assessments in risk analyses. However, Cederman and Weidmann (2017) provide an overview of the challenges that machine learning methods, such as neural networks and expert systems, face when used for predicting political violence and terrorism events whereas it is noteworthy that several of these challenges are less crucial for or can even be overcome by human experts. This is despite more recent machine learning methods having become more reliable at conflict prediction than earlier prediction models, often based on linear regression. For example, remaining challenges are geo-political variations of borders and territories as well as changing power of actors and their, by definition, rule-breaking behaviour. These significantly impede the ability to obtain suitable training data necessary for machine learning methods. Further, even if techniques, such as data scraping from online sources, generate vast data-bases to be used for training machine learning methods, it has been shown that only the quantity of conflict data alone does not enhance prediction accuracy, often due to additional noise. Rather, we need to consider the quality of our information. In this regard, sources like news reports on political violence seem to be stronger predictors than other, more conventional predictors of conflict, such as level of democracy. However, the potential issue with these is that for secondary sources the level of observed violence depends either on the level of actual violence or the probability of reporting, or both of them. Human experts on the other hand can infer knowledge and beliefs about causal mechanism and broader patterns about future changes of power relationships among geo-political actors and hence decide how much of historical data they take into account. In this way, human experts might even guide machine learning models given that they provide insight into the amount and type of information they use for an assessment. The advantage of explanation for certain assessments also enables decision-makers to make more informed decisions. That is, even if a machine learning method offers highly accurate predictions, a black-box model might not be usable in high-risk situations. Therefore, Subrahmanian and Kumar (2017) suggest that experts should be used to propose relevant independent variables that are included in a data set and explain predictions through corresponding narratives of their domain to enhance the understandability of predictions.

21.3 Recent Developments in Insurance Underwriting Due to Risk of Terrorism and SR & CC Events

We already established that while ARA might be of interest in a variety of industries, an industry in which a rigorous approach to quantifying and modelling adversarial risk is particularly key is insurance underwriting. In non-life insurance, so-called *low frequency-high impact* events are by definition observed only rarely and as such a main concern is the lack of relevant historical data for model quantification. Of main interest with regard to *non-natural perils* are terrorism events (Woo 2002; Chap. 22). In addition to the previous brief outline, Parnell et al. (2010), Enders and

Sandler (2009) and Chap. 22 provide overviews about models and research issues for terrorism risk analysis.

The pricing of terrorism risk in insurance has traditionally not been assessed from actuarial principles. Instead, it has been covered by the supply and demand balance in the insurance market while adjustments have been made based on less formal risk selection from site surveys Woo (2002). In the United States, for example, terrorism coverage was included in standard commercial insurance policies as an unnamed peril as part of all-risk commercial and private coverage for property and contents (Michel-Kerjan and Pedell 2006).

The more recent loss developments however led to the necessity of approaching its risk assessment more rigorously. A major turning point for the insurance industry and the reason for an increased focus on terrorism risk were the 9/11 attacks on the United States. These attacks caused an estimated monetary loss up to 60 billion US dollars whereas this amount is spread across various lines of business, such as property insurance, business interruption insurance and workers' compensation (DeMey 2003). Further, on a global scale, the 15 terrorist attacks with the highest casualty numbers have all happened since the year 1982 whereas many more near-miss events occurred which could have ranked among these (Michel-Kerjan and Pedell 2006). In this context, the relationship between the frequency of attacks and their severity can be modelled by a power law (Clauset et al. 2007; Clauset and Woodward 2013; Spagat et al. 2018), a finding similarly provided for war sizes already by the British polymath Lewis Fry Richardson (Richardson 1948). This means that attack severities several orders of magnitude larger than the mean can be common. This (global) development of terrorism risk through an increase in the number of frequencies and in severities underlines the urgent need for improved assessment methods for insurance underwriters.

21.4 Elicitation Protocol and Presentation of Seed and Target Questions

While the complete elicitation protocol of this study can be found in Werner (2017), in this section we briefly outline the main aspects of our elicitation. The method used for this elicitation is the Classical Model (Cooke 1991). Hence, a particular focus here is on the seed and target questions. For detailed overviews and introductions, see the original reference and more recently, Quigley et al. (2018) and other chapters in this book presenting the Classical Model.

After having introduced the experts to the Classical Model and provided them with training on assessing probabilities through quantiles and on the interpretation of the framing of our questions, we proceeded with eliciting first the seed and then the target questions.

In this study, we used both, predictions and retrodictions, as seed questions. The former are seed questions on variables which are about the future but will become

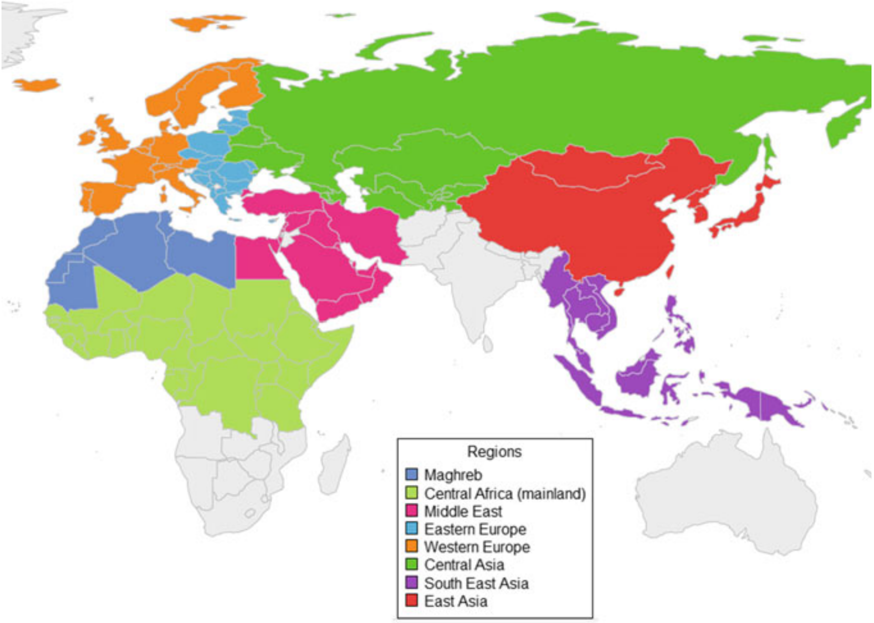

Fig. 21.1 Regions of interest for seed and target questions

known during the time frame of the study. The latter are seed questions on previously observed events (Quigley et al. 2018). Further, all of our seed questions are domain ones which means that they are from the same field of expertise as the target variables. Domain-specific predictions are usually seen as the ideal seed questions (Quigley et al. 2018).

In order to assess the global risk of terrorist attacks, we elicited expert judgements on the frequencies of terrorist attacks in various regions of the world. The regions of interest are shown in Fig. 21.1. For a complete list see Appendix 21.8.

The seed and target questions are formulated in a similar way and exemplary for all 14 of the former, which are about terrorist attacks (another 14 are on SR & CC events), seed questions S01 to S08 are shown below:

S01 – S03: For a terrorist attack* to be recorded as such, there must be evidence of an intention to coerce, intimidate or convey some other message to a larger audience (or audiences) than the immediate victims.

According to GTD (2016), what was the total number of terrorist attacks (any number of casualties) during the years 2010 to 2015 in the regions of [. . .]

S01 **Maghreb:**

5%ile:__________ 50%ile:__________ 95%ile:__________

- -

S02 **Central Africa (mainland):**

5%ile:__________ 50%ile:__________ 95%ile:__________

- -

S03 **Middle East:**

5%ile:__________ 50%ile:__________ 95%ile:__________

***Terrorist attack** = Any perpetrator group, any weapon type (e.g. biological, chemical, explosive, firearms etc.), any attack type (e.g. armed assault, bombing, facility/infrastructure attack, hostage taking etc.), any target apart from private persons (i.e. business, infrastructure, military, educational/religious institutions, etc.)

S04 – S06: For a terrorist attack* to be recorded as such, there must be evidence of an intention to coerce, intimidate or convey some other message to a larger audience (or audiences) than the immediate victims.

According to GTD (2016), what was the total number of terrorist attacks (any number of casualties) in ***East Asia*** during the time intervals of [. . .]

S04 **1970–1980:**

5%ile:__________ 50%ile:__________ 95%ile:__________

- -

S05 **1990–2000:**

5%ile:__________ 50%ile:__________ 95%ile:__________

- -

S06 **2005–2015:**

5%ile:__________ 50%ile:__________ 95%ile:__________

*__Terrorist attack__ = Any perpetrator group, any weapon type (e.g. biological, chemical, explosive, firearms etc.), any attack type (e.g. armed assault, bombing, facility/infrastructure attack, hostage taking etc.), any target apart from private persons (i.e. business, infrastructure, military, educational/religious institutions etc.)

S07 – S08: Terrorist attacks* are often targeting businesses. According to GTD (2016), of the total number of these attacks during 2010 to 2015, what has been the percentage of attacks targeting businesses in the regions of [. . .]

S07 Western Europe:

5%ile: ________ 50%ile: ________ 95%ile: ________

- -

S08 Eastern Europe:

5%ile: ________ 50%ile: ________ 95%ile: ________

*__Terrorist attack__ = Any perpetrator group, any weapon type (e.g. biological, chemical, explosive, firearms etc.), any attack type (e.g. armed assault, bombing, facility/infrastructure attack, hostage taking etc.), any target apart from private persons (i.e. business, infrastructure, military, educational/religious institutions etc.)

We observe that different formats of seed questions were elicited. Mainly, we asked the experts to assess frequencies of terrorist attacks whereas the region and (range of) years were modified (S01 – S06). In addition, we also elicited seed questions on percentage values for the target types (S07 – S08). The remaining seed questions varied only in that they were either on different years (and ranges), such as the predictive seed questions used, or on the changes in the number of terrorist attacks from one year to another. For seed questions on SR & CC events, the regions, years and targets were similarly varied and formulated in the same framing shown above.

It is important to note that a particularity for eliciting probabilities on adversarial risks, such as terrorist attacks in the above seed questions, is the definition of what constitutes a terrorist attack. This needs to be clarified and pointed out during the elicitation as it defines the probability space of the questions. Therefore, it has been listed for each question on terrorist attacks and is similarly shown for seed questions on SR & CC events.

Following the seed questions, we framed and elicited target questions, $T01 - T08$. These elicit the number of terrorist attacks for the coming year 2017–2018 as the elicitation was done in March 2017. The next eight target questions, T09 – T16, considered SR & CC events.

T01 – T08: How many terrorist attacks (according to the definition in the seed questions) will occur in the coming year (March 2017–March 2018) in the regions of [. . .]

T01 Maghreb:

5%ile: _________ 50%ile: _________ 95%ile: _________

⋮

T08 East Asia:

5%ile: _________ 50%ile: _________ 95%ile: _________

The elicitation of seed and target questions was held in a plenary format. This means that the experts worked through the questions individually, however, all experts were together for the introduction, motivation and training as well as feedback session by the facilitator. Further, individual expert's questions on clarifications of the questions have been heard by and explained to all experts which ensures they interpret everything in a similar way as best as possible.

21.5 Discussion of Elicitation Results

In total 16 experts participated in the elicitation, all with similar backgrounds and experiences as professionals in terrorism risk modelling and analysis in insurance underwriting. One expert is additionally also an academic in the field.

In this section, we present how the experts performed in the elicitation with regard to the Classical Model metrics for statistical accuracy and informativeness, and discuss the properties of the resulting aggregated judgement, the so-called Decision Maker (DM), and for comparison the equal weighting combination (EW). The seed questions create the basis for identifying the optimal performance-based weighting of experts which can then be used for combining experts' assessments on the target variables as DM. The EW combination is simply the average of all experts' assessments.

Following the seed questions presented (exemplary for all) in the previous section, Figs. 21.2, 21.3, 21.4, 21.5 and 21.6 show the experts' judgements for these. In addition to each expert's uncertainty range over the variable of interest per question, each figure includes the EW combination together with the performance-based DM weighting. The left-hand side of each horizontal line shows an expert's and the combined judgement's 5th quantile assessment, the right-hand side of the line the

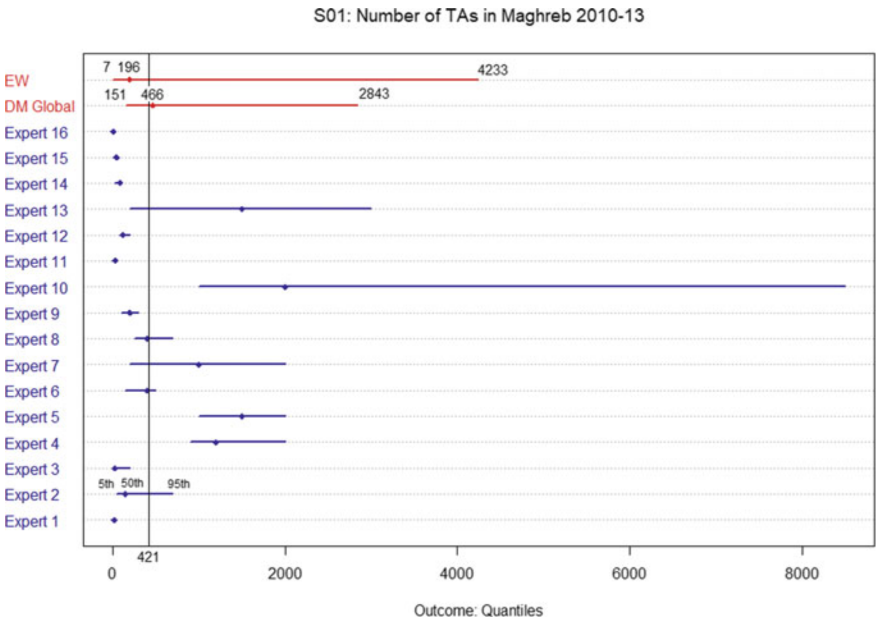

Fig. 21.2 Seed question on number of terrorist attacks in the Maghreb region, 2010–2013 (S01)

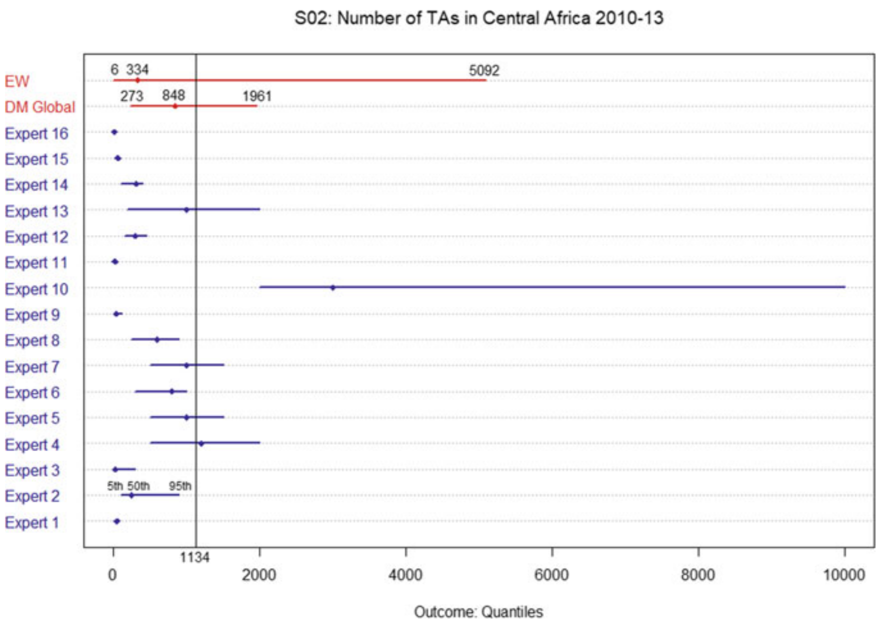

Fig. 21.3 Seed question on number of terrorist attacks in the Central Africa, 2010–2013 (S02)

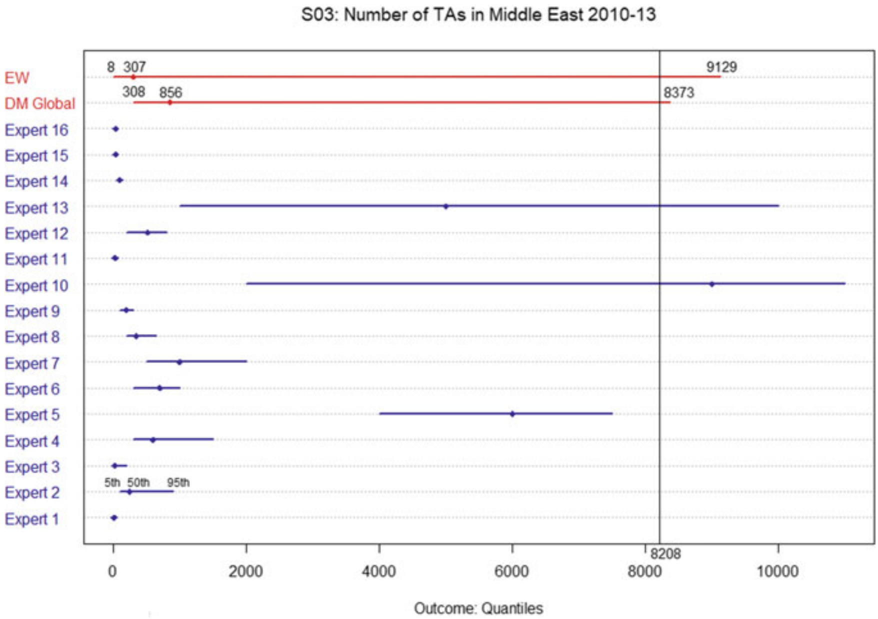

Fig. 21.4 Seed question on number of terrorist attacks in the Middle East, 2010–2013 (S03)

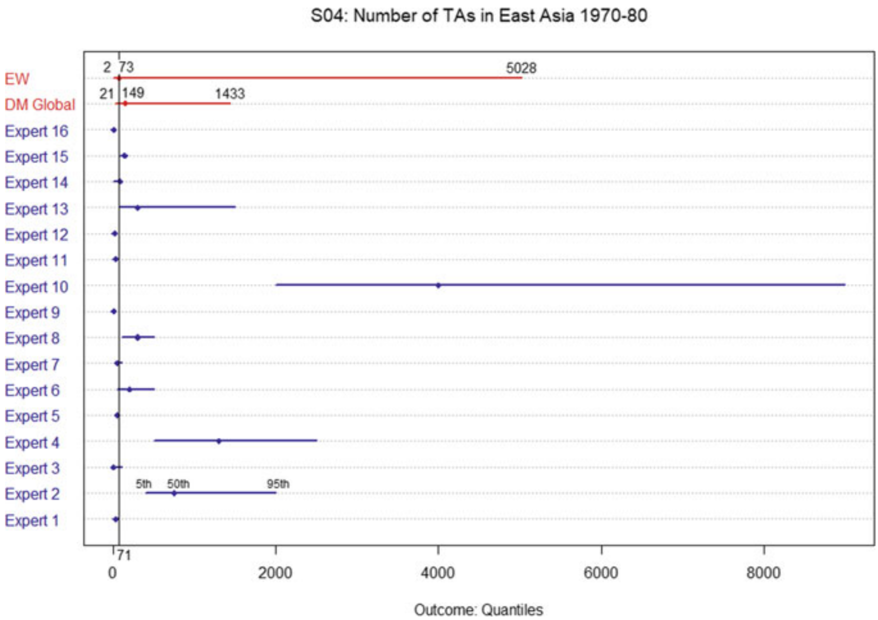

Fig. 21.5 Seed question on number of terrorist attacks in the Middle East, 2010–2013 (S04)

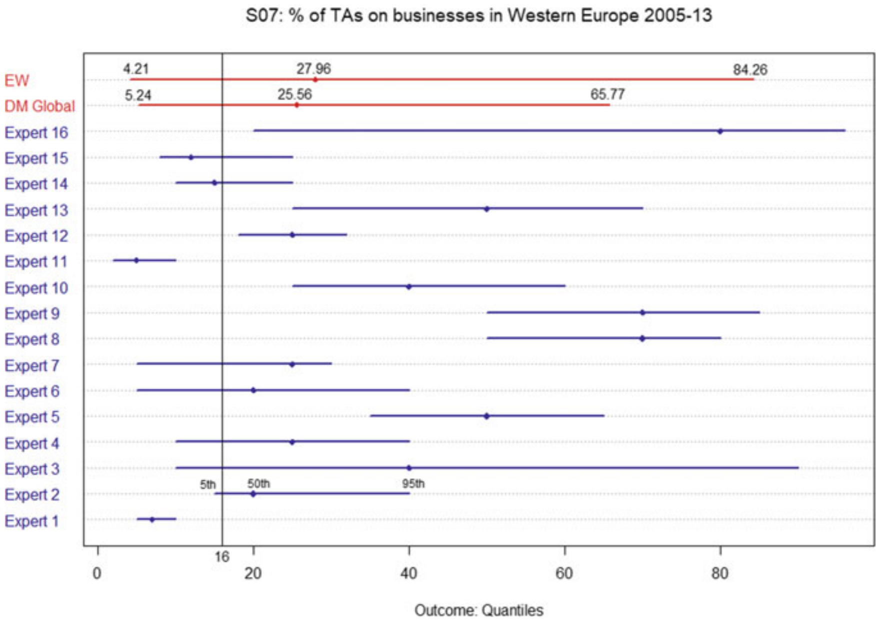

Fig. 21.6 Seed question on percentage of terrorist attacks in Western Europe, 2010–2013, targeting businesses (S07)

95th quantile and the median is given by the dot between the two ends. This is shown exemplary for all assessments for *Expert 1*'s distribution. The realisation is shown through the vertical line.

For the first three seed questions on terrorist attacks' frequencies, S01 – S03 (Fig. 21.2, 21.3 and 21.4), we observe that most experts' assessments are within the same range and that most distributions are narrow. In other words, we see that most experts are confident in their assessment. Nevertheless, several experts (*Expert 1, 3, 9, 11, 12, 14, 15* and *16*) do not include the actual realisation in any of these three questions as a result.

In contrast, *Expert 10* provides for all three questions large uncertainty bounds. Nevertheless, the realisation is missed for the first two, S01 – S02 (Fig. 21.2 and 21.3), and only includes it for the third seed question, S03 (Fig. 21.4).

The remaining experts adjust their assessments more often for each question and include the realisation more often.

The fourth seed question, S04 (Fig. 21.5), is part of a set of questions modifying the year range, in which terrorist attacks happened, for a particular region, in this case *East Asia*. We observe that most experts include the realisation for this 10-year period, even though several experts' assessments have, again, narrow uncertainty ranges.

Seed question S07 (Fig. 21.6) is exemplary for the questions which elicit the percentage of attacks that aim at specific target types, in this case *businesses*. We see

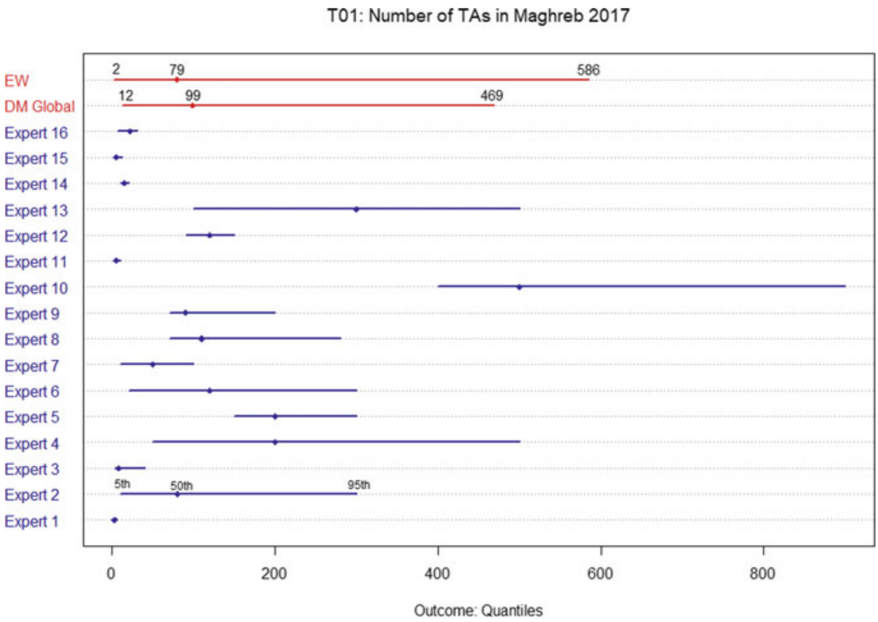

Fig. 21.7 Target question on number of terrorist attacks in the Maghreb region, 2017 (T01)

that the assessment of seven experts includes the realisation whereas one of these experts (*Expert 3*) is not informative in her/his assessment due to the wide uncertainty bounds given.

Next, Figs. 21.7 and 21.8 show the experts' assessments of the target questions together with the aggregated results (EW and DM) exemplary for the first and last target question, T01 and T08. All other target question results (for terrorism risk) are provided in Appendix 21.9.

Considering that the magnitudes on the horizontal axis change for each figure, we can see that the assessments are overall the most informative for *East Asia*. In the complete overview, we observe that they are also informative for *Eastern Europe*, *Central Asia*, *Western Europe* and *South East Asia*. This means that the experts overall are more confident about their prediction with regard to these regions. In contrast, the uncertainty is highest (again, among all experts) for the regions of *Middle East*, *Central Africa* and *Maghreb*.

Across the experts, we observe that similarly to the earlier seed questions (S01 – S03) the same expert (*Expert 10*) provides the widest uncertainty ranges with other ones (e.g. *Expert 4*) providing similarly uncertain judgements only for certain regions. Some experts (*Expert 1, 11, 14, 15* and *16*) consistently give narrow distributions for the target questions whereas their assessments are also the narrowest for the seed questions.

This difference in the experts' uncertainty ranges has implications on the aggregated results. As such, we see that for all target variables the performance-based

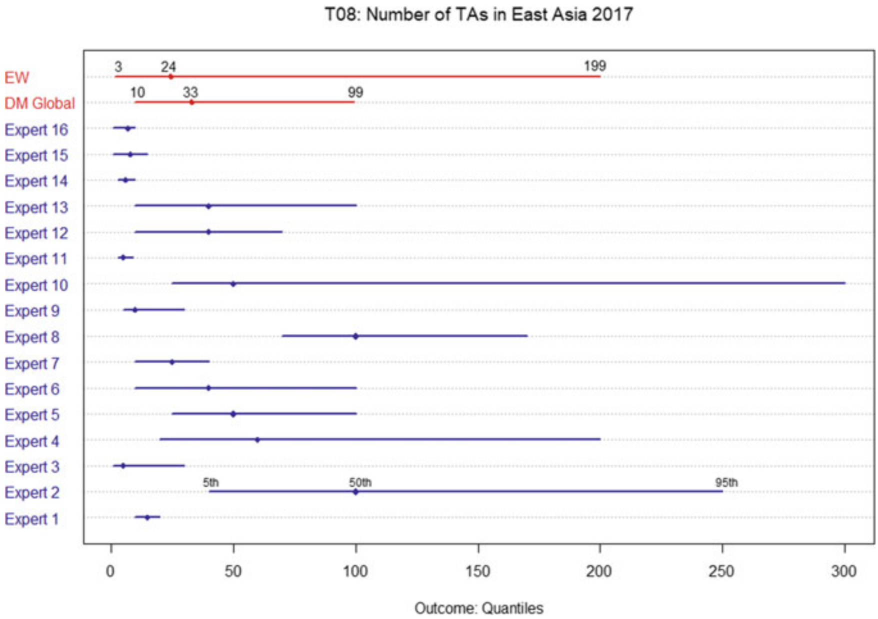

Fig. 21.8 Target question on number of terrorist attacks in the East Asia, 2017 (T08)

combination is more informative than the equal-weighted result. For all but one target question (T03 on the *Middle East*) this difference might be even regarded as considerable. The resulting median assessments of both types of combinations on the other hand are mostly in agreement. This is a frequently observed benefit of the Classical Model (Quigley et al. 2018), i.e. that the performance-based combination typically yields pooled assessments which are more informative than the result obtained by equally weighting judgements while being at least as statistically accurate.

21.6 Alternative Seed Questions for Adversarial Risk Problems

The seed questions used in the elicitation all consider the number of terrorist attacks directly or are based on that, for example, in form of a percentage or change (yearly difference). Nevertheless, in the dry-run of the elicitation, five additional, alternative seed questions were still included. While these were not used further in the later elicitation nor the weighting of experts, they served to test out other seed question types. This is important as we have less experience with using expert judgement methods and the Classical Model in adversarial risks contexts and there is indication that it is cognitively more complex to assess. In future applications, we might take the findings of this section as a basis for developing robust seed question when adversaries are a consideration.

The alternative seed questions were mainly on (1) potential contributing factors of terrorist attacks and SR & CCs which would be commonly included in models, e.g. as exogenous variables and (2) factors and conditions impeding a terrorist attack or SR & CC event.

Regarding the first, several research findings suggest that a relation of climate change to geo-political risks exists (Burke et al. 2014; Barnett 2018) (even though opposing views are also worth mentioning, such as Salehyan 2008 and Theisen et al. 2013). Therefore, a first alternative seed question on this relationship was as follows:

> A meta-analysis of studies that examine populations in the post-1950 era suggests that there is a clear statistically significant influence of climate on modern conflict (Burke et al. 2014). Large potential changes in precipitation and temperature regimes are projected for the coming decades with locations throughout the inhabited world expected to warm by +2 to +4 standard deviations (SDs) by 2050.
> According to Burke et al. (2014) analysis, what would be the percentage increase in the median frequency of intergroup conflicts due to a +1 SD change in climate toward warmer temperatures?
>
> 5%ile: ________ 50%ile: ________ 95%ile: ________

With a similar reasoning, the potential impacts of climate change in the form of resource scarcities are also commonly linked to geo-political risks, mostly with regard to water and food (Hendrix and Brinkman 2013). Hence, another alternative seed question concerned the number of food riots in certain regions of the world over specific time periods.

These alternative seed questions were regarded as cognitively complex, in particular the first one including standard deviations, while the link to geo-political risks was judged as not clear enough. In future, it might be still worth trying out more seed question of this kind, however, new findings in the relevant literature need to be included and possibly new training and framing methods should be considered.

A particular aspect of terrorism in this regard is *stochastic terrorism*. It is commonly defined as acts of violence by random extremists (often "lone wolfs"), motivated and ultimately triggered by political demagoguery in the mass media (Keats 2019; Hamm and Spaaij 2017). Keats (2019) provides the example of US president Trump *tweeting* a video of himself smashing the CNN logo which the Trump fan Sayoc might took as a motivation for supposedly mailing a pipe bomb to the broadcaster's headquarters. That is, while the attackers are not directly guided, nor provided with resources, to commit terrorist attacks, their attacks are motivated by messages in the media (whether intended as such or not). In other words, they are individually unpredictable, however, their motivating events can be observed and considered similarly as the above as contributing factors.

The seed questions on factors and conditions impeding the success of a terrorism attack or SR & CC event were on the number of military capacities of certain countries and state unions together with the capabilities of the respective national intelligence agencies.

While the connection to geo-political terrorism and SR & CCs risk was clear, in future for these seed question types to be more useful, we should consider two key principles of terrorism risk modelling that stem from the role of security and which Woo (2017) discusses in more detail.

The first is that "target substitution displaces terrorism threat". As terrorist will choose the easier of two similar targets, all terrorist targeting is relative and increasing security efforts for one possible target will often increase the likelihood of other, similar targets. As such, we cannot elicit the likelihood of one particular target in isolation. This is important when eliciting terrorism risk for specific targets on a local scale, for instance, a certain city and its main focal points of infrastructure or places of publicity relevance, but it might be also extended to the global level we have been looking at in this elicitation. That is, for the regions of Fig. 21.1 we need to consider whether additional security efforts have an impact on making other regions more attractive for attacks or whether the terrorist groups active in one particular region only focus on these locally without an interest or the resources for diverting to other countries (targets).

The second principle is that "terrorists follow the path of least resistance in weaponry". Similar to the previous principle, in an elicitation it is important to consider whether an increase in one target's security makes other targets more attractive due to less resistance. Again, this might be extended to the spatial level of this elicitation.

We should include the above principles, for example, by decomposing seed questions, on the resource capabilities and on terrorists' responses to likelihoods of defender actions, in order to account for the relative nature of targeting.

Both types of alternative seed questions will be important in future elicitations on adversarial risk and show the importance of closely following new developments and findings in modelling of terrorism and SR & CCs events. This will ensure that future possible seed questions are suitable and capture experts' knowledge on adversarial risk appropriately.

21.7 Conclusions

In this chapter, we have presented and discussed an expert judgement elicitation for geo-political risks. The adversarial nature of these risks poses a particular challenge for experts and hence their quantification. This study shows one of the first applications of structured expert judgement for adversarial risk and as such we point out several learnings from it to conclude the chapter.

First of all, we have seen that it is sensible to apply the Classical Model in adversarial settings, in particular as appropriate seed questions, a core element of the method can be found even for these types of problems. Overall, the experts' performances on the seed questions show that we can identify experts onto whom we can base the performance-based combined assessment sensibly to yield a more informative (while statistically accurate) distribution for our target variables than achieved with an equal-weight aggregation. When applying the Classical Model within a new application area, it might be problematic if no sensible seed questions can be found for which the experts feel comfortable making assessments or for which we obtain only poor calibration and informativeness scores.

A consideration for future elicitations on terrorist attacks, but also SR & CC events, with regard to the seed questions is the aforementioned importance of defining our events of interest appropriately. Some of our experts provided feedback that they agreed with our definitions of terrorist attacks and SR & CC events, however, also pointed out that other ones are possible and depending on these an assessment can vary considerably. An example is whether we consider only terrorist attacks with casualties or also ones without them. Depending on the region, the former might be considerably lower than the latter.

For some regions, such as the Middle East, we have seen that most experts provide wider uncertainty bounds. In these cases, it might be of interest to include a more rigorous structuring part of experts' knowledge and beliefs about future scenarios in future elicitations. In a related elicitation on the dependence between these regions' frequencies of terrorist attacks (Werner et al. 2018), we have used a structuring method prior to a quantitative elicitation. While the method used is for dependence assessments through exploring conditional scenarios, a similar method could be used also when eliciting marginal distributions (at least for regions with higher uncertainty).

When not only considering the frequency of terrorist attacks and SR & CCs but also the severities in future elicitations it is important that we account for the fat-tailed distributions, often approximated by a power law. This can provide further challenges for experts, however, if dealt with in a structured manner, expert judgements provide an important source of information in particular when, e.g. machine learning methods do not have enough training data (Werner et al., 2017).

Lastly, our experts had all similar experiences by working in the same industry for several years. When eliciting uncertainty from experts on adversarial risk, it might enhance the elicitation results and the discussion thereof if including other types of experts, such as terrorism experts from academic institutions or journalism.

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21.8 Appendix 1

Detailed list of regions from seed and calibration variables

In detail, the regions of interest for the seed and target questions are as follows:

Maghreb: Algeria, Libya, Mauritania, Morocco, Tunisia

Central Africa (mainland): Benin, Burkina Faso, Burundi, Cameroon, Central African Republic, Chad, Congo, Djibouti, DR Congo, Equatorial Guinea, Eritrea, Ethiopia, Gabon, Gambia, Ghana, Guinea, Guinea-Bissau, Ivory Coast, Kenya, Liberia, Mali, Niger, Nigeria, Rwanda, Senegal, Sierra Leone, Somalia, South Sudan, Tanzania, Togo, Uganda, Western Sahara

Middle East: Bahrain, Egypt, Iran, Iraq, Israel, Jordan, Kuwait, Lebanon, Oman, Qatar, Saudi Arabia, Syria, Turkey, United Arab Emirates, Yemen

Eastern Europe: Albania, Bosnia-Herzegovina, Bulgaria, Croatia, Cyprus, Czech Republic, Estonia, Greece, Hungary, Latvia, Lithuania, Macedonia, Moldova, Montenegro, Poland, Romania, Serbia (and Montenegro), Slovakia, Slovenia

Western Europe: Austria, Belgium, Denmark, Finland, France, Germany, Iceland, Ireland, Italy, Luxembourg, Malta, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom

Central Asia: Armenia, Azerbaijan, Belarus, Georgia, Kazakhstan, Kyrgyzstan, Russia, Tajikistan, Turkmenistan, Ukraine, Uzbekistan

South East Asia: Brunei, Cambodia, East Timor, Indonesia, Laos, Malaysia, Myanmar, Palau, Papua New Guinea, Philippines, Thailand, Vietnam

East Asia: China, Japan, Mongolia, North Korea, South Korea, Taiwan.

21.9 Appendix 2

Target variables elicitation results of other regions

The other region's target variable elicitation results are (Figs. 21.9, 21.10, 21.11, 21.12, 21.13 and 21.14):

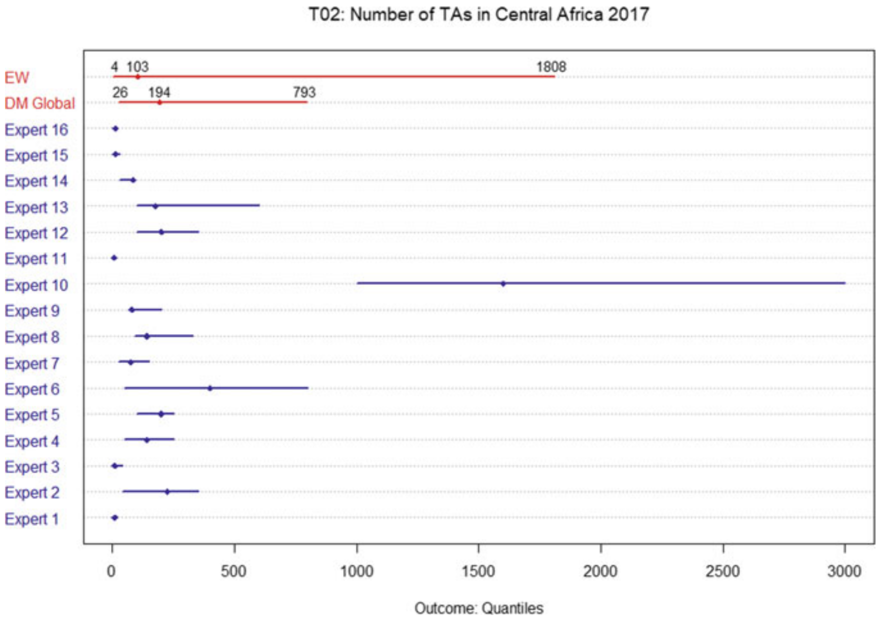

Fig. 21.9 Target question on number of terrorist attacks in Central Africa, 2017 (T02)

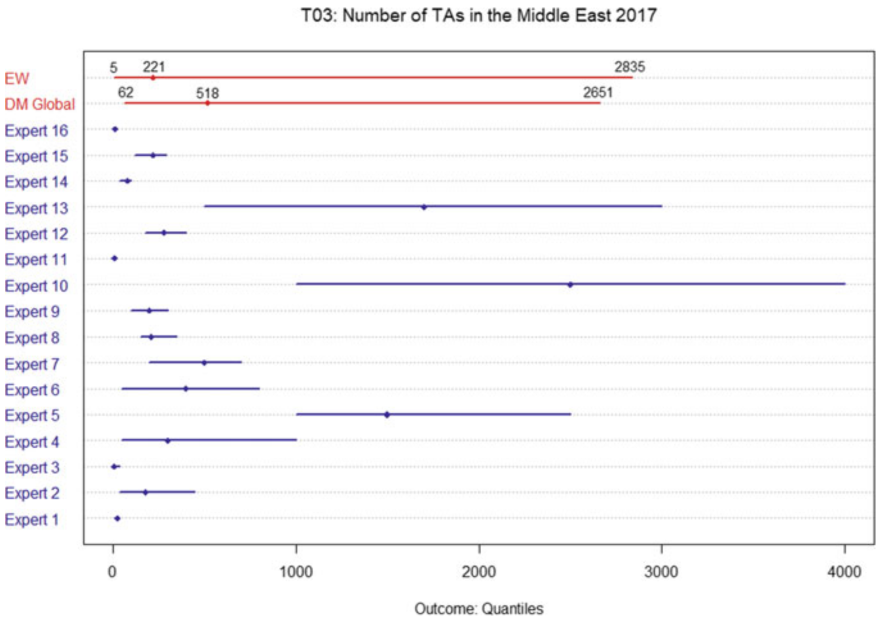

Fig. 21.10 Target question on number of terrorist attacks in the Middle East, 2017 (T03)

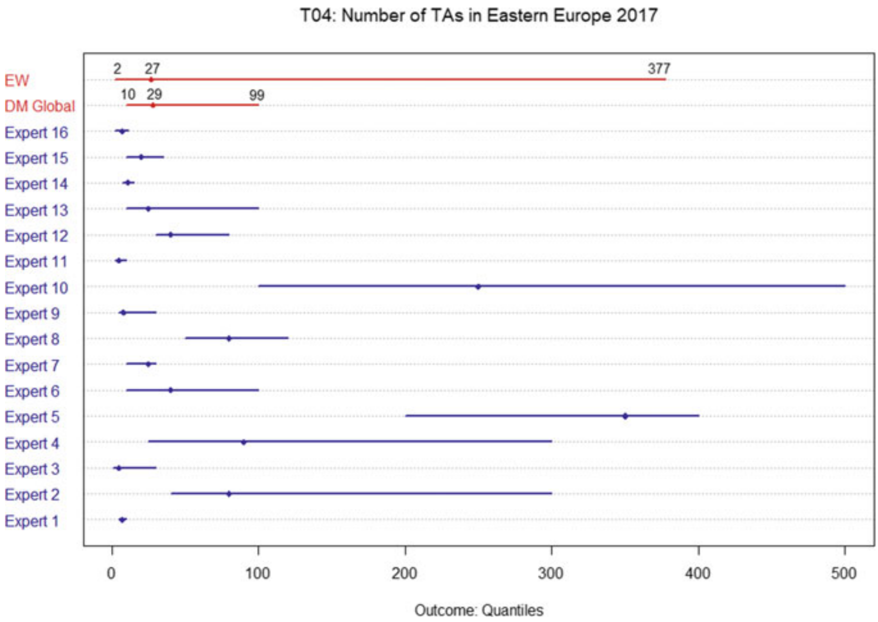

Fig. 21.11 Target question on number of terrorist attacks in Eastern Europe, 2017 (T04)

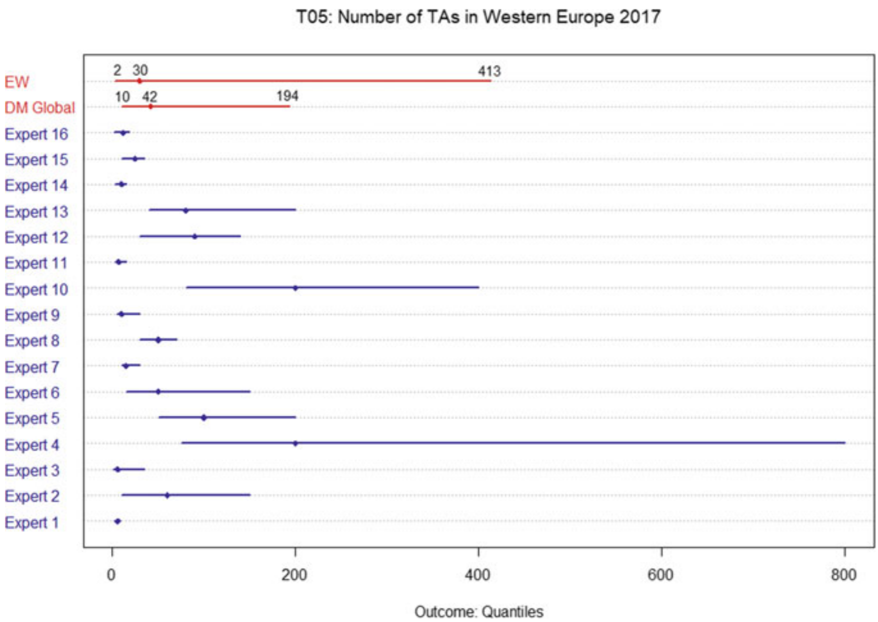

Fig. 21.12 Target question on number of terrorist attacks in Western Europe, 2017 (T05)

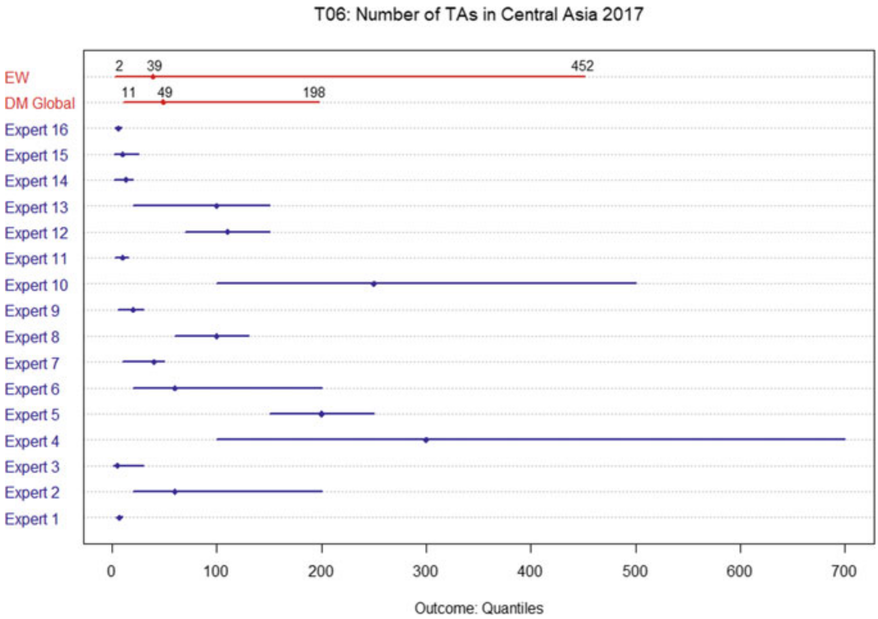

Fig. 21.13 Target question on number of terrorist attacks in Central Asia, 2017 (T06)

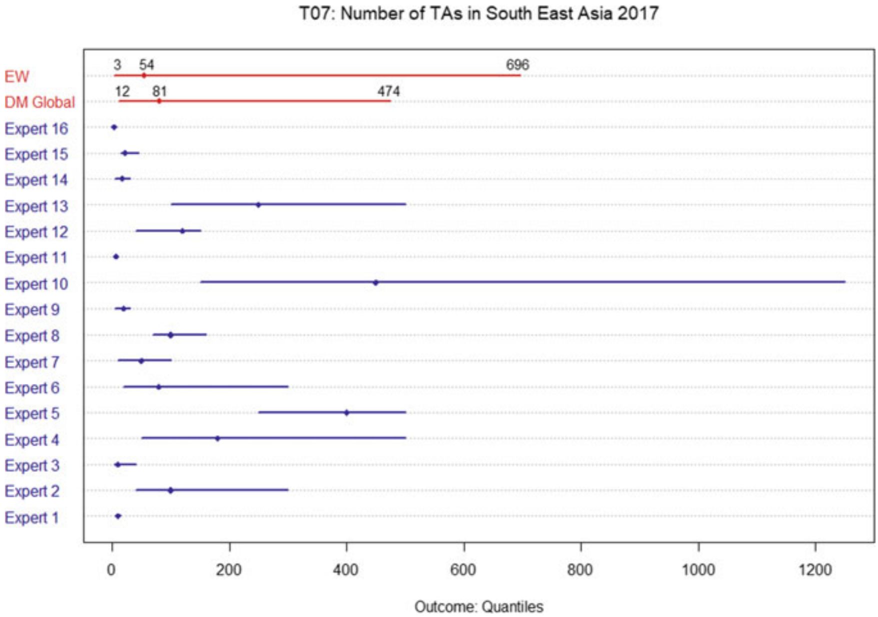

Fig. 21.14 Target question on number of terrorist attacks in South East Asia, 2017 (T07)

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