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COMBINING SIMULATION WITH A BIASED-RANDOMIZED HEURISTIC TO DEVELOP PARAMETRIC BONDS FOR INSURANCE COVERAGE AGAINST EARTHQUAKES

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ABSTRACT

The social and economic impact of natural catastrophes on communities is a concern for many governments and corporations across the globe. A class of financial instruments, parametric hedges, is emerging in the (re)insurance market as a promising approach to close the protection gap related to natural hazards. This paper focuses on the design of such parametric hedges, which have the objective of maximizing the risk transferred subject to a budget constraint. With Greece as a case study, one of the most seismic prone European regions, with limited seismic insurance penetration, this paper proposes a biased-randomized algorithm to solve the optimization problem. The algorithm hybridizes Monte Carlo simulation with a heuristic to generate a variety of solutions. A simulation stage allows for analyzing the payout distribution of each solution. Results show the impact of the problem resolution on the transferred risk and on the distribution of triggered payments.

1 INTRODUCTION

Large-scale seismic events occurred in recent years have re-emphasized the important role of insurance as a mitigation strategy (Franco 2014). When large-scale catastrophic events occur, such as the liquefaction damages experienced in the 2010-2011 New Zealand seismic events (King et al. 2014), traditional insurance policies may become cumbersome to process, whereas insurance payments maybe urgently required to prompt the recovery process. The large number of simultaneous claims and the associated damage inspections typically require a long time to process, in the order of months, or even years. The frequent delays and subjective nature of the claims approval process associated with traditional earthquake insurance has increased the need for alternative products. Simulation models have been used in the past to analyze the impact that seismic events might have over critical infrastructures, such as electric or gas networks (Portante et al. 2009; Portante et al. 2010). This work combines simulation techniques with biased-randomized algorithms (Grasas et al. 2017) in order to investigate the performance and computational burdens of an emerging category of parametric catastrophe hedges, which are designed to help closing the protection gap in the natural hazard insurance market (Guy Carpenter 2014; Guy Carpenter 2017).

This work focuses on parametric hedges for earthquake hedges. As presented in Franco et al. (2018) and Franco et al. (2019), the region of interest is divided into a set of cubes and each cube is assigned a threshold earthquake magnitude. If an earthquake happens in the region of interest and its magnitude attains or exceed the threshold magnitude in the cube that contains the event hypocenter, insurance payments are triggered without the need for a lengthy claim evaluation period. Such a parametric trigger mechanism has the advantage of transparency, and can be tailored to the clients' budget. As such, they could conceivably be sold in the financial markets as catastrophe (cat) bonds, derivatives (Cummins 2008), or as (re)insurance. One disadvantage of parametric insurance policies is that they exhibit high basis risk, i.e.: *(i)* agreed upon payments may be triggered with an event causing insignificant or limited damage; or *(ii)* no payments may be triggered despite the occurrence of a seismic event causing damage (Franco 2010; Franco 2013). Hence, the aforementioned magnitude thresholds need to be configured carefully, in a way such that the transferred risk is maximized without exceeding a limiting budget (Calvet et al. 2017). For solving the underlying optimization problem, this paper proposes a biased-randomized heuristic algorithm (Figure 1). The proposed biased-randomized algorithm combines Monte Carlo simulation with a heuristic procedure to generate multiple solutions of optimization problem, with different characteristics. The most 'promising' solutions are then evaluated throughout a second simulation stage that takes into account the stochastic nature of the underlying seismic model adopted. This allows for analyzing the payout distribution associated with each proposed solution. In particular, since any earthquake event tends to have a very low annual rate, the triggered payments within any given year will exhibit a very large level of variance. As such, the payout distribution of a parametric catastrophe bond is of high interest to policy holders and policy providers during contract negotiations. In this work Monte Carlo simulation is used both during the solution-generation procedure and to asses the payment distribution of each promising solution. In the next section, the conceptual approach of parametric hedges is presented. Section 3 describes the underlying optimization problem, while Section 4 and Section 5 present the algorithm which leads to its solution. As an example, the proposed algorithm is applied to Greece in Section 6. Section 7 draws the conclusions.

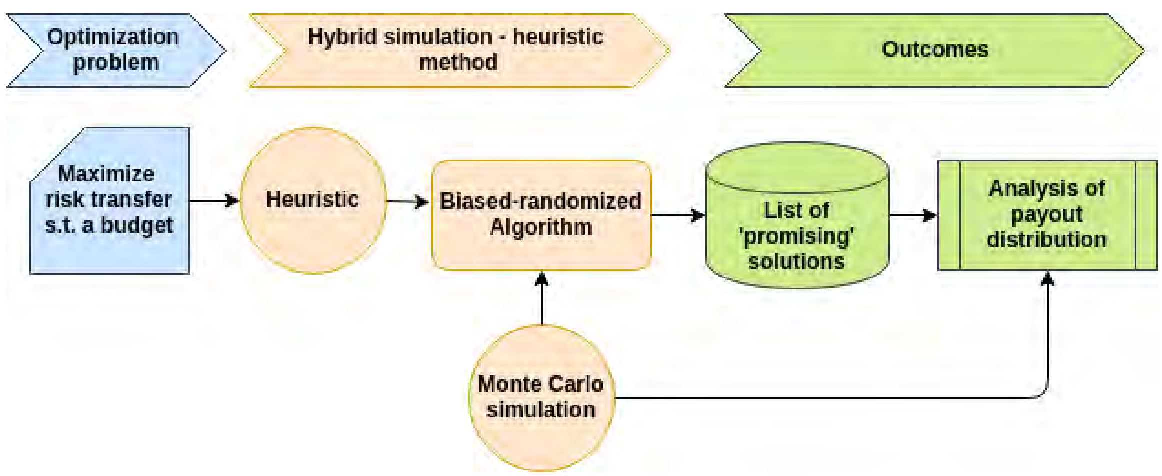

Figure 1: A visual schema of our hybrid simulation - heuristic method.

2 CONCEPTUAL APPROACH

Following Franco et al. (2018), Franco et al. (2019), the parametric insurance considered in this work is based on dividing the Earth's crust into cubes, where each cube is defined by minimum and maximum values of longitude, latitude, and depth. Each cube is assigned a threshold magnitude. If an earthquake occurs inside that cube (i.e., the hypocenter is located inside the cube), and the magnitude of the earthquake is greater than or equal to the magnitude threshold of that cube, the insurance policy is executed and the agreed upon payments made. Information about location of the hypocenter and the magnitude of earthquakes is publically available in near-real-time from trusted sources, such as the U.S. Geological Survey (https://www.usgs.gov/) (Wald and Franco 2016; Wald and Franco 2017). This cube-based parametric structure is outlined in Franco (2013) and it is defined via a "payment table" that is both easy to understand for the policy holder and transparent with respect to the necessary conditions under which payments are triggered. The resolution of the grid and threshold magnitudes creates an environment in which basis risk can be minimized whilst transferred risk is maximized. In particular, a fine resolution grid in both the horizontal and vertical direction will be able to capture site amplification effects, such as basin effects, and deep fault mechanisms, such as crustal subduction. Data regarding the rates of earthquakes of different magnitudes and the associated losses is available from existing earthquake catastrophe models –such as those developed by AIR Worldwide (https://www.air-worldwide.com/) or similar companies. For instance, Lohmann and Yue (2011) describes techniques and underlying assumptions typically employed in the building of catastrophe models. These data are used as inputs for the optimization problem of selecting threshold magnitudes for each cube. The underlying optimization problem consists in selecting the threshold magnitudes for each cube, such that transferred risk (financial value of losses caused by trigger events multiplied by the probability that such events occur, i.e. occurrence rate) is maximized under a budget constraint (based on the total trigger rate). Different thresholds correspond to different trigger rates and risk levels for each cube. In this work, we propose a solving approach based on a biased-randomized algorithm. With a calculated upper bound on the maximum risk that can possibly be transferred as a reference point, we then perform simulation experiments of the parametric solutions generated by the biased-randomized algorithm.

The results of these experiments illustrate the impact of grid resolution on the risk that can be transferred and on the distribution of triggered payments. A fine resolution grid typically allows for higher levels of transferred risk as they allow the threshold magnitudes to vary more precisely in response to local changes in seismicity. However, this also increases the size of the optimization problem, which severely limits the use of exact optimization methods. Our biased-randomized algorithm can solve large-sized instances and randomization means it can be used to generate an array of alternative solutions. Despite transferring similar amounts of expected risk, alternative solutions may have fundamentally different payout distributions, as the simulation experiments will reveal. Such an approach adds to the potential for developing personalized parametric insurance policies. Moreover, the biased-randomized algorithm also allows for obtaining a set of strong candidate solutions, whose sensitivity under earthquake event uncertainty could also be analyzed using simulation. This work proposes a method for deriving a set of strong candidate solutions from those generated by the biased randomization algorithm. The method takes into account the results of the simulation analysis, including the payout distribution.

3 THE STOCHASTIC OPTIMIZATION PROBLEM

This section provides a more formal description of the stochastic optimization problem being considered. Our main goal is to maximize the total risk transferred subject to a maximum rate threshold (budget constraint). The risk associated with an earthquake event of a particular magnitude in a given region is defined as the product of the loss caused by that earthquake event and the rate associated with that earthquake event. The total risk is then the sum of the risk associated with all possible earthquake events within the region of interest. The risk associated with a particular earthquake event is transferred via parametric earthquake catastrophe hedge if the threshold magnitude associated with the cube in which that earthquake might occur is lower or equal to the magnitude of the earthquake event. As such, the aim is to select threshold magnitudes –for each cube of an earthquake catastrophe hedge– such that the total transferred risk is maximized whilst the sum of the rates of earthquake events with magnitudes attaining or exceeding the threshold magnitude of the cubes containing their hypocenters do not exceed the total maximum rate, i.e., the client's budget.

Let $C = \{1,2,\ldots,n\}$ represent a set of n cubes, and E_i the set of earthquake events associated with cube $i \in C$. These events might be collected from historic earthquakes or from stochastic catalogs obtained via commercial models. For some cube $i \in C$, let $e \in E_i$ denote a single element of data, i.e., an observed earthquake of magnitude m_e with hypocenter inside cube i, where $m_e \in (0,10)$ according to the Richter scale (Boore 1989). Let L_e denote the loss associated with observation e, and let R_e denote its rate of occurrence. Notice that both the loss and the occurrence rate will be random variables in most real-life applications. This work accounts for earthquake occurrence rate uncertainty via a Monte Carlo simulation analysis. Given a cube $i \in C$, let $D_i = \{m_e \mid e \in E_i\}$ denote the set of permissible trigger magnitude thresholds for cube i. Let $x_i \in D_i$ denote the 'trigger' magnitude, i.e., the minimum magnitude actually covered by the insurance for cube i (these x_i are the decision variables). Finally, let $E_i^+ = \{e \in E \mid m_e \geq x_i\}$, that is, the set of trigger events given the cubes threshold magnitude. Based on this data, in this case generated from a commercial model, the total transferred risk f can be computed as follows:

$$f = f(x_1,x_2,\ldots,x_n;L_e,R_e) = \sum_{i=1}^{n} \sum_{e \in E_i^+} L_e \cdot R_e$$

Also, the expected value for the total trigger rate is computed as follows:

$$g = g(x_1,x_2,\ldots,x_n;R_e) = \sum_{i=1}^{n} \sum_{e \in E_i^+} R_e$$

Hence, the goal is to maximize the expected value of the total risk transferred:

$$\max E\left[f(x_1,x_2,\ldots,x_n;L_e,R_e)\right]$$

Subject to the following budget constraint:

$$g(x_1,x_2,\ldots,x_n;R_e) \leq r_{max}$$

where r_{max} is the threshold total rate of qualifying events occurring within a year (i.e., a budget that limits the maximum number of events that can be covered). It is low values of r_{max} that will make such catastrophe bonds attractive for investors, but also reduce the potential returns. The total rate of qualifying trigger events is calculated by summing the rates of earthquakes with magnitudes over x_i for each cube under consideration.

4 A BIASED-RANDOMIZED ALGORITHM FOR SOLVING THE PROBLEM

Biased-randomization techniques propose the use of skewed probability distributions and Monte Carlo simulation to introduce non-uniform randomness into a given heuristic (Faulin and Juan 2008). These techniques have been successfully applied to solve different combinatorial optimization problems related, among others, to vehicle routing (Faulin et al. 2008; Calvet et al. 2016), vehicle packing (Dominguez et al. 2016), facility location (De Armas et al. 2017), and scheduling (Martin et al. 2016; Gonzalez-Neira et al. 2017). This section provides an overview description of the biased-randomized algorithm we have developed to solve the aforementioned problem. The algorithm is based in a heuristic that starts by setting all cube thresholds to their maximum values. This is the zero risk and zero trigger rate initial solution. The heuristic then generates a candidate list of cube thresholds to lower. This list is sorted according to the loss divided by the rate associated with the next lowest threshold for the cube (instantaneous rate of increase of transferred risk if those cube thresholds are lowered). Following this, a cube threshold is selected randomly from the candidate list according to a skewed probability distribution as described in Grasas et al. (2017). Thus, by combining Monte Carlo simulation to guide the selection process inside the heuristic we transform a greedy constructive process into a probabilistic constructive process. The selection of new cube thresholds continues until no more thresholds can be lowered without violating the total trigger rate constraint. At this point, one iteration of the biased-randomization algorithm has been completed. Repeating this procedure results in different generated solutions due to the incorporation of randomness to the procedure. The previous algorithm is described next with additional low-level details in order to facilitate its implementation:

1. Inputs: Catalogue of possible earthquake events ($E_i\ \forall i \in C$), their associated losses ($L_e\ \forall e \in E_i,\ \forall i \in C$), their rates ($R_e\ \forall e \in E_i,\ \forall i \in C$), and threshold magnitude interval size (Δ_m)
2. For each cube $i \in C$, set the threshold magnitude x_i to the maximum level (i.e., $x_i \leftarrow 9.9,\ \forall i \in C$)
3. Set to zero both the aggregated trigger rate and transferred risk, i.e.: $g \leftarrow 0$ and $f \leftarrow 0$
4. While the trigger rate constraint is not violated (i.e., while $g \leq r_{max}$), do the following:
   (a) Generate a list of cubes $i \in C$ whose threshold magnitudes can be decreased by one level without violating the trigger rate constraint
   (b) Sort the list of candidate cubes according to the following criterion (from higher to lower values): $(l_{i^-})/(r_{i^-})$, where l_{i^-} represents the expected loss associated with lowering one level the current value of x_i, and r_{i^-} represents the expected rate associated with lowering one level the current value of x_i. In other words, this criterion measures the instantaneous rate of increase in risk transfer due to lowering the threshold magnitude of cube i with respect to the corresponding increase in trigger rate
   (c) Select a cube c from the candidate list using a biased skewed distribution, thereby introducing a biased randomization into this greedy procedure
   (d) Lower the threshold magnitude of the cube c and update the total trigger rate and risk transfer, i.e.: $g \leftarrow g + r_{c^-}$, $f \leftarrow f + r_{c^-} \cdot l_{c^-}$ and $x_c \leftarrow x_c - \Delta_m$
5. Return $(x_1, x_2, \ldots, x_n)$, g, and f

We propose this biased-randomized algorithm as an ideal method for generating alternative solutions, which can be presented as candidate solutions to potential policy holders.

5 HYBRID SIMULATION-OPTIMIZATION SOLVING APPROACH

In addition to quickly generating solutions with a close-to-optimal transferred risk, our biased-randomized algorithm can also provide a decision maker with solutions showing unique characteristics. As noticed in Juan et al. (2009), this is an interesting feature that cannot be typically offered by exact methods. In the following, we present an approach for selecting a diverse range of promising candidate solutions, which might be of interest to decision makers. The solutions were generated by the biased-randomized algorithm, and are non-dominated according to the criteria of average transferred risk, the coefficient of variation of the losses associated with simulated years in which at least one cube was triggered, and the first quartile, median, and third quartile of the losses associated with simulated years in which at least one cube was triggered. The approach that was considered for selecting a set of candidate solutions was to take the set of solutions with the minimum and maximum values for the five main criteria described above.

Figure 2 shows a flow chart of the procedure which combines our heuristic with simulation to generate candidate solutions which might be of interest to decision makers. In particular, after each iteration of the biased-randomized algorithm, the generated parametric earthquake insurance policy is tested in simulation to reveal the distribution of triggered payments. Following this, the set of non-dominated solutions is updated. Here, a non-dominated solution is defined as one which has at least one associated performance measure for which another solution in the set does not have a better score. A solution is dominated if it has: *(i)* a lower average transferred risk; *(ii)* a higher coefficient of variation of triggered payments in simulated years in which at least one cube is triggered; or *(iii)* a lower first, second, or third quartile (of the same statistic). Once *maxIterations* iterations of this procedure have been completed, the two methods of selecting diverse sets of alternative solutions are applied.

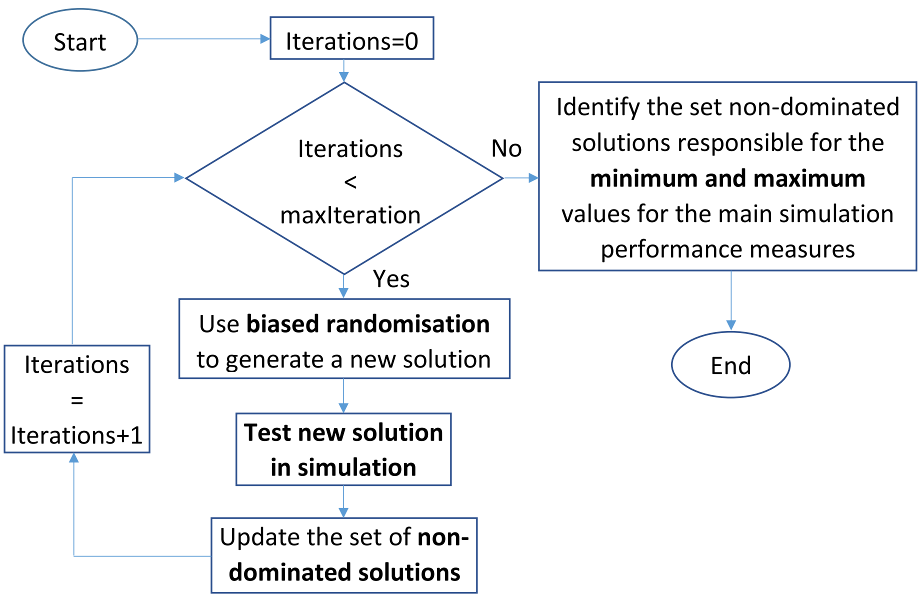

Figure 2: Flowchart of the process of identifying a diverse set of strong candidate solutions.

Figure 3 shows that 9 of the non-dominated solutions out of $1,000$ solutions generated by the biased randomization algorithm were responsible for the minimum and maximum values for the five main criteria. It shows that the characteristics of the non-dominated solutions yielded from the biased-randomization algorithm can vary by a large amount with respect to the five criteria of interest. It also appears to be the case that average risk tends to be negatively correlated with the coefficient of variance of the triggered payments in the year in which at least one cube is triggered. This result simplifies the manager's decision since low variance of triggered payments and high risk transfer are both desirable characteristics. The results for the first, second, and third quartiles of triggered payments indicate, intuitively, that solutions with a high average risk have higher values for this statistics. Likewise, solutions with a lower average transferred risk have lower values for these statistics. This first approach for promising candidate solutions is useful for approximating the full range of solutions that can be generated from the proposed biased randomization algorithm. All in all, high-risk transfer solutions are available, but with different variance characteristics with respect to the coefficient of variation of the losses associated with triggered cubes in $200,000$ simulated years. Whilst the annual rate of a trigger event is constrained to a low value of 0.0095, paying attention to the distribution of triggered insurance claims for the simulated years where at least one cube is triggered might be of interest to an investor or other decision maker.

6 EXPERIMENTAL RESULTS

In this section, the optimization problem is solved for a variety of levels of discretization. The resultant solutions are then subject to long-term simulations that allow to reveal the probability distribution of the covered loss incurred in triggered cubes. A simple upper bound on the total possible risk that can be transferred can be computed by identifying the top ranked earthquake events in terms of risk, which account for as much of the total trigger rate budget as possible. This upper bound can be used to show that the biased randomization algorithm is capable of generating high-quality solutions in terms of risk transfer.

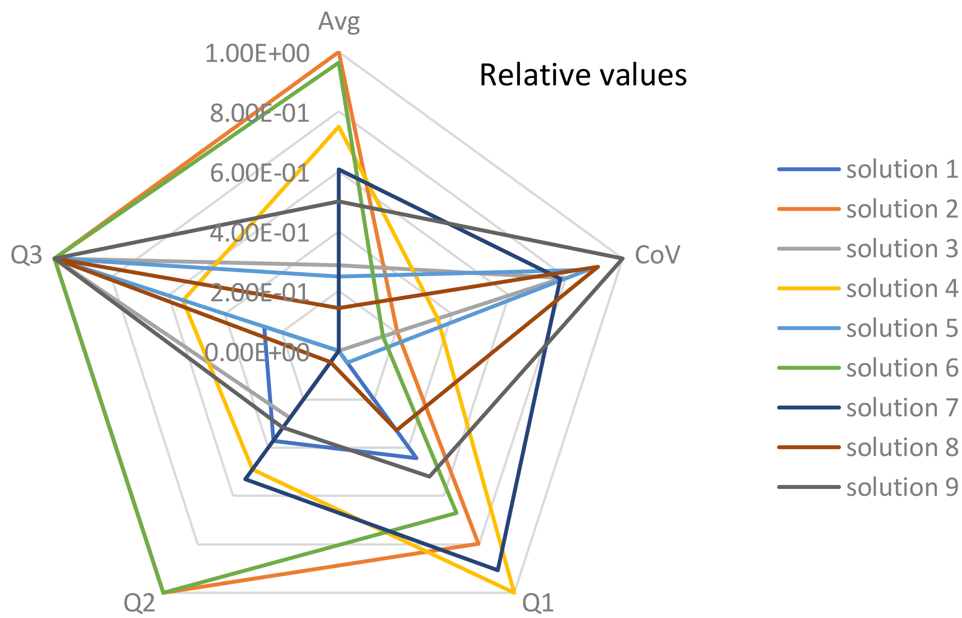

Figure 3: Illustration of variety in important features of solutions generated using biased randomization.

Hence, our approach represents an ideal source of varied solutions, which can provide decision makers with solutions with fundamentally different trigger behaviours.

6.1 Discretization of Earthquake Data

The input data is based on a catalogue of instances of earthquakes occurring in Greece and the immediately surrounding areas. A commercial earthquake catastrophe simulation model was used to generate the data set relevant for this region. The whole data set is designed to capture the distributions of earthquake events that may occur in the target region within one year. For each element of data a latitude, longitude, focal depth, magnitude, and loss are reported. The cube-based trigger mechanism groups earthquakes according to the cube in which they occur.

6.2 Simulation Model for Trigger Policies

In this section the earthquake reinsurance parametric trigger simulation is described. One run of the simulation corresponds to simulating a year of waiting for earthquakes to happen in each cube. Within any given populated region, earthquake rates are rare events, specially for earthquakes within narrow ranges of magnitudes. Since the maximum trigger rate used in this work is approximately once every 100 years, the simulation has to be repeated a large number of times in order to get an accurate estimate of the distribution of triggered payments. In this work, unless otherwise stated, $1,000,000$ years are simulated. This value provides total trigger rates and transferred risk estimates, which agree closely with the corresponding parameters of the r_{max} and objective value (3), respectively. A pseudo-code of this procedure is provided next:

1. Inputs: $(x_1, x_2, \ldots, x_n)$ (threshold magnitudes for each cube as generated by the heuristic-based procedure), catalogue of possible earthquake events (E_i $\forall i \in C$), their associated losses (L_e $\forall e \in E_i,\ \forall i \in C$), and their rates ($R_e$ $\forall e \in E_i,\ \forall i \in C$)

2. Set $totalCoveredLosses \leftarrow 0$
3. For each cube $i \in C$:
   (a) If $uniformRand(0,1) < \sum_{e \in E_i | m_e \geq x_i} R_e$
   (b) Then $totalCoveredLosses \leftarrow totalCoveredLosses + \sum_{e \in E_i | m_e \geq x_i} L_e$
4. Return: $totalCoveredLosses$

The inputs of the simulation model are the threshold magnitudes for each cube, the catalogue of possible earthquake events, their associated losses and rates. In each run of the simulation we generate a uniform random number and compare it to the probability that a trigger event occurs in that cube within one year. The probability of a trigger event in a given cube is computed as the sum of the rates of the potential earthquake events in that cube, as far as its associated magnitude reaches the threshold magnitude for that cube. If the generated random number is less than the trigger probability for that cube, a trigger event is registered and the associated covered losses are recorded. For each simulated year, a total covered loss value is recorded. In this work, we use simulation to validate the solutions generated by the biased randomization algorithm with respect to the total expected transferred risk and total trigger rate. Additionally, the distribution of total covered losses that occur in years in which at least one trigger event occurs are of high interest. This is because the relatively low total trigger rate constraint means that years in which trigger event do occur will exhibit total covered losses far in excess of the corresponding expected total covered losses / expected total risk transfer. This, again, is an important consideration for decision makers.

6.3 The Effect of the Level of Cube Discretization

As an example, we apply the proposed algorithm to the case of Greece, among the most seismic prone regions in Europe, nonetheless characterized by limited seismic insurance penetration. The region of interest extends for 15 longitude and 13 latitude degrees, and 100 km of depth. The control problem for our application divides the region of interest into 26 latitude layers, 30 longitude layers, 2 depth layers, and each cube has 10 possible threshold magnitude levels. This makes a total of $1,560$ cubes and a decision problem with $15,600$ binary decision variables –since one threshold magnitude has to be selected for each cube. The proposed application relies on the AIR Worldwide European Earthquake Model (Catrader v19.1) (Rong et al. 2011; Lai et al. 2012). The following experiment investigates the impact of increasing the fineness of the discretization level associated with: *(i)* the number of cubes per depth layer; *(ii)* the number of depth layers; and *(iii)* the number of threshold magnitudes.

Table 1 shows that increasing the number cubes per depth layer increases the risk that can be transferred. This makes sense when considering that finer cube discretization increases the ability to target high risk areas without also increasing the total trigger rate with low risk events within the same cube. For the largest number of cubes per depth layer, approximately 92% of the maximum possible risk transfer was achieved. Table 1 shows that the results of the model and the simulation results are in close agreement with respect to the average risk transfer and total trigger rate, which can be interpreted as a validation of both the model and the simulation model. The final five columns of Table 1 indicate, at the quartile level, the distribution of the triggered payments in simulated years in which at least one trigger event occurred. From the perspective of the policy provider, this represents the worst case performance of each parametric solution. The first thing to notice is that the losses –which occur in years when at least one trigger event occurs– are far higher than the overall average transferred risk, even in terms of the minimum triggered amounts –let alone the maximum triggered amounts. Since the minimum and maximum non-zero triggered payments that occur in $1,000,000$ simulated years can be considered outliers, an important alternative metric is to consider the difference between the first and third quartile values. In particular Table 1 suggests that larger numbers of cubes per layer decreases the size of this interval, i.e.: in non-zero triggered payment years, the variance of triggered payments is lower for higher numbers of cubes per depth layer. This observation might be interpreted as higher resolution cube grids leading to more robust parametric solutions, where a more robust solution is one for which the triggered payment values are more stable or reliable. The algorithm was implemented as a single threaded Java application. For the case of 30 by 26 cubes per layer each iteration of biased randomisation took 0.82 seconds and 15.23 seconds for the case of 90 by 85 cubes per layer.

Table 1: The impact of increasing the fineness of the discretization of the number of cubes.

			BR	Simulation							
Longitude longitude, intervals	Number of cubes	Decision variables	Average relative risk	Average relative risk	Probability of trigger event	Relative risk distribution for non-zero covered loss simulated years				
						Min	Q1	Q2	Q3	Max
30 , 26	1560	15600	0.736	0.743	0.00956	7.7	35.4	68.0	91.0	461.5
40 , 35	2800	28000	0.831	0.832	0.00948	22.9	54.3	68.4	106.2	304.1
50 , 45	4500	45000	0.851	0.842	0.00945	21.6	52.7	70.3	96.9	572.2
60 , 55	6600	66000	0.886	0.867	0.00926	28.0	57.0	69.5	97.0	462.8
70 , 65	9100	91000	0.895	0.903	0.00955	33.3	55.7	71.0	92.7	450.2
80 , 75	12000	120000	0.927	0.933	0.00942	40.5	58.1	78.5	94.3	502.3
90 , 85	15300	153000	0.921	0.915	0.00947	32.7	54.9	70.9	94.3	537.3

In comparison to the results of Table 1, Table 2 shows that increasing the number of depth layers is a less effective strategy for increasing the total amount of risk that can be transferred as the maximum relative risk transfer is approximately 85% compared to the 92% that was achieved for the case where the number of cubes per depth layer was increased. The final five columns of Table 2 indicate that increasing the number of depth layers has a similarly negligible impact on the distribution of triggered payments in years where at least one trigger event occurs. The explanation for this result is that, in general, the earthquake events with the largest associated risk tend to be those which occur close to the earth's surface. As such, increasing the number of depth layers only marginally increases the level of control over the trigger thresholds at this important region of the earth's surface. For 1 depth layer one iteration of biased randomisation took 0.52 seconds and 5.60 seconds for 20 depth layers.

Table 2: The impact of increasing the fineness of the discretization of the number of depth layers.

			BR	Simulation						
Depth layers	Number of cubes	Decision variables	Average relative risk	Average relative risk	Probability of trigger event	Relative risk distribution for non-zero covered loss simulated years				
						Min	Q1	Q2	Q3	Max
1	780	7800	0.756	0.754	0.00947	10.8	39.5	72.9	109.2	355.7
2	1560	15600	0.736	0.743	0.00956	7.7	35.4	68.0	91.0	461.5
3	2340	23400	0.729	0.740	0.00957	4.7	44.0	54.5	91.0	313.7
4	3120	31200	0.806	0.801	0.00938	10.8	49.3	78.4	108.1	536.2
5	3900	39000	0.798	0.806	0.00956	13.2	48.0	68.0	91.9	461.5
6	4680	46800	0.800	0.792	0.00940	16.7	47.9	68.0	97.2	333.1
8	6240	62400	0.793	0.787	0.00935	12.5	47.9	68.0	90.1	368.1
10	7800	78000	0.819	0.825	0.00950	13.7	50.2	68.0	101.6	489.9
12	9360	93600	0.809	0.778	0.00910	12.1	50.4	68.0	103.4	477.4
14	10920	109200	0.816	0.811	0.00944	24.1	54.1	69.5	91.9	504.2
16	12480	124800	0.823	0.829	0.00946	29.4	49.9	69.8	94.7	461.7
18	14040	140400	0.839	0.844	0.00943	24.1	49.8	68.0	106.1	611.3
20	15600	156000	0.826	0.817	0.00933	20.9	55.5	70.3	100	527.8

Table 3 shows that increasing the fineness of the discretization of the threshold earthquake magnitudes helps to increase the total risk that can be transferred up to a point. In particular, beyond 20 magnitude intervals there are diminishing returns in terms of further increase in risk transfer. Below 20 magnitude intervals the total risk transfer drops rapidly. The final five columns show that for 20 magnitude intervals or more further increases in the number of magnitude intervals does not fundamentally change the distribution of triggered payments in years when at least one cube is triggered. For 1 magnitude interval one iteration of biased randomisation took 0.97 seconds, and 1.10 seconds for 20 magnitude intervals.

Table 3: The impact of increasing the fineness of the discretization of the threshold magnitude levels.

			BR	Simulation						
Magnitude intervals	Number of cubes	Decision variables	Average relative risk	Average relative risk	Probability of trigger event	Relative risk distribution for non-zero covered loss simulated years				
						Min	Q1	Q2	Q3	Max
1	1560	1560	0.024	0.024	0.00948	0.0	2.6	2.6	2.6	3.6
2	1560	3120	0.552	0.557	0.00953	3.4	21.5	39.5	78.4	329.9
5	1560	7800	0.680	0.681	0.00952	5.7	51.0	55.8	75.7	537.5
10	1560	15600	0.736	0.743	0.00956	7.7	35.4	68.0	91.0	461.5
20	1560	31200	0.791	0.800	0.00956	21.4	48.0	65.3	112.2	384.1
40	1560	62400	0.798	0.802	0.00954	21.3	48.0	67.6	107.3	497.3
60	1560	93600	0.796	0.809	0.00957	22.5	53.8	65.2	96.4	431.9
80	1560	124800	0.803	0.797	0.00940	22.8	50.1	65.2	96.4	308.0
100	1560	156000	0.818	0.825	0.00940	32.2	55.7	70.3	96.4	503.9

All else being equal (control problem configuration), increasing the fineness of the discretization of the depth layers has the least impact on increasing the risk that can be transferred. The fineness of the discretization of the cubes within each depth layer and the set of possible threshold magnitudes are roughly equally as important as each with respect to the total amount of risk that can be transferred. With regard to the overall scalability of the approach, we have solved this problem for data regarding the country of Greece and demonstrated that the proposed algorithm can be solved within a matter of minutes for very fine discretisations, for finer discretisations there are diminishing returns with regard to the achieved total transferred risk.

7 CONCLUSION

In this article we have presented a process to design a type of emerging parametric form of earthquake insurance policy. A biased-randomized constructive algorithm was proposed to solve the underlying optimization problem. This algorithm hybridizes Monte Carlo simulation with a heuristic procedure. Also, a well-defined method for yielding an array of strong candidates to present to policy holders and policy providers was presented. The presented parametric earthquake insurance policies have the advantage of simplicity and transparency in addition to an accelerated claim approval system. This feature is beneficial for the speedy recovery from damages caused by seismic events. Additionally, these parametric solutions lend themselves well as the basis of new financial instruments, which can be traded on the financial markets. The proposed biased-randomized algorithm has the feature that a large collection of candidate solutions can be generated very rapidly. The resulting solutions can then be subject to a simulation analysis in order to estimate their payment distributions. An approach for systematically generating sets of alternative solutions, each with distinct characteristics, was presented. The proposed method yields the solutions responsible for the minimum and maximum values for the main simulation criteria of interest. It was found that, in general, the proposed biased-randomized algorithm generates solutions which exhibit a low variance of triggered payment if the total risk transfer is high. At the same time, these solutions exhibit a high variance of triggered payments if the total risk transfer is low. Such alternative solutions may be of practical value as policy holders and providers both need to agree upon which payment table is selected for their agreement.

In future work, this simulation model will be extended for the case where the input data comes with known parameter value errors. For example, the loss and rate values may have been estimated based on limited data.

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