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Design and assessment of pro-poor financial soft policies for expanding cities

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A R T I C L E I N F O

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A B S T R A C T

Recent major earthquake disasters have highlighted the effectiveness of financial soft policies (e.g., earthquake insurance) in transferring seismic risk away from those directly impacted and complementing 'hard' disaster risk mitigation measures (e.g., structural retrofit). However, the benefits of existing financial soft policies are often not guaranteed. This may be attributed to: (1) their low penetration rate (e.g., in the case of earthquake insurance); (2) the fact that they typically neglect the explicit needs of low-income sectors in (developed and developing) modern societies, who are often disproportionately impacted by natural-hazard driven disasters; and/or (3) their failure to consider the time-dependent nature of urban exposure. We contribute towards addressing these shortcomings by proposing a flexible framework for designing and assessing bespoke, people-centred, household-level, compulsory financial soft policies (including conventional earthquake insurance, disaster relief fund schemes, income-based tax relief schemes, or a combination of these) across cities under rapid urban expansion. The proposed framework leverages the Tomorrow's Cities Decision Support Environment, which aims to facilitate pro-poor disaster-risk-informed urban planning and design in developing country contexts. The framework specifically enables decision makers to strategically design and then assess the pro-poorness of mandatory soft policies, using financial impact metrics that discriminate losses on the basis of income. We showcase the framework using the hypothetical expanding city, "Tomorrowville", successfully identifying pro-poor seismic-risk-related financial soft policies for different instances in the lifetime of the urban system.

1. Introduction

Catastrophic events such as earthquakes can cause substantial direct economic impacts due to physical damage and downtime, in addition to widespread human losses (casualties). Financial ('soft') earthquake risk mitigation measures (e.g., disaster relief funds) aim to protect the assets of individuals or entities from earthquakes by providing monetary compensation for any damages incurred [1,2]. These measures can complement 'hard' disaster risk mitigation measures such as seismic retrofitting [3] and other techniques such as earthquake early warning [4,5].

Earthquake insurance is a well-known soft measure for seismic risk mitigation. A typical residential earthquake insurance policy provides homeowners with coverage for direct physical damages to properties caused by an earthquake event. The insurance premium, i.e., the price paid by the insured to the insurer, can consist of (1) a flat rate for everyone [6,7]; or (2) a risk-based rate determined on building structural type, building location, building replacement cost, etc [8,9]. Residential earthquake insurance

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policies are widely available in California, New Zealand, Chile, Japan, Turkey, and Taiwan, for instance. They have played a significant role in the recovery of housing following major earthquake disasters in recent years. For example, after the 2010 Chile earthquake (with a moment magnitude of 8.8, herein referred to as M), insurance mechanisms covered about 27% of the total estimated losses, and there was rapid payment of insurance claims [10]. Following the 2010 and 2011 New Zealand earthquakes (M7.1 and M6.3, respectively), more than 167,000 dwelling claims were settled through a public earthquake insurance scheme run by the Earthquake Commission [11]. Even though earthquake insurance policies are widespread across the world, their effectiveness is not guaranteed. This is because their penetration rate (i.e., percentage of assets with earthquake insurance coverage) varies greatly. For instance, the penetration rate is as low as 12% in California and below 30% in Japan [12], which is primarily due to the high cost of the associated insurance premiums [13]. Furthermore, these policies do not explicitly address the needs of low-income groups, who have historically been disproportionately impacted by earthquake disasters (due to their inability to pay for emergency supplies, post-disaster repairs, etc) [14–17].

Other financial disaster-relief tools, e.g., post-disaster cash transfers to disaster-affected people, do not sufficiently recognise the amplified needs of low-income people either. For example, in the post-earthquake housing reconstruction program led by the Government of Nepal after the 2015 Nepal earthquake (M7.8), an equal amount of financial assistance was paid to each eligible homeowner regardless of income level, leaving many low-income households struggling to afford their reconstruction costs [18]. These policies' lack of consideration for the specific requirements of low-income people is likely to bottleneck post-disaster recovery rather than speed it up as intended. Moreover, as urban areas expand in the future, population grows, asset wealth piles up, and physical and social vulnerabilities evolve, it is becoming increasingly important to model and quantify tomorrow's risks rather than focusing on static impacts associated with current conditions [19]. However, the constrained structure of typical financial soft policies (e.g., the annual timeframe of insurance policies) prevents the consideration of future urban expansion and associated amplified risks.

This study contributes towards addressing the aforementioned shortcomings of conventional earthquake-risk-related financial soft policies, using the Tomorrow's Cities Decision Support Environment (TCDSE) [20]. The TCDSE supports decision making in a collaborative environment, in which various decision makers, local communities, and experts are involved from the outset in risk-based, pro-poor urban design and planning [21]. It incorporates advanced hazard modelling approaches, views risk through a democratised lens, and is explicitly pro-poor in its outlook, i.e., seeks solutions that do not result in disproportionate disaster impacts for low-income households (details to follow in Section 2.6). We leverage the TCDSE to develop a framework for flexibly facilitating the design and assessment of bespoke compulsory financial soft policies related to residential properties in rapidly expanding urban contexts, with a strong focus on the extent to which these policies are pro-poor across the lifetime of the urban system. This work represents a distinct advancement over similar existing studies on financial disaster risk management tools, which either do not adopt a pro-poor perspective [22,23], or do not consider forward-looking policies and their effectiveness in the context of future (uncertain) urban development [24,25]. The compulsory financial soft policies considered in this study encompass, for instance, components of conventional earthquake insurance and income-based tax relief schemes, with any type of payment triggering mechanism (indemnity-based or parametric). The framework involves performing probabilistic seismic loss assessments that account for time-dependent seismic hazard. The resulting time-based loss curves are used to design various financial soft policies formulated as regular insurance schemes and/or income-based taxes. Finally, we evaluate the considered financial soft policies against a novel household-level financial impact metric that distinguishes the effect of the policies across different income groups. We demonstrate the proposed framework using an expanding hypothetical city (virtual urban testbed) "Tomorrowville". Tomorrowville imitates a global-south urban setting in terms of its socio-economic and physical aspects [26]. It is a 2 km × 3 km city that will undergo rapid future urbanisation to accommodate over 10,000 more households in the next 50 years.

2. Proposed framework

We leverage the Tomorrow's Cities Decision Support Environment [20] to propose a framework for facilitating the design and assessment of compulsory household-level financial soft policies in cities under future urban expansion. The framework, as shown in Fig. 1, has four main calculation modules: (1) **Seismic Hazard Modelling**; (2) **Physical Infrastructure Impact**; (3) **Social Impact**; and (4) **Computed Impact Metrics**. Decision makers first design candidate soft policies (within the **Policy Bundles** module), which are applied to a specific time-dependent urban plan (in the **Urban Planning** module), to produce an overall **Visioning Scenario**. A pre-determined household-level financial impact metric (I_{hh}) is quantified to assess the loss-mitigation effectiveness of the candidate policies, considering the residential exposure within the conditional urban plan, the time-dependent seismic hazard calculations produced in the **Seismic Hazard Modelling** module, and physical and social vulnerability information respectively stored in the **Physical Infrastructure Impact** and **Social Impact** modules. I_{hh} is then translated into a Poverty Bias Indicator (PBI), which measures the extent to which low-income households are disproportionately burdened with residual earthquake-induced financial losses. Each iteration of the framework evaluates the impacts associated with one **Visioning Scenario**, and more specifically the combination of one (or more) candidate financial soft policy(ies) and one conditional urban layout. Through multiple iterations of the framework, decision makers can identify the optimal pro-poor policy bundle (and its underlying financial soft policies), which corresponds to the lowest PBI. The proposed framework captures the uncertainties in the calculations involved in modules (1) to (4) using Monte Carlo sampling, which is similar to the approach adopted in Cremen et al. [27]. That is, random variables in modules (1) to (3) are sampled multiple times from their underlying probability distributions and fed into the calculation of the household-level financial impact metric in module (4). Thus, the household-level financial impact metric is consequently a random variable. The modules of the framework are briefly introduced in this section. Details of the framework's application to the Tomorrowville case study are discussed in Section 3.

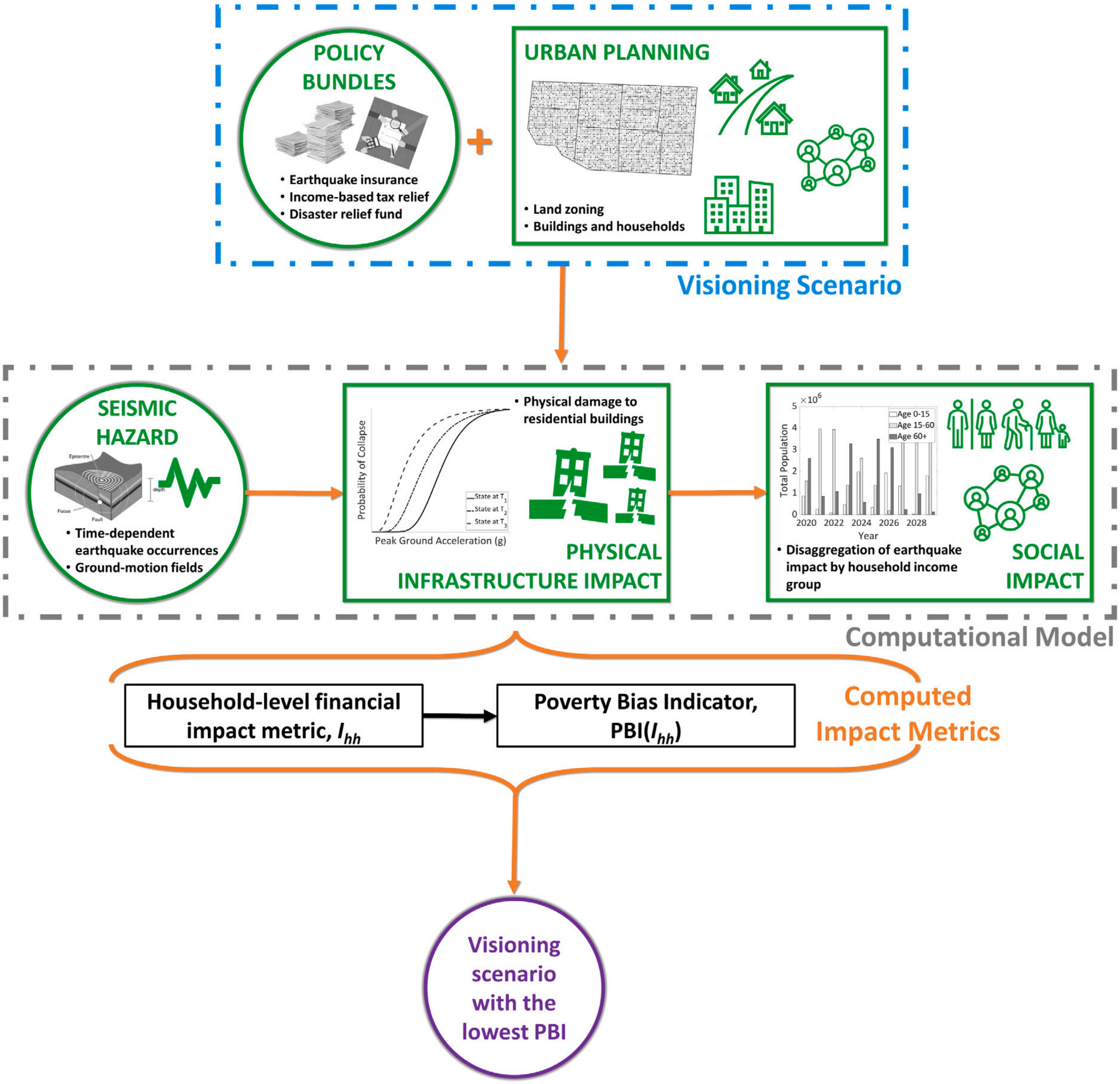

Fig. 1. A flowchart of the proposed framework to design and assess pro-poor financial soft policies.

2.1. Urban planning

The **Urban Planning** module encompasses a conditional urban plan detailing land use, building portfolio, and underlying household and individual information for a specific temporal instant. If decision makers aim to design and assess policies for immediate implementation in today's city, the input to the **Urban Planning** module would be the current layout of the urban context of interest. If the goal is to design policies for the future, considering urban expansion and changes in land use, the required input for the **Urban Planning** module would be a proposed or projected urban plan consisting of a land use plan and projections of the building portfolio, underlying household information, and socioeconomic and demographic information for each individual within a household. The information on land use, buildings, households, and socioeconomic and demographic information are spatially related within a geographic information system (GIS) database.

2.2. Policy bundles

The **Policy Bundles** module encapsulates one or more compulsory financial soft policies designed to transfer earthquake-related financial risk. These policies could include, for instance, components of conventional earthquake insurance, a disaster relief fund scheme, an income-based tax relief scheme, or a combination of these. They may also alter the financial burden on households across different social (e.g., income) groups. For example, a financial soft policy could be a compulsory city-wide earthquake insurance scheme or a scheme to disburse post-disaster relief fund to a more limited target group, e.g., low-income households.

2.3. Seismic hazard modelling

The **Seismic Hazard Modelling** module estimates earthquake-event features (e.g., source/rupture features) and resulting earthquake-induced ground-motion intensity measures (IMs) at the locations of considered buildings. The outputs of this module are ground-motion fields for multiple IMs, e.g., peak ground acceleration (PGA), spectral accelerations at different structural periods (SAs), peak ground velocity (PGV), and peak ground displacement (PGD), which are computed in a probabilistic sense. A probabilistic expression of seismic hazard considers the uncertainties in the rupture features and occurrence time, which is more relevant for decision-making in the insurance sector than single-scenario modelling [27]. Probabilistic seismic hazard modelling also allows for the direct consideration of the fault's rupture history, which often leads to more accurate estimation of seismic hazard [28]. Ground-motion fields can be simulated using a ground-motion model (GMM), e.g., Campbell and Bozorgnia [29], among many others summarised in Douglas [30]. Spatial correlation and cross-IM correlation models (e.g., Jayaram and Baker [31], Markhvida et al. [32]) can be used in addition to GMMs to produce more accurate ground-motion fields, especially when the sites of interest are distributed over a typical city scale [33]. Ground-motion fields could also be simulated using physics-based models, which tend to produce more accurate characterisations of shaking intensities than empirical GMMs, but demand significantly more computation power and time [5,34,35] that inhibits their widespread use in probabilistic seismic hazard analysis.

2.4. Physical infrastructure impact

The **Physical Infrastructure Impact** module uses the outputs of the **Seismic Hazard Modelling** module to calculate earthquake-induced physical damages to residential buildings and the associated asset losses. This module encompasses fragility relationships and/or vulnerability relationships, which can either be pre-selected for the case-study physical infrastructure of interest or derived using numerical/analytical or empirical approaches [36].

Specifically, given the outputs from the **Seismic Hazard Modelling** module, i.e., simulated ground-motion fields, the **Physical Infrastructure Impact** module utilises fragility relationships to sample the damage state of each residential building [37]. It then uses damage-to-loss ratios or consequence models [38,39] to compute the asset loss (i.e., repair costs) as a percentage of building replacement cost. Alternatively, vulnerability relationships can be used to directly estimate the loss ratio (or some other loss measurement) caused by a certain level of simulated ground-motion intensity. By repeating the loss estimation for all ground-motion simulations, annual exceedance loss curves and expected annual losses of all residential buildings ($EAL_{bld,b}$, building-level expected annual losses for the bth residential building) as well as more aggregated losses can be obtained.

2.5. Social impact

The **Social Impact** module uses outputs from the **Physical Infrastructure Impact** module to compute household-level earthquake financial impacts (e.g., $EAL_{hh,i}$, household-level expected annual losses for the ith household), also accounting for pertinent social characteristics. More specifically, this module distinguishes household-level financial burdens on the basis of relevant socioeconomic information (i.e., income), and can further disaggregate these impacts across other social groupings, e.g., age and gender of household head, if necessary. Note that the calculations in the **Social Impact** module can be affected by the financial soft policies imposed in the **Policy Bundles** module.

2.6. Computed impact metrics

The **Computed Impact Metrics** module uses outputs from the **Computational Model**, i.e., the **Physical Infrastructure Impact** and **Social Impact** modules, to quantify the impacts of a **Visioning Scenario** via the lens of a pre-determined household-level financial impact metric. The **Computed Impact Metrics** module calculates this impact metric for each household and then translates it into a single-valued Poverty Bias Indicator (PBI), which measures the extent to which low-income households are disproportionately burdened in terms of the financial impact of interest. For a correct evaluation with the PBI, the financial impact metric used should involve an appropriate income-based normalisation (e.g., by replacement value). The PBI was originally introduced as the Poverty Exposure Bias Indicator in Winsemius et al. [40], and modified by Cremen et al. [27]. For a given household-level financial impact metric, the PBI adopted in this framework is expressed as follows:

$$PBI = \frac{\mathbb{E}(I_{low})}{\mathbb{E}(I_{port})} - 1 \tag{1}$$

where $\mathbb{E}(I_{low})$ is the mean value of the household-level financial impact metric across all low-income households and $\mathbb{E}(I_{port})$ is the average value across all households. A negative value of PBI indicates that the set of financial soft policies contained in the **Policy Bundles** module are pro-poor, i.e., the financial losses that result from their implementation do not disproportionately affect low-income households. The lower the negative-valued PBI is, the more pro-poor the associated financial soft policy (and the overall **Visioning Scenario**) is. We note that although the framework primarily aims to facilitate the selection of the **Visioning Scenario** with the lowest PBI, it can also be leveraged to compare the extent to which one **Visioning Scenario** is more pro-poor than another.

3. Case-study description

We use the expanding hypothetical city (virtual urban testbed) "Tomorrowville" (see Mentese et al. [26]) as our case study to demonstrate the proposed framework. Tomorrowville imitates a global-south urban setting in terms of its socioeconomic and physical characteristics [26]. In this case study, we design and assess eight compulsory financial soft policies related to Tomorrowville residential buildings (and their households) using the proposed framework. The candidate soft policies involve conventional earthquake insurance strategies, as well as income-based financial relief tax schemes. To demonstrate the importance of focusing on the future (and generally different temporal instances) of an urban context and its underlying dynamic exposure, we examine two scenarios of urban layout in this case study: the current urban layout of Tomorrowville and a 50-year projection of its urban layout, considering rapid future urban expansion. We account for both time-dependent and time-independent seismic hazard associated with three hypothetical strike-slip faults near Tomorrowville, as shown on the left panel of Fig. 2. Note that due to the synthetic nature of the selected case study and the corresponding absence of some validated risk-related models, a number of simplified but necessary assumptions on certain inputs to the calculations (including seismic hazard information and the underlying details of the developed financial soft policies) will be made in this instance. This implies that the results of the case study should be treated as a simple demonstration of the framework's capabilities, rather than as being ready for implementation in any real-life setting.

3.1. Urban planning

We examine two scenarios of urban layout (encompassed in the **Urban Planning** module) in this case study, namely "TV0" and "TV50_total". TV0 refers to the current urban layout of Tomorrowville, whereas TV50_total refers to a possible future urban layout of Tomorrowville in 50 years. Note that TV50_total includes new buildings to be built in Tomorrowville in the next 50 years (TV50_b2) and the existing buildings of TV0. Fig. 2 shows TV0 and TV50_total on its central and right panels, respectively. The main constituents of each urban layout include a land use plan, a building portfolio (containing building information, such as building location, structural type, code level, number of storeys, building area, and the households associated with each residential building), and underlying household/individual databases (containing socioeconomic and demographic data of each person in each household, such as income group, gender, and age). We specifically focus on residential buildings in this study, given the nature of the policies under investigation. TV0 contains 3,423 residential buildings and 7,809 households whereas TV50_total contains 8,713 residential buildings and 17,810 households. Households within the same polygon belong to the same income group. Residential polygons are categorised into low-, middle-, and high-income social categories. There are 4,236, 1,705, and 1,868 low-, middle-, and high-income households, respectively in TV0, while there are 6,766, 3,059, and 7,985 low-, middle-, and high-income households, respectively in TV50_total.

Table 1 provides an exhaustive list of building typologies in Tomorrowville and the number of residential buildings of each typology in TV0 and TV50_total. Low-code and low-rise (i.e., between one and four storeys) "Brick and mud walls" buildings (typology No. 2) dominate the residential building portfolio of TV0, while high-code low-rise "Masonry-infilled reinforced concrete frames" buildings (typology No. 7) dominate the residential building portfolio of TV50_total. Over 64% of low-income households live in low-code and low-rise "Brick and mud walls" buildings (topology No. 2) in TV0, whereas most low-income households live in buildings of topologies No. 2 (41%) and No. 7 (39%) in TV50_total. In TV0, about 48% of high-income households live in buildings of typologies No. 7 and No. 10 – two of the most expensive and strongest building types – while this percentage increases to 88% in TV50_total. Table 1 also provides the construction cost for each building type, which is adapted from Mesta et al. [41]. In this case study, we assume that households within a multi-family building equally share the total repair costs of their residential building incurred in a given seismic event. The average total replacement costs for low-, middle-, and high-income households in TV0 are €5,348, €8,511, and €11,902, respectively, while the average total replacement cost for low-, middle-, and high-income households in TV50_total increase to €7,201, €11,450, and €23,809, respectively. Building typology No. 1 has the lowest average total replacement cost per household of €3,521 in both TV0 and TV50_total, whereas building typology No. 7 has a much higher average total replacement cost of €12,411 and €16,405 in TV0 and TV50_total, respectively (note that the larger average total replacement cost for this typology in TV50_total is a result of increasing average building sizes).

3.2. Policy bundles

3.2.1. Financial soft policy

Eight financial soft policies are designed in this demonstration. We assume that Tomorrowville households are owner occupied, such that a household's financial seismic losses (and any household-specific required monetary input for a related financial soft policy) are shouldered by its residents. The proposed policies include some adapted involvement of the main parameters in an earthquake insurance contract, i.e., premium, deductible, limit, and coinsurance factor. Premium is the amount of money that the insured pays to the insurer. Deductible (D, the amount of money that the insured party needs to pay towards an insurance claim), limit (C, the highest amount of a claim covered by an insurance contract), and coinsurance factor (γ, the percentage of losses paid by the insurer after the insured party pays the deductible) constitute a typical payout function [42] that determines the insurance payout (IP), as follows:

$$IP(L) = \begin{cases} 0 & L \leq D \\ \gamma \cdot (L - D) & D \geq L \leq C \\ \gamma \cdot (C - D) & L \geq C \end{cases} \tag{2}$$

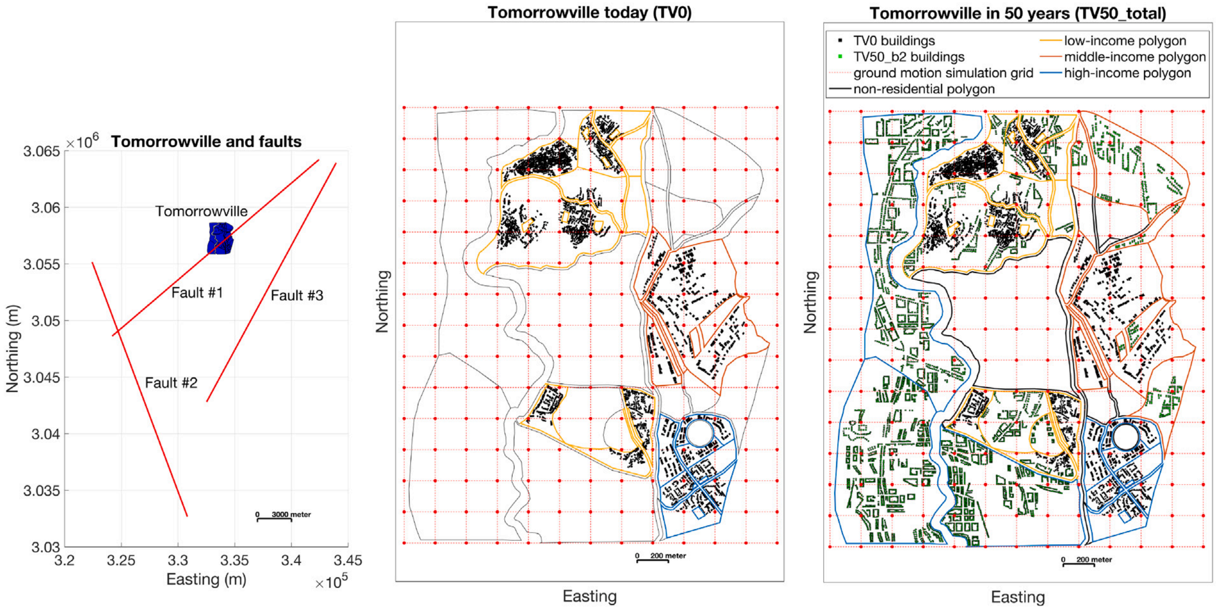

Fig. 2. The left panel shows the hypothetical seismic sources considered for Tomorrowville. All three faults are vertical strike-slip faults with a length of 24 km and an annual rate of exceeding an $M4.0$ earthquake (ν_0) of 0.09. The middle panel shows the residential buildings in today's Tomorrowville (TV0), and the right panel shows the residential buildings projected to be present in Tomorrowville in 50 years (TV50_total). Note that ground-motion fields are simulated on a 200 m × 200 m grid (marked on red in the right and central panels) across the polygons of Tomorrowville.

Table 1
The building typologies present in each considered urban plan and their assumed construction costs. 'Low-rise' refers to buildings between one and four storeys and 'mid-rise' refers to buildings between five and seven storeys.

Building typology	Material + lateral resisting system	Code level	Height	Construction cost (×200 EUR/m^2)	Count (TV0)	Count (TV50_total)
No. 1	Adobe	Low	Low-rise	0.40	81	81
No. 2	Brick and mud walls	Low	Low-rise	0.60	1907	1907
No. 3	Brick and cement walls with flexible floor slabs	Low	Low-rise	0.70	266	266
No. 4	Brick and cement walls with rigid floor slabs	Low	Low-rise	0.75	262	262
No. 5	Masonry-infilled reinforced concrete frames	Low	Low-rise	0.85	243	243
No. 6	Masonry-infilled reinforced concrete frames	Moderate	Low-rise	0.95	190	190
No. 7	Masonry-infilled reinforced concrete frames	High	Low-rise	1.00	234	4552
No. 8	Masonry-infilled reinforced concrete frames	Low	Mid-rise	0.95	7	7
No. 9	Masonry-infilled reinforced concrete frames	Moderate	Mid-rise	1.00	19	19
No. 10	Masonry-infilled reinforced concrete frames	High	Mid-rise	1.10	64	1036
No. 11	Stone and mud	Low	Low-rise	0.60	150	150

where L refers to the total assessed seismic loss, i.e., ground-up loss, of a building, and all other variables are as previously defined. For example, under an earthquake insurance contract with a deductible (D) of €1,000, a limit (C) of €40,000, a coinsurance factor (γ) of 1.0, and a ground-up loss (L) of €50,000, the insured homeowner needs to pay a deductible of €1,000 and bears an additional €10,000 loss above the limit, whereas the insurer who underwrites the insurance policy covers the remaining amount, i.e., the insurance payout (IP), of €39,000. While a typical earthquake insurance deductible rate ranges between 10 to 15% [43], a pro-poor approach could be achieved by setting the value of D based on household income (e.g., D could equal zero for those of the lowest income), alleviating or at least mitigating any financial difficulties experienced due to post-earthquake repairs. A payout function translates the household's expected annual loss ($EAL_{hh,i}$) into the household's expected annual financially protected loss ($EAIL_{hh,i}$) and the household's expected annual financially unprotected loss ($EAUL_{hh,i}$), which is analogous to expected annual insured loss and expected annual uninsured loss, respectively, in a traditional earthquake insurance scheme (we adopt the former

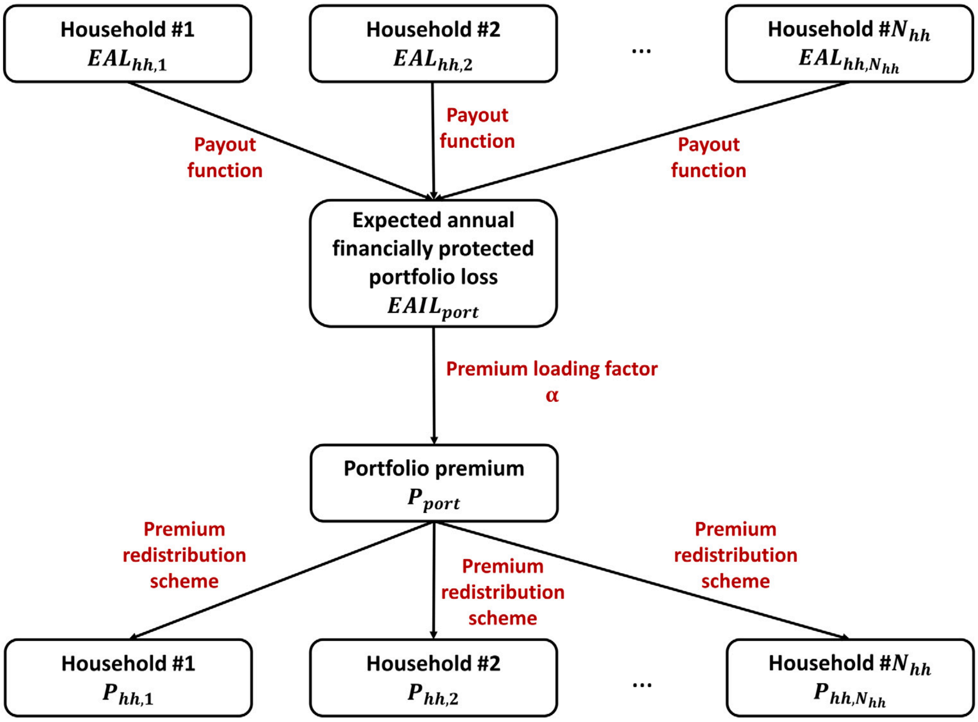

Fig. 3. Outline design of financial soft policies considered in this study, which consist of a payout function and a premium redistribution scheme. $EAL_{hh,1}$, $EAL_{hh,2}$ are the expected annual loss of households No. 1 and No. 2, respectively. N_{hh} is the total number of households in Tomorrowville. $EAIL_{port}$ is the expected annual financially protected loss of the residential building portfolio, α is the premium loading factor of 1.25. P_{port} is the total amount of premiums collected from all households in the portfolio, whereas $P_{hh,1}$ and $P_{hh,2}$ are the individuals premiums payable by households No. 1 and No. 2, respectively. Premiums are imposed on households as (mandatory) income taxes.

terminology herein, since the scope of considered financial soft policies extends beyond traditional earthquake insurance). Note that $EAIL_{hh,i}$ is calculated by integrating the annual exceedance financially protected loss curve for the associated building and divided by the number of households occupying it. $EAIL_{hh,i}$ summarises information on a range of earthquake scenarios, occurrence rates, and associated expected financially protected losses into a single average dollar loss, and is an effective means of communicating seismic risk to building owners and insurers [44]. The summation of $EAIL_{hh,i}$ across all households is the expected annual financially protected loss of the residential building portfolio ($EAIL_{port}$). Multiplying $EAIL_{port}$ by a premium loading factor α gives the portfolio premium (P_{port}), i.e., the total premium that needs to be collected across all financially protected households. The premium loading factor α (> 1) covers uncertainty in the underlying policy risk models as well as business administration costs [8]. For this case study, we adopt a premium loading factor of 1.25, in line with Gentile et al. [3]. Fig. 3 summarises the underlying design of financial soft policies considered in this case study. Each candidate financial soft policy consists of a payout function and a premium redistribution scheme, which alters the distribution of P_{port} among households in various ways, in the form of (compulsory) income-based taxes.

3.2.2. Payout function

In this case study, we examine two representative payout functions as shown in Table 2. Note that we adopt a coinsurance factor (γ) of 1.0 for all considered payout functions. Payout function No. 1 is uniform across all income groups; a deductible (D) of €1,000 and a limit (C) of €40,000 are imposed on each household, regardless of its income. The C of €40,000 fully covers the total replacement cost of over 98% of residential buildings occupied by low-income households, which is likely to have far-reaching positive consequences as these households can find it difficult to secure funds from private sources (e.g., private loans, insurance, etc.) for post-earthquake housing recovery [45]. Note that the absolute values of C should be considered as illustrative rather than as being ready for immediate implementation in a real-life setting. Payout function No. 2 adopts different D's for different income groups. D is €6,400, €4,800, and €1,600 for high-, middle-, and low-income households, respectively, which roughly correspond to 5 to 20% of the average total replacement cost of residential buildings in TV0 and TV50_b2.

3.2.3. Premium redistribution scheme

As shown in Fig. 3, the redistribution scheme is used to compute the premium for each household as some proportion of the portfolio premium (P_{port}). The premium redistribution scheme allows the policymaker to flexibly determine the premiums payable by different households, thereby creating opportunities to reduce the financial burden placed on low-income households in particular; the premium imposed on a given household may be a function of its income bracket and its expected annual financially protected

Table 2
Parameters of the payout functions considered in this study. The values for deductible and limit are in EUR.

Payout function	Deductible (high-income)	Deductible (middle-income)	Deductible (low-income)	Limit	Coinsurance factor
1	1,000	1,000	1,000	40,000	1.0
2	6,400	4,800	1,600	40,000	1.0

Table 3
Four premium redistribution schemes considered in this study. $EAIL_h$, $EAIL_m$, and $EAIL_l$ are the total annual expected financially protected loss of the high-, middle-, and low-income groups, respectively, whereas $EAIL_{hh,i}$ refers to the expected annual financially protected loss of the ith household ($i = 1, 2, \ldots, N_{hh}$, where N_{hh} is total number of households). N_h, N_m, and N_l are the number of high-, middle-, and low-income households respectively. α refers to the premium loading factor. $\alpha = 1.25$ is adopted for this study.

Premium redistribution scheme	Total premiums (middle- and high-income)	Total premiums (low-income)	Household-by-household distribution within each income group
1	$\alpha \cdot (EAIL_l + EAIL_m + EAIL_h) \cdot \frac{N_m+N_h}{N_{hh}}$	$\alpha \cdot (EAIL_l + EAIL_m + EAIL_h) \cdot \frac{N_l}{N_{hh}}$	Flat-rated
2	$\alpha \cdot (EAIL_m + EAIL_h)$	$\alpha \cdot EAIL_l$	Proportional to $EAIL_{hh,i}$
3	$\alpha \cdot (EAIL_m + EAIL_h + 0.8 \cdot EAIL_l)$	$\alpha \cdot 0.2 \cdot EAIL_l$	Proportional to $EAIL_{hh,i}$
4	$\alpha \cdot (EAIL_m + EAIL_h + 0.8 \cdot EAIL_l)$	$\alpha \cdot 0.2 \cdot EAIL_l$	Flat-rated

Table 4
Eight financial soft policies considered for this case study.

Soft policy	Payout function	Premium redistribution scheme
1	1	1
2	1	2
3	1	3
4	1	4
5	2	1
6	2	2
7	2	3
8	2	4

loss ($EAIL_{hh,i}$), for instance. The premium for each household (e.g., $P_{hh,i}$), shown on the bottom of Fig. 3, is imposed in the form of a mandatory tax.

Table 3 summarises the four premium redistribution schemes considered in this case study. Premium redistribution scheme No. 1 imposes a flat-rated (i.e., identical) premium on each household, regardless of its $EAIL_{hh,i}$ and income group. This scheme reflects earthquake insurance approaches in Taiwan and New Zealand [6,7]. Chile also adopts a flat-rated premium, charged as a uniform percentage of the total replacement cost of a residential building [46]. Premium redistribution scheme No. 2 distributes premiums based on $EAIL_{hh,i}$ values, which broadly reflects the earthquake insurance programs of Turkey, California, and Japan [9]. Premium redistribution schemes No. 3 and 4 transfer 80% of the expected annual financially protected loss of the low-income group ($EAIL_l$) within the entire portfolio to middle- and high-income groups, thereby mitigating the financial burden on the low-income. This is a novel, pro-poor approach to designing financial soft policies (to the best of our knowledge). Premium redistribution scheme No. 3 then specifies that the total premiums imposed on each income group are distributed to each associated household in proportion to $EAIL_{hh,i}$ values, while premium redistribution scheme No. 4 imposes flat-rated premiums on each household within a given income group. The permutation of two considered payout functions and four premium redistribution schemes leads to eight candidate soft policies, as shown in Table 4. These soft policies, represented in the **Policy Bundles** module of Fig. 1, are evaluated one by one using the proposed framework.

3.3. Seismic hazard modelling

We account for three hypothetical vertical strike-slip faults (all 24 km long) in the proximity of the case-study area. The left panel of Fig. 2 shows the locations of these faults relative to Tomorrowville. We assume all faults are capable of generating both non-characteristic and characteristic events. We assume that the moment magnitude (M) of non-characteristic events follows the Gutenberg–Richter magnitude frequency distribution [47] and their occurrence follows a Poisson distribution. We assume a slope of occurrence $b = 1$, a minimum magnitude of $m_0 = 4.0$, and a maximum magnitude for non-characteristic events of $m_u = 6.5$. We assume the magnitude of characteristic events follows a truncated normal distribution and that their occurrence follows a Weibull distribution [48]. Note that the Weibull distribution is selected over other available (more sophisticated) time-dependent occurrence models, i.e., lognormal-distributed model [49] and Brownian passage time model [50], due to its simplicity [28], which is justified on the basis of the hypothetical nature of the examined case study. We assume that the mean magnitude of characteristic events is $m_c = 7.0$, and the standard deviation of the characteristic-event magnitude distribution is $\sigma_{Mc} = 0.25$. The magnitude of characteristic events is truncated such that $m_c - 2\sigma_{Mc} < M < m_c + 2\sigma_{Mc}$, that is, $6.5 < M < 7.5$. We assume the mean and standard deviation

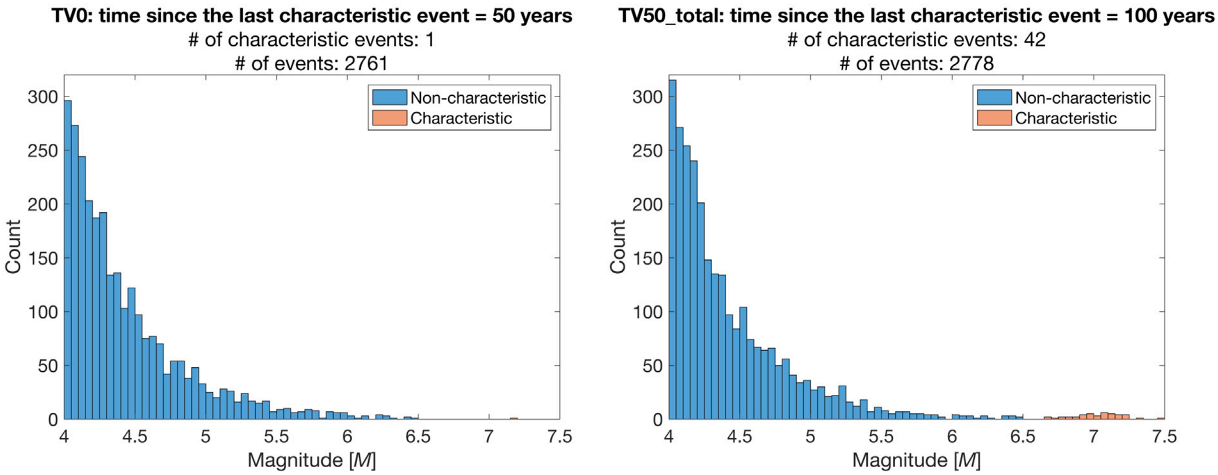

Fig. 4. The distribution of earthquake magnitudes of events in the earthquake catalogues generated for TV0 (for which the time elapsed since the last characteristic event is assumed to be 50 years) and TV50_total (for which the time elapsed since the last characteristic event is assumed to be 100 years). The magnitude of non-characteristic events ($4.0 < M < 6.5$) is assumed to follow a Gutenberg–Richter magnitude frequency distribution, whereas the magnitude of characteristic events ($6.5 < M < 7.5$) is assumed to follow a truncated normal distribution.

Table 5
Fragility relationships for each building typology in Tomorrowville. θ_{DS1} to θ_{DS4} are the medians of the fragility relationships for $DS = 1$ to 4, respectively. β_{DS1} to β_{DS4} are the dispersions of the fragility relationships for $DS = 1$ to 4, respectively.

Building typology	Intensity measure	θ_{DS1}	θ_{DS2}	θ_{DS3}	θ_{DS4}	β_{DS1}	β_{DS2}	β_{DS3}	β_{DS4}
No. 1	SA(T = 0.3 s)	0.399	0.861	1.238	1.577	0.586	0.586	0.586	0.586
No. 2	PGA	0.057	0.098	0.147	0.223	0.406	0.404	0.358	0.310
No. 3	PGA	0.057	0.119	0.214	0.361	0.451	0.349	0.286	0.247
No. 4	PGA	0.124	0.175	0.295	0.445	0.326	0.300	0.254	0.254
No. 5	SA(T = 0.09 to 0.56 s)	0.109	0.255	0.578	0.689	0.228	0.228	0.218	0.217
No. 6	SA(T = 0.10 to 0.57 s)	0.137	0.633	1.577	2.016	0.223	0.223	0.223	0.223
No. 7	SA(T = 0.13 to 0.79 s)	0.180	0.677	4.915	5.773	0.223	0.223	0.223	0.223
No. 8	SA(T = 0.18 to 1.11 s)	0.048	0.203	0.313	0.314	0.301	0.276	0.252	0.253
No. 9	SA(T = 0.19 to 1.12 s)	0.031	0.268	0.793	1.036	0.268	0.268	0.268	0.268
No. 10	SA(T = 0.22 to 1.30 s)	0.039	0.322	4.027	5.352	0.259	0.259	0.259	0.259
No. 11	SA(T = 0.3 s)	0.057	0.098	0.147	0.223	0.406	0.404	0.358	0.310

of the inter-arrival time of characteristic events are $\mu_T = 200$ years and $\sigma_T = 50$ years, respectively. We use Monte Carlo sampling to simulate two sets of 10,000 one-year earthquake catalogues, considering the time elapsed since the last characteristic event is 50 years (corresponding to the TV0 scenario) and 100 years (corresponding to the TV50_total scenario), respectively. Fig. 4 shows the distribution of the magnitudes of the earthquakes simulated for TV0 and TV50_total. Each set of catalogues comprises over 2,700 events, most of which are time-independent events. The longer it has been since the last characteristic event, the more frequently characteristic events occur in a catalogue. Therefore, the earthquake catalogues for TV50_total include more characteristic events than those for TV0, as shown in Fig. 4.

We simulate spatial cross-correlated ground-motion fields across the polygons of Tomorrowville, using the GMM in Campbell and Bozorgnia [29] and the spatial and cross-IM correlation model in Markhvida et al. [32]. We use Monte Carlo sampling to simulate 100 sets of ground-motion fields for each event, on a 200 m × 200 m grid shown in Fig. 2 [51]. This number of simulations is deemed appropriate, since it provides relatively stable physical infrastructure impact assessment results (see Section 4 for details). We use the ground-motion intensity values simulated at each grid point as a proxy for these values at nearby building sites.

3.4. Physical infrastructure impact

Table 5 summarises the fragility relationships associated with each building typology in Tomorrowville. The new buildings added in TV50_total are of building typologies No. 7 and No. 10, which are in general much stronger than buildings that already exist in TV0, as shown in Table 5. Further details on the physical vulnerability of Tomorrowville can be found in Gentile et al. [36]. We consider a deterministic damage-to-loss ratio for each damage state (DS): 0.07 for $DS = 1$, 0.15 for $DS = 2$, 0.50 for $DS = 3$, and 1.00 for $DS = 4$ [52]. In this case study, the outputs of this module include the annual exceedance loss curve, the annual expected loss for each residential building in Tomorrowville ($EAL_{bld,b}$), and the expected annual portfolio loss (EAL_{port}; i.e., the summation of $EAL_{bld,b}$).

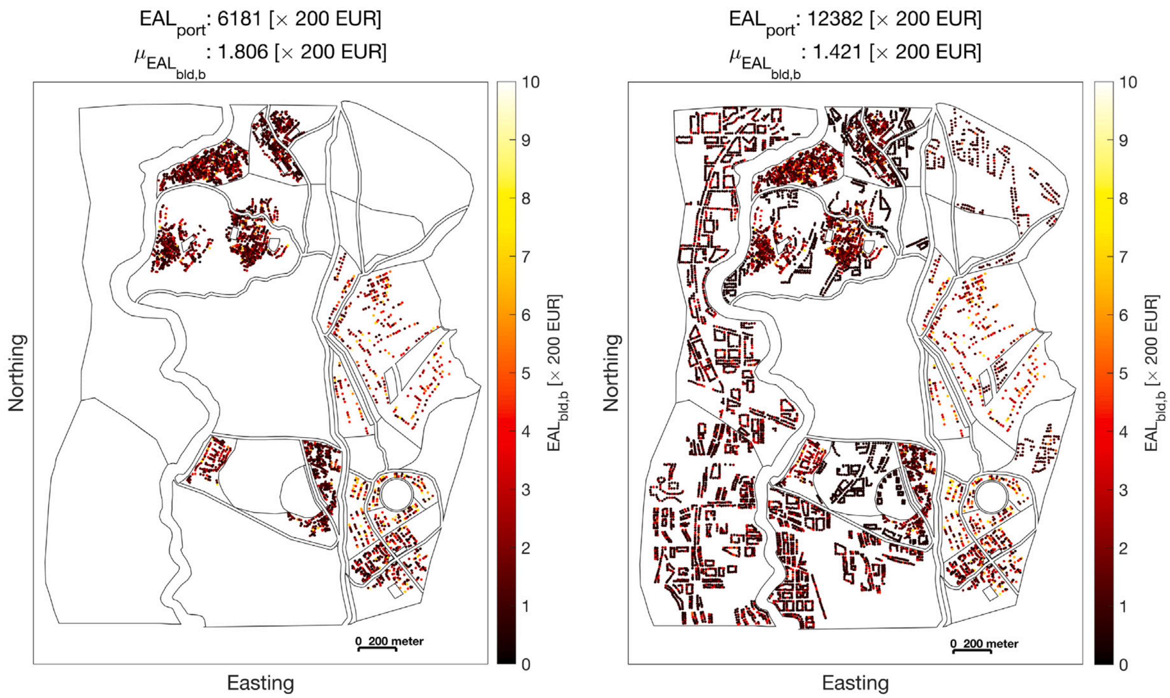

Fig. 5. Expected annual losses of residential buildings ($EAL_{bld,b}$) in TV0 (left panel) and TV50_total (right panel). TV0 includes 3,423 residential buildings, whereas TV50_total contains an additional 5,290 new residential buildings as part of rapid urban expansion. $\mu_{EAL_{bld,b}}$ is the average $EAL_{bld,b}$ of all residential buildings.

3.5. Social impact

The module calculates the expected annual loss of each household ($EAL_{hh,i}$) using outputs from the **Physical Infrastructure Impact** module (i.e., $EAL_{bld,b}$) and associated household information of each building. This module uses the payout and premium redistribution functions (defined in Section 3.2) to calculate the expected annual financially protected loss of each household ($EAIL_{hh,i}$), the total expected annual financially protected loss of low-, middle-, and high-income households, respectively ($EAIL_l$, $EAIL_m$, $EAIL_h$, respectively), the expected annual financially protected portfolio loss ($EAIL_{port}$), the expected annual financially unprotected loss of each household ($EAUL_{hh,i}$), the expected annual financially unprotected portfolio loss ($EAUL_{port}$), the premium (i.e., tax) payable by each household ($P_{hh,i}$), and the portfolio premium (P_{port}).

3.6. Computed impact metrics

We propose a novel household-level financial impact metric, herein referred to as "unprotected loss ratio" ($I_{hh,i}$), to quantify the financial impact of the candidate soft policies on each household. This metric is a holistic measurement of the earthquake-related financial burden on households. $I_{hh,i}$ can be mathematically formulated as follows:

$$I_{hh,i} = \frac{EAUL_{hh,i} + P_{hh,i}}{RPC_{hh,i}} \tag{3}$$

where $RPC_{hh,i}$ refers to the total replacement cost of each household and all other variables are as previously defined. For multi-family buildings, we assume the households equally share the building's total replacement cost. The higher $I_{hh,i}$ is, the heavier the earthquake-related financial burden on the household is. We then aggregate $I_{hh,i}$ to compute $\mathbb{E}(I_{low})$ and $\mathbb{E}(I_{port})$, for input to the PBI calculation expressed in Eq. (1).

4. Results

Fig. 5 displays the spatial distribution of $EAL_{bld,b}$, for TV0 (on the left) and TV50_total (on the right). It can be seen in the right panel of Fig. 5 that pre-existing buildings from TV0 generally have higher $EAL_{bld,b}$ than those of TV50_b2. The average $EAL_{bld,b}$ of buildings in TV50_total ($\mu_{EAL_{bld,b}}$) is smaller than that of TV0, due to the relatively low vulnerabilities of the new buildings added as part of TV50_b2. However, as seen in Fig. 6, the mean portfolio loss of TV50_total is approximately twice that of TV0 (for any given annual rate of exceedance), because the total building value significantly increases as the urban area expands. By comparing the

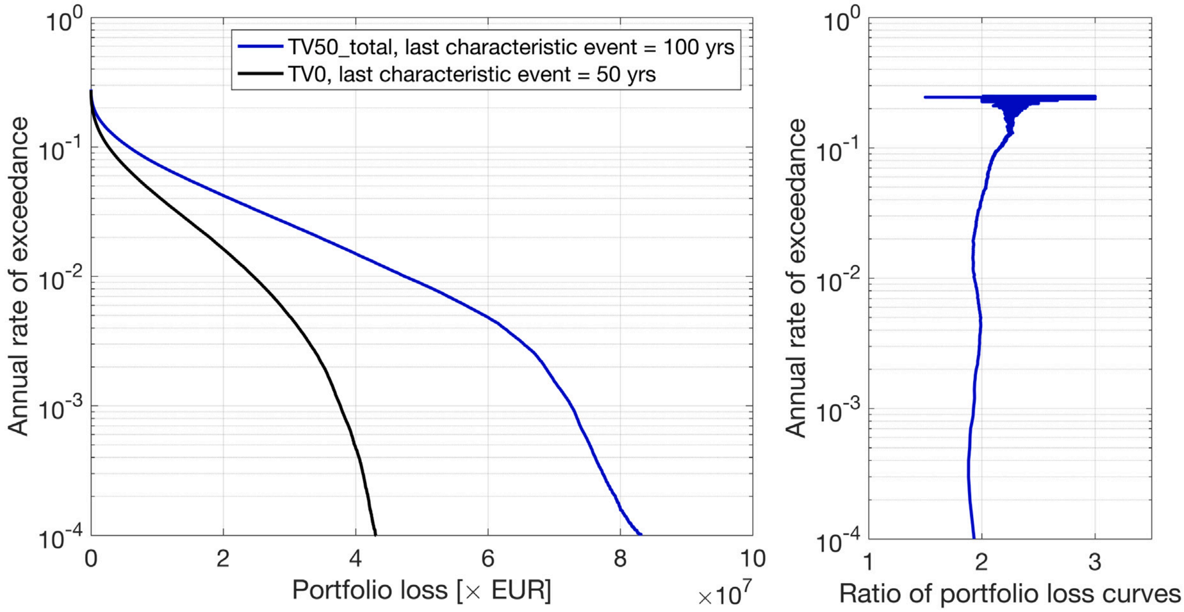

Fig. 6. Left panel: Mean portfolio loss curves for TV0 and TV50_total, averaged over the 100 Monte Carlo samples generated for each considered earthquake event. Right panel: The ratio of the average portfolio loss curve for TV50_total to that of TV0.

Table 6
The average expected annual loss for each building type. $\mu_{EAL_{bld,b}}$ is measured in the unit of 200 EUR.

Building typology	$\mu_{EAL_{bld,b}}$ (TV0)	$\mu_{EAL_{bld,b}}$ (TV50_total)
No. 1	0.212	0.276
No. 2	2.005	2.317
No. 3	2.317	2.726
No. 4	1.276	1.579
No. 5	1.685	2.114
No. 6	1.286	1.556
No. 7	0.608	0.578
No. 8	4.384	5.548
No. 9	3.614	4.406
No. 10	2.755	2.786
No. 11	2.117	2.340

two panels of Fig. 5, we can also see that the $EAL_{bld,b}$ of TV0 buildings increases in TV50_total, due to the time-dependent nature of the seismic hazard. The longer it has been since the last characteristic event, the more likely the next characteristic event is to occur, increasing the hazard and the expected annual losses. The effect of increasing seismic hazard is further reflected in Table 6, which summarises the $\mu_{EAL_{bld,b}}$ for each building topology in TV0 and TV50_total, respectively.

Fig. 7 displays the mean portfolio loss curves associated with payout functions No. 1. (left panel) and No. 2 (right panel); see Table 2 for details. It can be seen that payout function No. 1 results in a greater value of $EAIL_{port}$ compared to payout function No. 2.

The mean premiums payable by households of each income group under each financial soft policy are shown in Table 7. These values are generally lower in TV50_total compared to TV0 because of a lower $\mu_{EAL_{bld,b}}$. Soft policies No. 1 to 4 that adopt payout function No. 1 result in higher premiums compared to the other soft policies that adopt payout function No. 2, because of the higher $EAIL_{port}$ associated with payout function No. 1. Because payout function No. 2 specifies lower deductibles for middle- and low-income groups and buildings occupied by middle- and low-income people are in general less seismic-resistant compared to those occupied by the high-income (because of their greater financial capacity to afford more seismically resistant buildings), the average $EAIL_{hh,i}$ is higher for low-income and middle-income than for high-income, despite the fact that low-income and middle-income people occupy cheaper buildings. Thus, under financial soft policy No. 6 (consisting of payout function No. 2 and premium redistribution scheme No. 2 that distributes premiums on the basis of $EAIL_{hh,i}$), low- and middle-income households pay,

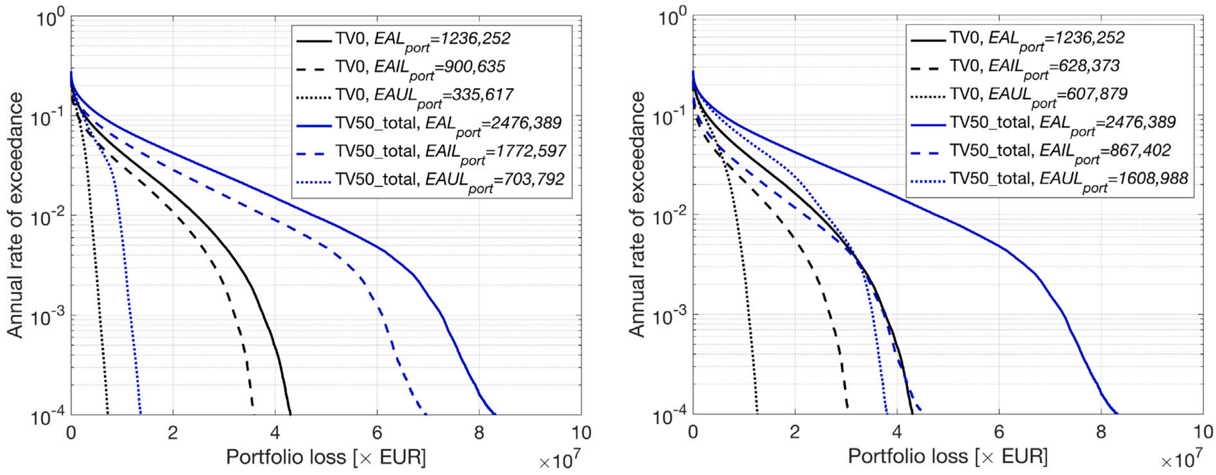

Fig. 7. Mean protected and unprotected portfolio loss curves for TV0 and TV50_total, under payout functions No. 1 (left panel) and No. 2 (right panel). The expected annual portfolio loss (EAL_{port}), expected annual financially protected portfolio loss ($EAIL_{port}$) and expected annual financially unprotected portfolio loss ($EAUL_{port}$) associated with each payout function are shown in EUR.

Table 7
Mean premiums (in EUR) paid by households per income group and the computed Poverty Bias Indicator (PBI) under each financial soft policy.

Scenario	Financial soft policy	Low income	Middle income	High income	PBI
TV0	1	144	144	144	0.343
	2	145	140	147	0.284
	3	29	273	288	−0.339
	4	29	281	281	−0.280
	5	101	101	101	0.263
	6	122	84	69	0.304
	7	24	210	172	−0.229
	8	24	191	191	−0.163
TV50_total	1	124	124	124	0.679
	2	116	118	134	0.642
	3	23	169	193	−0.080
	4	23	186	186	−0.081
	5	61	61	61	0.508
	6	96	64	30	0.684
	7	19	140	66	0.024
	8	19	86	86	0.154

on average, higher premiums than high-income households. As can be seen from the results in Table 7, soft policies No. 3, 4, 7, and 8 that employ premium redistribution schemes No. 3 or No. 4 burden low-income group households with significantly lower premiums compared to the other soft policies that adopt premium redistribution schemes No. 1 or No. 2.

Fig. 8 shows the mean, median, and 25th to 75th percentile range of $I_{hh,i}$, computed for households in each income group under each financial soft policy for TV0 and TV50_total scenarios, respectively. Also shown are PBI values for each financial soft policy. The average unprotected loss ratio ($\mathbb{E}(I_{hh,i})$) of TV50_total is lower than that of TV0 because of its relatively higher seismic resistance. Soft policies No. 3 and No. 7 lead to the lowest value of $\mathbb{E}(I_{hh,i})$ in both TV0 and TV50_total. Soft policies No. 1, 2, 5, and 6, which are not explicitly designed to be pro-poor, yield the highest values of $I_{hh,i}$ for low-income households as expected (see Fig. 8). The positive values of PBI obtained for these policies (as shown in Table 7) further indicate that they result in a disproportional financial burden on low-income households. Soft policies No. 3, 4, 7, and 8, which are all explicitly designed to lower financial burdens on low-income households, result in a negative (i.e., pro-poor) value of PBI in TV0 as expected. However, only soft policies No. 3 and 4 lead to a negative PBI value in TV50_total. The positive PBI of policies No. 7 and 8 in TV50_total can be attributed to a combination of: (1) the fact that low-income households in TV50_total have higher values of $I_{hh,i}$ than in TV0 (due to an elevated average valuation of the associated residential properties); and (2) the flat-rated nature of premium redistribution scheme No. 4 in the case of policy No. 8, which results in some low-income households paying a much higher amount of the total low-income premium than they would under a scheme that charges premiums in proportion to $EAIL_{hh,i}$. The fact that policies No. 7 and 8 lead to negative PBI values in TV0 but positive PBI values in TV50_total highlights the need to adopt a future-focused approach in the design of soft policies for cities under rapid urban expansion like Tomorrowville.

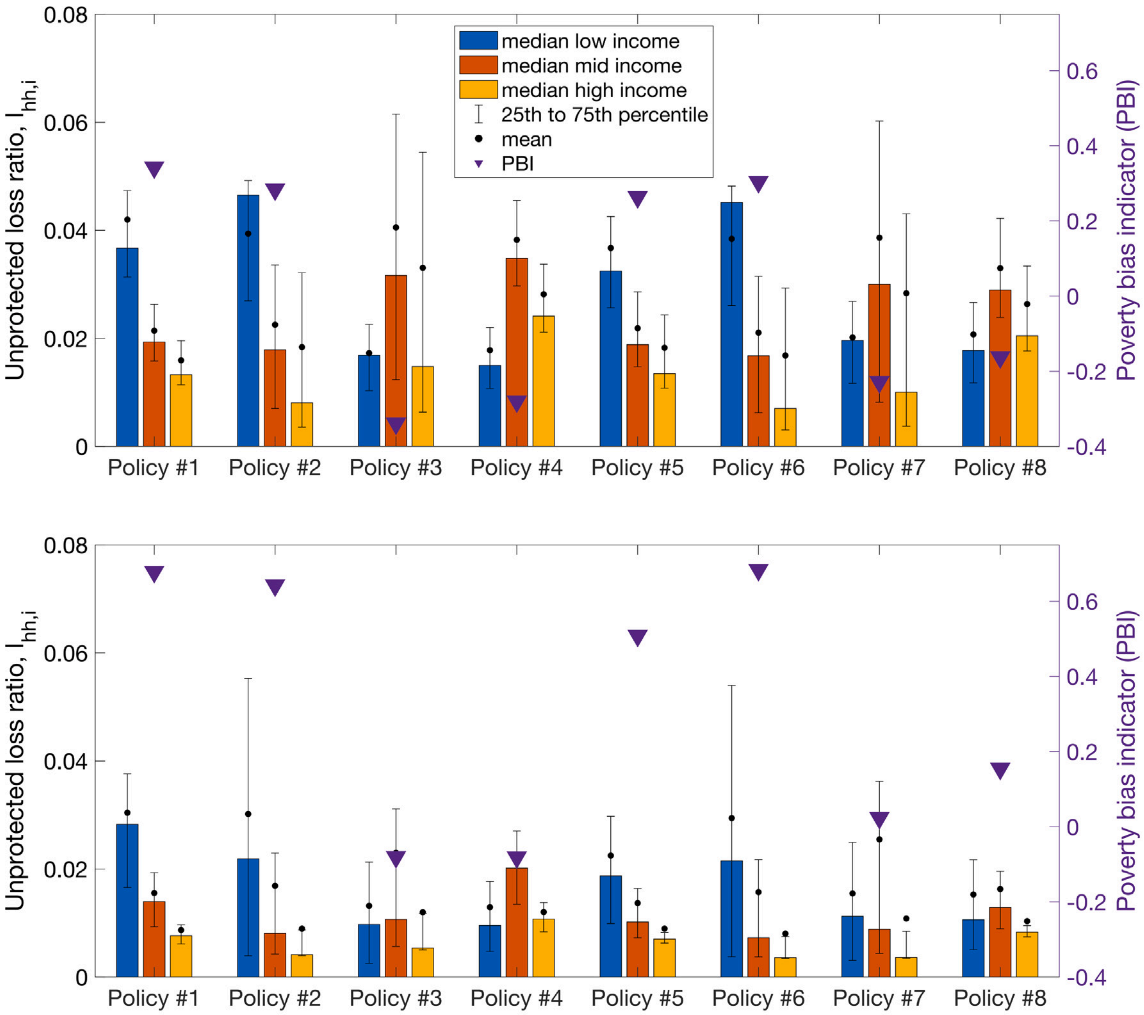

Fig. 8. $I_{hh,i}$ calculated for each candidate financial soft policy, and both TV0 and TV50_total. The top panel shows the results for TV0 (time since the last characteristic event = 50 years) and the bottom panel shows the results for TV50_total (time since the last characteristic event = 100 years). Corresponding PBI values are also shown.

We can observe that policy No. 3 is the most pro-poor financial soft policy for TV0, whereas policy No. 4 is the most pro-poor for TV50_total. We note that it is intuitive (and expected) that a financial soft policy with a premium redistribution scheme No. 3 or No. 4 – which explicitly transfers losses from low-income households to wealthier ones – would produce the lowest PBI. However, the fact that the optimal financial soft policy changes between the conditional urban plans illustrates the importance of dynamically assessing the extent to which financial soft policies are pro-poor, as urban areas expand and physical and social vulnerabilities change.

5. Sensitivity to time since the last characteristic earthquake

The time-dependent seismic hazard analysis we perform in the **Seismic Hazard Modelling** module relies on specific (assumed) constraints related to fault rupture history. In this section, we investigate the impacts of alternative assumptions regarding the time since the last characteristic event (using only TV50_total). We specifically consider two additional times since the last characteristic event for TV50_total (i.e., 50 years in the future): 150 years and 60 years.

Fig. 9 provides (left panel) the mean portfolio loss curves of residential buildings in TV50_total, for different assumed times since the last characteristic event: 100 years, 150 years, and 60 years. It can be seen (as expected) that the longer it has been since the last characteristic event, the larger the associated EAL_{port} becomes. The right panel provides the ratio of each mean portfolio loss curve to that of the curve for a 100-year period elapsed since the last characteristic event. For a 1% annual exceedance rate, it can

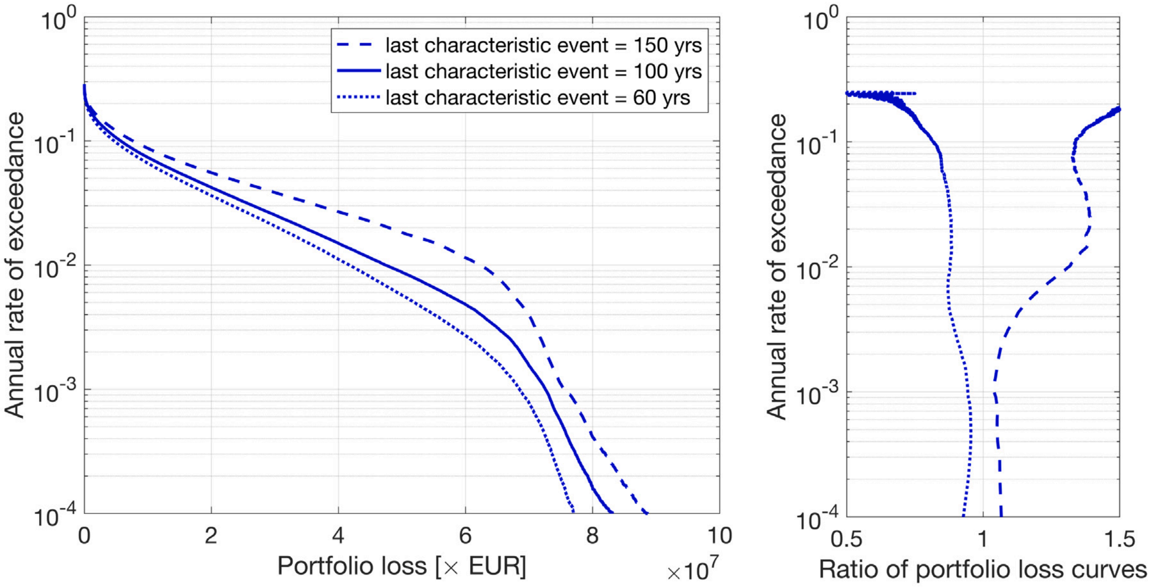

Fig. 9. Left panel: mean portfolio loss curves of residential buildings in TV50_total, considering a time since the last characteristic event (in 50 years) of 150, 100, and 60 years. Right panel: Mean portfolio loss curves for TV50_total and different times since the last characteristic event, normalised by the corresponding curve for a 100-year period since last characteristic event.

Table 8
Mean premiums (in EUR) paid by households per income group and the computed Poverty Bias Indicator (PBI) under each financial soft policy in TV50_total considering the time since last characteristic event being 60 years and 150 years, respectively.

Scenario	Financial soft policy	Low income	Middle income	High income	PBI
TV50_total (last characteristic event = 60 years)	1	106	106	106	0.684
	2	99	100	115	0.651
	3	20	143	165	−0.058
	4	20	159	159	−0.059
	5	51	51	51	0.515
	6	81	53	24	0.692
	7	16	118	54	0.043
	8	16	72	72	0.181
TV50_total (last characteristic event = 150 years)	1	169	169	169	0.663
	2	155	156	169	0.619
	3	31	222	267	−0.134
	4	31	254	254	−0.142
	5	87	87	87	0.488
	6	131	90	48	0.659
	7	26	186	100	−0.026
	8	26	124	124	0.087

be seen that the mean portfolio loss for a time since the last characteristic event of 60 years is 12% less than that for a time since the last characteristic event of 100 years, whereas the mean portfolio loss for 150 years since the last characteristic event is 31% higher. The ratios of mean portfolio loss curves approach unity as the annual exceedance rate decreases, indicating that variations in the time since the last characteristic event have relatively lower impact on the right tail of the mean portfolio loss curve.

Table 8 summarises both the mean premiums payable by households of each income group and PBI values, for each considered financial soft policy and the two additional considered times since the last characteristic event. As expected, the premiums associated with a 150-year time period since the last characteristic event are on average higher than those associated with a 100-year time gap (see Table 7), whereas the premiums associated with 60-year lag since the last characteristic event are the lowest. Fig. 10 provides both $I_{hh,i}$ values calculated for each income group and PBI values under each considered soft policies, for the two alternative seismic hazard scenarios. Soft policies No. 3 and No. 7 still result in the overall lowest $\mathbb{E}(I_{hh,i})$ in both alternative scenarios. It can

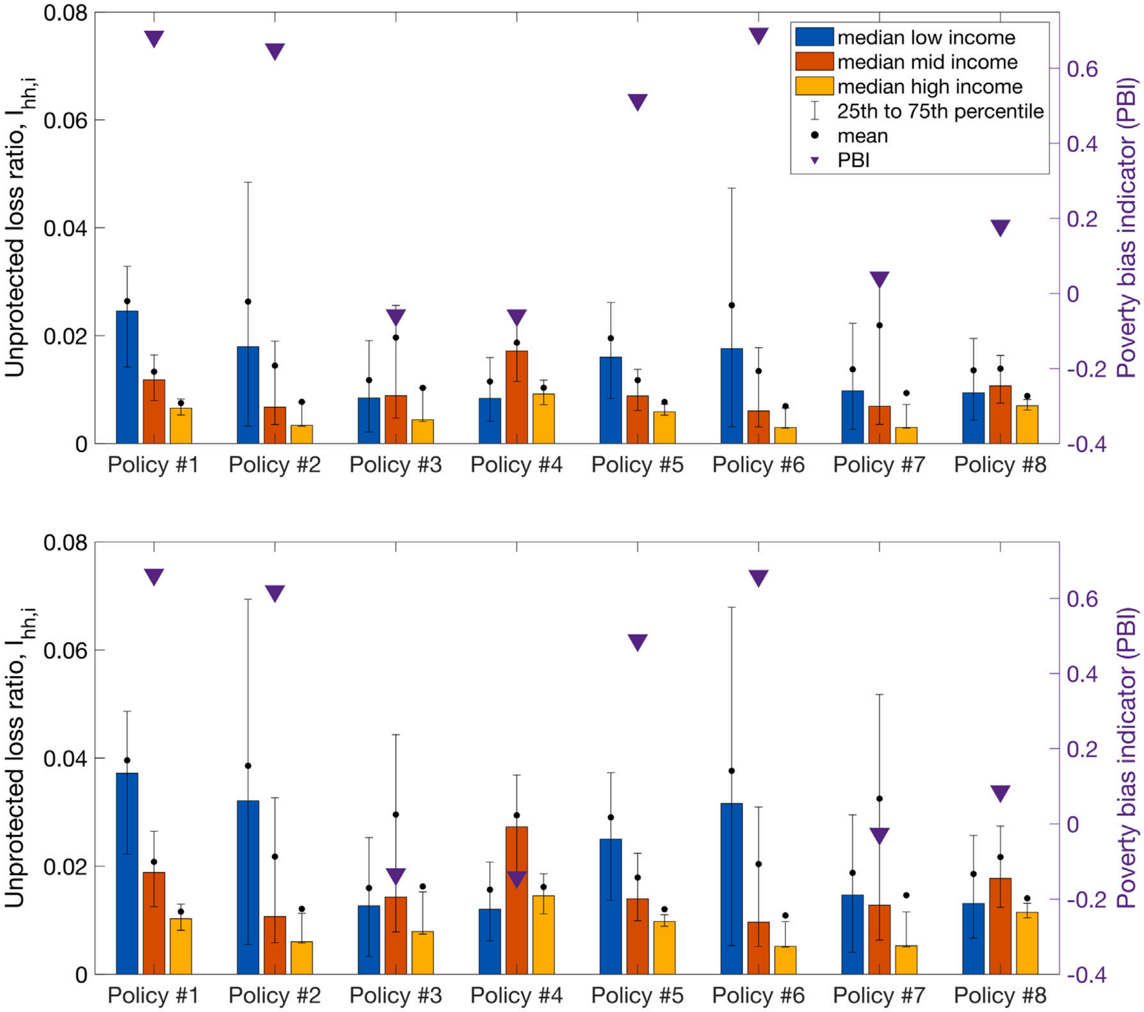

Fig. 10. $I_{hh,i}$ calculated for candidate soft policies applied to TV50_total, considering two alternative assumptions about the time since the last characteristic event (in 50 years): 60 years (top panel) and 150 years (bottom panel). Corresponding PBI values are also shown.

be observed that policy No. 4 remains the most pro-poor financial soft policy for TV50_total, regardless of the assumed time since the last characteristic event, although there are variations in the absolute values of PBI. This means that policy No. 7 is considered sufficiently pro-poor if the time since the last characteristic event is 150 years (produces a negative PBI value) but not so adequate if we assume that the last characteristic event occurred 60 or 100 years ago (produces a positive PBI value). These results highlight the importance of considering the history of relevant faults in the proposed optimal policy selection process.

6. Conclusions and future work

We leverage the Tomorrow's Cities Decision Support Environment [20] to propose a framework for designing and quantitatively assessing compulsory, seismic-risk-related, people-centred, household-level financial soft policies for expanding cities. This framework explicitly focuses on the disproportionate financial burdens often imposed on low-income people as a result of earthquake disasters, using novel impact metrics that distinguish losses on the basis of pertinent socioeconomic information. Stakeholders such as urban planning authorities, community representatives, and researchers can use the framework for informed decision making on the design of pro-poor financial soft policies for implementation in future (as well as present) earthquake-prone urban communities.

We demonstrate the proposed framework, through designing and assessing a number of different compulsory financial soft policies for the hypothetical expanding city of Tomorrowville [26]. We showcase the framework's capacity to identify financial soft

Table 9
Explanation of acronyms adopted in the paper.

Acronym or symbol	Explanation
TCDSE	Tomorrow's Cities Decision Support Environment
$I_{hh,i}$	Financial impact metric (unprotected loss ratio) of the ith household
hh	Subscript denoting "household"
i	Household index
PBI	Poverty bias indicator
GIS	Geographic information system
IM	Intensity measure
PGA	Peak ground acceleration
PGD	Peak ground displacement
PGV	Peak ground velocity
SA	Spectral accelerations
GMM	Ground motion model
$EAL_{bld,b}$	Expected annual loss of the bth building
bld	Subscript denoting "building"
b	Building index or slope of earthquake occurrence
$\mu_{EAL_{bld,b}}$	Average $EAL_{bld,b}$ of all residential buildings.
$EAL_{hh,i}$	Expected annual loss of the ith household
$EAIL_{hh,i}$	Expected annual financially protected loss of the ith household
$EAUL_{hh,i}$	Expected annual financially unprotected loss of the ith household
$EAIL_{port}$	Expected annual financially protected loss of the residential building portfolio
$EAUL_{port}$	Expected annual financially unprotected loss of the residential building portfolio
$\mathbb{E}(I_{low})$	Mean value of the financial impact metric across low-income households
$\mathbb{E}(I_{port})$	Mean value of the financial impact metric across all households
$port$	Subscript denoting "portfolio"
$\mathbb{E}(I_{hh,i})$	The average unprotected loss ratio of all households
TV0	Current urban layout of Tomorrowville
TV50_total	A possible future urban layout of Tomorrowville in 50 years
TV50_b2	New buildings to be built in Tomorrowville in the next 50 years
v_0	The annual rate of exceeding an $M4.0$ earthquake
M	Moment magnitude of earthquake events
IP	Insurance payout
L	Total assessed seismic loss
D	Deductible
C	Limit (the highest amount of a claim covered by an insurance contract)
γ	Coinsurance factor
P_{port}	Portfolio premium
$P_{hh,i}$	Premium payable by the ith household
N_{hh}	Total number of households
α	Premium loading factor
$EAIL_l$	The expected annual financially protected loss of the low-income group
$EAIL_m$	The expected annual financially protected loss of the middle-income group
$EAIL_h$	The expected annual financially protected loss of the high-income group
l	Subscript denoting "low-income" group
m	Subscript denoting "middle-income" group
h	Subscript denoting "high-income" group
$RPC_{hh,i}$	The total replacement cost of the ith household
m_0	Minimum magnitude for non-characteristic events
m_u	Maximum magnitude for non-characteristic events
m_c	Mean magnitude of characteristic events
σ_{M_c}	Standard deviation of the characteristic-event magnitude distribution
μ_T	Mean of the inter-arrival time of characteristic events
σ_T	Standard deviation of the inter-arrival time of characteristic events
DS	Damage state
θ_{DS1} to θ_{DS4}	Medians of the fragility relationships for $DS = 1$ to 4
β_{DS1} to β_{DS4}	Dispersion of the fragility relationships for $DS = 1$ to 4

policies that are adequately pro-poor in terms of the earthquake-related impacts experienced as a result of their implementation. We also illustrate the framework's usefulness in comparing the extent to which different soft policies are pro-poor in their approach. Our case-study application of the framework highlights the importance of adopting a future-focused approach in the design of financial soft policies, by revealing that the "optimal" (i.e., most pro-poor) financial soft policy may depend on the exact configuration of the urban system (i.e., layout of the building portfolio as well as the underlying physical and social vulnerabilities) that evolves in time. Policies deemed sufficiently pro-poor today do not necessarily remain pro-poor in the future. We further investigate the impact of time-dependent seismic hazard on the pro-poorness of policies. We find that varied assumptions on the fault's history (and therefore different temporal instances in the fault's cycle) can lead to different conclusions on the pro-poorness of a given financial soft policy, emphasising the importance of accounting for the dynamic (time-dependent) nature of risk in relevant policy-related decision-making contexts.

The proposed framework exclusively focuses on compulsory financial soft policies for residential earthquake risk mitigation. However, most national or regional financial soft policies of this type (i.e., earthquake insurance schemes) are optional and do not have a high penetration rate for a variety of reasons, one of them being the myopia of insurance purchasers [53–56]. People tend to cancel their insurance policies after a disaster if they do not suffer damages in a certain timeframe. For example in California, earthquake insurance take-up rate spiked after the 1994 Northridge earthquake, whereas relatively few households purchase insurance coverage in this state nowadays [55]. Considering this typical behaviour, our findings, which show an increase in the price of insurance premiums as the time elapsed since the last characteristic event lengthens, underline the importance of ensuring that financial soft policies are both compulsory but also pro-poor. Future work could focus instead on the design of non-compulsory seismic risk mitigation measures (e.g., optional earthquake insurance policies) and their effectiveness for various levels of uptake.

Future work could also assess the long-term effects of earthquake-risk-related financial soft policies on post-earthquake housing recovery and population displacement. Many studies have identified financing as a critical driver of post-disaster housing recovery and a significant predictor of a homeowner's post-disaster decision to rebuild or relocate [57,58]. Moreover, insurance is one of the major funding sources for post-disaster housing recovery [45,59]. Our framework could be leveraged towards addressing this research gap, for specific investigations into the extent to which the long-term recovery of low-income people can be improved as a result of certain financial soft policies [60–62].

7. Acronyms and symbols

Table 9 summarises acronyms and symbols adopted in the paper.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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