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Development and Assessment of Pro-poor Financial Soft Policies for Earthquake-prone Urban Communities

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ABSTRACT: Recent earthquake events 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, such as seismic retrofitting. However, the benefits of existing financial soft policies are often not guaranteed. Among other factors, this may be attributed to their low penetration rate (e.g., in the case of earthquake insurance) and the fact that they typically neglect the explicit needs of low-income populations. We facilitate a way to address such shortcomings by proposing a framework for designing and assessing bespoke, people-centred, household-level, compulsory financial soft policies related to earthquake risk (including conventional earthquake insurance, income-based tax relief schemes, or a combination of these) across urban areas. The proposed framework leverages the Tomorrow’s Cities Decision Support Environment, which aims to promote pro-poor risk-sensitive urban planning through strong local engagement. The framework specifically enables decision makers to design and assess the pro-poorness of mandatory financial soft policies, using financial impact metrics that discriminate earthquake-disaster losses on the basis of income. We showcase the framework using "Tomorrowville", a hypothetical city that reflects a global-south urban setting in terms of its socioeconomic and physical aspects.

1. INTRODUCTION

Earthquakes can cause substantial direct economic impacts due to physical damage and downtime. Financial (‘soft’) seismic risk mitigation measures (e.g., disaster relief funds) protect the assets of individuals or entities from earthquakes by providing monetary compensation for damages incurred (Franco, 2014). These measures can complement ‘hard’ seismic risk mitigation measures such as seismic retrofitting (Gentile et al., 2021).

Earthquake insurance is a well-known soft measure for seismic risk mitigation. A typical residential earthquake insurance policy provides homeowners with coverage for 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; or (2) a risk-based rate determined on building structural type, building location, building replacement cost, etc (Goda et al., 2014). Residential earthquake insurance policies are widely available (e.g., in California, New Zealand, and Turkey).

However, penetration rates (i.e., percentages of assets with insurance coverage) vary greatly. Moreover, these policies do not explicitly address the needs of low-income households, who have been historically disproportionately impacted by natural-hazard-driven disasters (due to their inability to pay for emergency supplies, post-disaster repairs, etc.; Winsemius et al., 2018). Other financial disaster-relief tools, e.g., post-disaster cash transfers, do not sufficiently recognise the amplified needs of low-income people either. For example, after the 2015 Nepal earthquake ($M7.8$), an equal amount of financial assistance was provided by the Government of Nepal to homeowners regardless of income level, leaving many low-income households struggling to afford reconstruction costs (Rawal et al., 2021).

This study facilitates an approach to addressing the aforementioned shortcomings of conventional earthquake-risk-related financial soft policies, using the Tomorrow's Cities Decision Support Environment (TCDSE) (Cremen et al., 2023). 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 planning (Galasso et al., 2021). We leverage the TCDSE to develop a framework for designing and assessing bespoke compulsory financial soft policies related to residential properties, with a strong focus on the extent to which these policies are pro-poor. The compulsory financial soft policies considered in this study encompass, for instance, components of conventional earthquake insurance and income-based tax relief schemes. We demonstrate the proposed framework using a hypothetical city "Tomorrowville".

2. PROPOSED FRAMEWORK

The proposed framework, as shown in Figure 1, has four calculation modules within the Computational Model: (1) Seismic Hazard Modelling; (2) Physical Infrastructure Impact; (3) Social Impact; and (4) Computed Impact Metrics. The decision makers first design candidate 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 earthquake-induced financial losses. Each iteration of the framework evaluates the impacts associated with one Visioning Scenario. Through multiple iterations of the framework, decision makers can identify the optimal pro-poor policy bundle (and the overall Visioning Scenario), 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. (2022).

2.1. *Urban planning*

The Urban Planning module encompasses a conditional urban plan detailing land uses, the 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, 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. 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, an income-based tax relief scheme, or a combination of those.

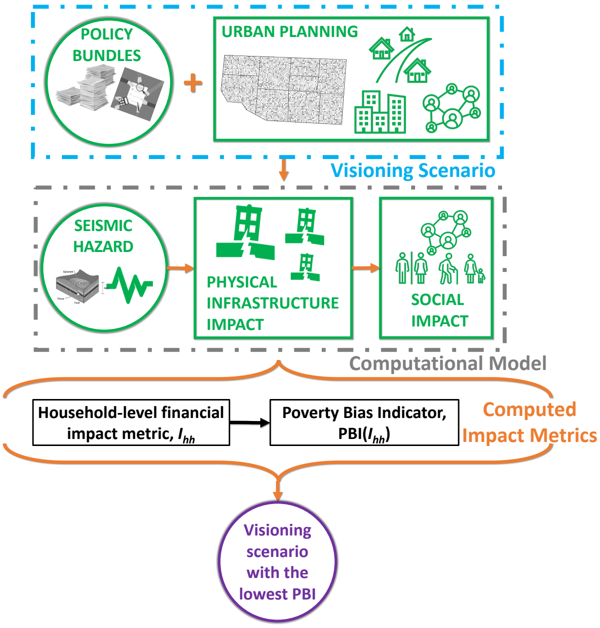

Figure 1: A flowchart of the proposed framework to design and assess pro-poor financial soft policies.

They may also alter the financial burden on households across different social (e.g., income) groups.

2.3. Seismic hazard modelling

The Seismic Hazard Modelling module estimates relevant earthquake-event features (e.g., source/rupture features) and resulting earthquake-induced ground-motion intensity measures (IM) at the locations of considered residential buildings. The outputs of this module are ground-motion fields for multiple intensity measures, e.g., peak ground acceleration (PGA), spectral accelerations at different structural periods (SA), peak ground velocity (PGV), and peak ground displacement (PGD), which are computed in a probabilistic sense. These fields can be simulated using a ground-motion model (GMM), e.g., Campbell and Bozorgnia (2014). Spatial correlation and cross-IM correlation models (e.g., Markhvida et al., 2018) can also be used to produce more accurate fields. Seismic hazard can be modelled using a single-scenario or probabilistic approach (considering uncertainties in the rupture features and occurrence times). The latter method is more suitable for decision making in the insurance sector (Cremen et al., 2022) and therefore the context of the proposed framework, and is adopted herein.

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 (i.e., repair costs). Given the simulated ground-motion fields, this module utilises fragility relationships to sample the damage state (DS) of each residential building. It then uses damage-to-loss ratios or consequence models to compute the asset loss as a percentage of building replacement cost. Alternatively, vulnerability relationships can be used to directly estimate the loss ratio 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 (e.g., $EAL_{bld,b}$, building-level expected annual losses for the bth residential building) 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. The calculations in this 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 to quantify the impacts for a Visioning Scenario through 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. The *PBI* was originally introduced as the Poverty Exposure Bias Indicator in Winsemius et al. (2018), and modified by Cremen et al. (2022). For a given household-level financial impact metric, the *PBI* adopted in this framework is expressed as follows:

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

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 its mean value across all households. A negative value of *PBI* indicates that the 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 propoor the associated financial soft policies (and overall Visioning Scenario). The framework primarily aims to facilitate the selection of the Visioning Scenario with the lowest *PBI*, but can also be leveraged to compare the extent to which one Visioning Scenario is more pro-poor than another.

3. CASE STUDY

We use the 2 km $\times$ 3 km hypothetical city "Tomorrowville" (see Mentese et al., 2022) as our virtual testbed to demonstrate the proposed framework. Tomorrowville imitates a global-south urban setting in terms of its socioeconomic and physical characteristics. 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 financial soft policies involve conventional earthquake insurance strategies and income-based financial relief tax schemes. We focus on the current urban layout of Tomorrowville (known as "TV0") and account for seismicity related to three nearby hypothetical strike-slip faults.

3.1. Urban planning

TV0 (shown in Figure 2) includes Tomorrowville's current land use plan, a building portfolio (containing 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). TV0 contains 3,423 residential buildings and 7,809 households. Households within the same polygon belong to the same income group. Residential polygons are categorised into low-, middle-, and high-income categories. There are 4,236, 1,705, and 1,868 low-, middle-, and high-income households, respectively.

See Table 1 in Wang et al. (2023) for an exhaustive list of building typologies in Tomorrowville. Low-code "brick and mud walls" buildings (typology No.2) dominate Tomorrowville's current residential building portfolio; over 64% of low-income households live in buildings of this typology. On the other hand, 48% of high-income households live in high-code "Masonry-infilled reinforced concrete frame" buildings (typologies No.7 and 10) - two of the most expensive and strongest building types. In this case study, we assume that repair costs of multi-family residential buildings are equally attributed to all households that live within them. The average replacement costs for low-, middle-, and high-income households are €5,348, €8,511, and €11,902, respectively.

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. Deductible (D, the amount of money that the insured party need 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 (Goda et al., 2014) that determines the insurance payout

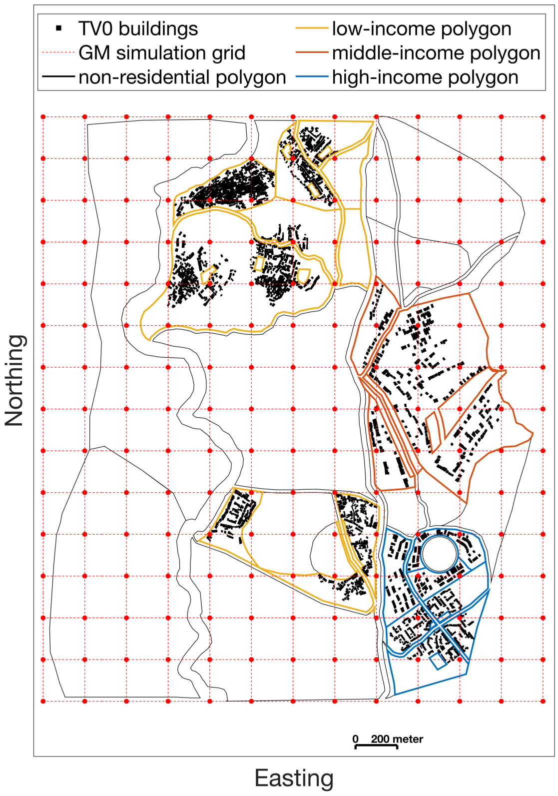

Figure 2: Residential buildings in Tomorrowville (TV0).

(IP), as follows:

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

where L refers to the total assessed seismic loss, i.e., ground-up loss, of a building. 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. $EAIL_{hh,i}$ is calculated by integrating the annual exceedance financially protected loss curve for the associated building and dividing by the number of households occupying it. 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. For this case study, we adopt a premium loading factor of 1.25, in line with Gentile et al. (2021). Each financial soft policy consists of a payout function and a premium redistribution scheme (as shown in Table 2).

3.2.2. *Payout function*

In this case study, we examine two representative payout functions. Payout function No.1 is uniform across all income groups; a D of €1,000 and a 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. Payout function No.2 adopts different D's for different income groups. D is €6,400, €4,800, and €1,600 for high-income, middle-income, and low-income, respectively, which roughly correspond to 5 to 20% of the average total replacement cost of residential buildings in TV0. We adopt a coinsurance factor (γ) of 1.0 for both payout functions.

3.2.3. *Premium redistribution scheme*

The premium redistribution scheme (PRS) is used to compute the premium for each household as some proportion of P_{port}. PRS 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. The premium for each household is imposed in the form of a mandatory tax.

Table 1 summarises the four PRSs considered in this case study. PRS No.1 imposes a flat-rated premium on each household, which reflects earthquake insurance approaches in New Zealand (Middleton, 2001). PRS No.2 distributes premiums based on $EAIL_{hh,i}$ values, which broadly reflects the earthquake insurance programs of Turkey and California (Goda et al., 2014). PRSs No.3 and 4 transfer 80% of the expected annual financially protected loss of the low-income group within the entire portfolio ($EAIL_l$) to middle- and high-income groups, thereby mitigating the financial burden on the low-income. PRS 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 PRS No.4 imposes flat-rated premiums on each household within a given income group.

3.3. Seismic hazard modelling

We account for three hypothetical vertical strike-slip faults in the proximity of Tomorrowville (see Figure 2 in Wang et al. (2023) for details). We assume all faults can generate non-characteristic and characteristic events. We assume that the moment magnitude (M) of non-characteristic events follows the Gutenberg-Richter magnitude frequency distribution (Gutenberg and Richter, 1944) and their occurrence follows a Poisson distribution. We assume a slope of occurrence $b = 1$, and a minimum and maximum magnitude for non-characteristic events of 4.0 and 6.5, respectively. We assume the magnitude of characteristic events follows a truncated normal distribution for $6.5 < M < 7.5$, with mean 7.0 and standard deviation 0.25 and that their occurrence follows a Weibull distribution. The mean and standard deviation of the inter-arrival time of characteristic events are 200 and 50 years, respectively. We use Monte Carlo sampling to simulate 10,000 one-year earthquake catalogues, considering the time since the last characteristic event is 50 years.

We simulate spatial cross-correlated ground-motion fields across Tomorrowville, using the GMM in Campbell and Bozorgnia (2014) and the spatial and cross-IM correlation model in Markhvida et al. (2018). We use Monte Carlo sampling to simulate 100 sets of ground-motion fields for each event, on a 200 m $\times$ 200 m grid shown in Figure 2. 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

See Table 5 in Wang et al. (2023) for the fragility functions associated with each building typology in Tomorrowville, which are used in conjunction with a set of deterministic damage-to-loss ratios for each DS: 0.07 for $DS = 1$, 0.15 for $DS = 2$, 0.50 for $DS = 3$, and 1.00 for $DS = 4$ (Cosenza et al., 2018). In this case study, the outputs of this module include the annual exceedance loss curve, $EAL_{bld,b}$, and the expected annual portfolio loss (EAL_{port}; i.e., the summation of $EAL_{bld,b}$).

3.5. Social impact

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

Figure 3 displays the mean portfolio annual exceedance loss curves associated with payout functions No.1 (left panel) and No.2 (right panel). Payout function No.1 results in greater financially protected losses than payout function No.2. The mean premiums payable by households of each income group are shown for each policy in Table 3. Policies No.1 to 4 that adopt payout function No.1 result in higher premiums, because of its larger $EAIL_{port}$ value compared to payout function No.1. Because payout function No.2 specifies lower deductibles for middle- and low-income households and buildings occupied by these people are in general less seismic-resistant compared to those occupied by the high-income, the average $EAIL_{hh,i}$ is higher

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

PRS	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 2: Eight financial soft policies considered for this case study.

Policy	Payout function	PRS	Policy	Payout function	PRS
1	1	1	5	2	1
2	1	2	6	2	2
3	1	3	7	2	3
4	1	4	8	2	4

for low- and middle-income people than for high-income people. Policies No.3, 4, 7, and 8 that employ PRSs No.3 or No.4 burden low-income households with significantly lower premiums compared to the other policies.

Figure 4 shows the mean, median, and 25th to 75th percentile range of $I_{hh,i}$, computed for households in each income group under each policy. Also shown are *PBI* values for each policy. Policies No.3 and No.7 lead to the lowest value of $\mathbb{E}(I_{hh,i})$. 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 Figure 4). The positive values of *PBI* obtained for these policies further indicate that they result in a disproportional financial burden on low-income households. 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* as expected.

5. CONCLUSIONS

We leverage the Tomorrow's Cities Decision Support Environment (Cremen et al., 2023) to propose a framework for designing and quantitatively assessing compulsory, seismic-risk-related people-centred, household-level financial soft policies for

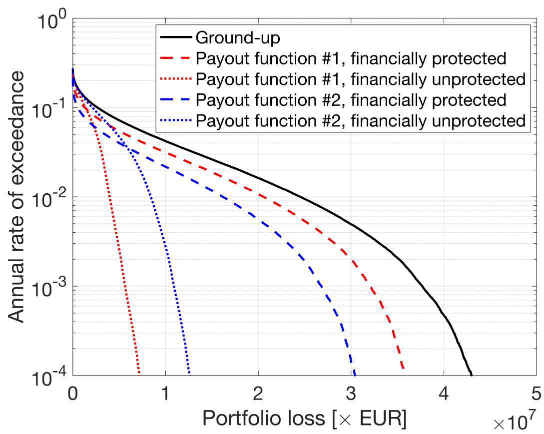

Figure 3: Mean ground-up, financially protected and unprotected portfolio annual exceedance loss curves.

Table 3: Mean premiums (in EUR) paid by households per income group and the computed Poverty Bias Indicator (PBI) for each financial soft policy.

Policy	Low-income	Middle-income	High-income	*PBI*
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

earthquake-prone urban areas. This framework explicitly focuses on addressing the disproportionate earthquake-related financial burdens often imposed on low-income people, using novel impact metrics that distinguish losses on the basis of pertinent socioeconomic information. We demonstrate the proposed framework through designing and assessing a number of different compulsory financial

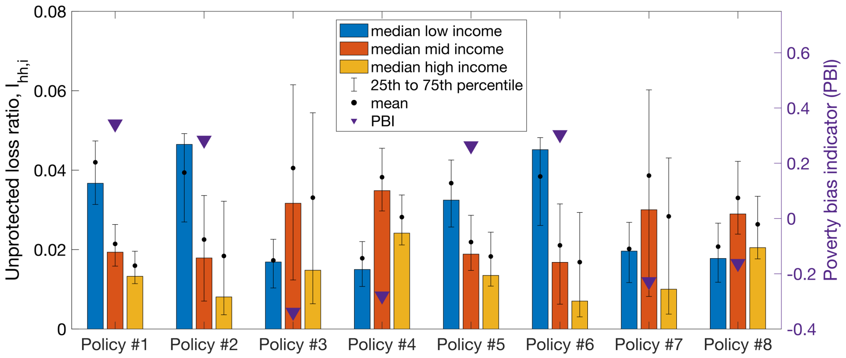

Figure 4: $I_{hh,i}$ calculated for each candidate financial soft policy. Corresponding PBI values are also shown.

soft policies for the hypothetical city of Tomorrowville (Mentese et al., 2022). This demonstration showcases the framework's capacity to identify financial soft policies that are pro-poor in terms of the earthquake-related impacts experienced as a result of their application. 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 current (and future) earthquake-prone urban communities.

6. ACKNOWLEDGEMENTS

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