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# Quantification of disaster impacts through household well-being losses

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**Natural disaster risk assessments typically consider environmental hazard and physical damage, neglecting to quantify how asset losses affect households' well-being. However, for a given asset loss, a wealthy household might quickly recover, while a poor household might suffer major, long-lasting impacts. This research proposes a methodology to quantify disaster impacts more equitably by integrating the three pillars of sustainability: environmental (hazard and asset damage), economic (macro-economic changes in production and employment) and social (disaster recovery at the household level). The model innovates by assessing the impacts of disasters on people's consumption, considering asset losses and changes in income, among other factors. We apply the model to a hypothetical earthquake in the San Francisco Bay Area, considering the differential impact of consumption loss on households of varying wealth. The analysis reveals that poorer households suffer 19% of the asset losses but 41% of the well-being losses. Furthermore, we demonstrate that the effectiveness of specific policies varies across cities (depending on their built environment and social and economic profiles) and income groups.**

Direct economic asset losses—the monetary value of damage to physical assets[1,2]—are routinely used to measure the impact of natural disasters when they occur and to quantify the risk posed by natural hazards. Consequently, they are the main financial metric for tracking disaster risk-reduction progress. This approach generates essential insights for managing interactions among natural hazards and the built environment, in partial fulfilment of the first Priority for Action of the 2015–2030 Sendai Framework for Disaster Risk Reduction (understanding disaster risk)[3]. However, direct economic asset losses provide an incomplete measure of the total cost of any event. Other loss dimensions include lost wages and other income, interruption of educational and health services, disruption caused by temporary or permanent relocation and decreased consumption[4–7]. Furthermore, direct economic asset losses cannot be used to measure many of the benefits associated with the other three Sendai Priorities for Action: strengthening governance, investing in resilience and enhancing preparedness for effective response. At all scales, emergency preparedness, formal and informal coping mechanisms, and humanitarian relief affect the immediate and long-term consequences of disasters, even when they do not reduce direct asset losses.

The UN Sustainable Development Goals[8] and the Sendai Framework for Disaster Risk Reduction[3] call for enhanced protection of people disproportionately affected by disasters, such as the poor—another aspect that direct economic asset losses fail to address. By definition, wealthy individuals have the most assets to lose. Therefore, asset losses often proxy their experience of a shock. The poor are under-represented in asset loss calculations[9] and lack the resources to smooth income shocks and recover their asset stock while maintaining predisaster consumption[9,10]. Therefore, the poor are more likely than the wealthy to forego consumption of food, health or education, and to take longer to recover from a shock[11–15].

Here we address two limitations of traditional risk assessments that focus on asset losses. First, we model the macro-economic consequences of the disaster, assessing how damage affects economic output in various sectors, and the implication on jobs and incomes. Second, we use well-being loss to capture the disparate effect of disasters on different socioeconomic groups throughout the recovery period. Based on classical welfare economics, well-being loss is a measure of the utility of consumption lost during household's recovery from shock[16]. The lost consumption includes the loss of labour income and housing services, cost of reconstruction, and use of resources such as savings or insurance payouts in the process of recovery.

Measuring disaster impacts with utility instead of consumption allows one to account for the differential impact of losing US$1 in consumption, as a function of wealth. While richer individuals can reduce their consumption with limited impact on their well-being, poorer individuals cannot. At the extreme, the very poor have to reduce consumption of food, education or health care. The impact of such cuts on well-being can be large and, for children, can have lifelong consequences[17,18].

The well-being quantification methodology in this paper integrates the three aspects of sustainability: environmental (the impact of the hazard), economic (the cost of damages and implication for jobs and income) and social (the distributional impact of the shock and the role of socioeconomic factors). It builds on previous research[19,20] and uses a multistage simulation that explicitly quantifies damages to the built environment, postdisaster dynamics of economic sectors and changes in household consumption across socioeconomic groups, while propagating modelling uncertainties. While previous approaches for evaluating disaster management policies typically focused on assessing the effect of either predisaster risk reduction[21–23], preparedness and early warning[24] or insurance[22], the proposed methodology allows evaluation of policies pertaining to all stages of the disaster management cycle[25].

To illustrate the methodology, we evaluate San Francisco Bay Area earthquake losses and compare the effect of several mitigation options. We show the importance of including social aspects in risk assessments: well-being losses are strongly influenced by factors other than asset damage, such as predisaster income, access to capital and postdisaster changes in labour income. This can cause

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the geographic extent and severity of well-being losses to extend far beyond the distribution of direct asset losses. We also demonstrate the value of the well-being loss metric in evaluating and comparing physical and social intervention strategies. We show that the effectiveness of different strategies varies across cities, depending on their building stock, socioeconomic profile, income sources and location relative to the hazard. As far as we are aware, no previous study has quantitatively compared regional risk mitigation strategies considering an impact metric that can be equitably applied across households with different wealth levels.

## Asset and well-being loss assessment

The proposed methodology innovates by integrating four distinct models to calculate well-being losses at the household level. First, the environmental hazard (in our case, earthquake ground motion) is simulated at a regional scale for a particular event scenario. To take into account the uncertainty associated with spatially distributed hazard, uncertainty models that consider the joint distribution of shaking throughout the region are used to generate multiple ground motion maps[26,27].

Then, for each of the ground motion maps, damage to the built environment is assessed, considering residential, commercial and industrial buildings. Damage is determined at the individual building level and uncertainty is captured by simulating the damage states with varying probabilities of occurrence. Depending on the building occupancy type and replacement cost, a damage state is translated to a repair cost (or direct asset loss) and time[28].

Once physical damages and associated losses are simulated, their effect on the productivity of economic sectors is determined by using a dynamic adaptive regional input–output model[19,29]. Productivity is affected by destruction of productive capital (for example, factories, equipment or machinery), decrease in demand due to reduced consumption, increase in demand due to reconstruction, and supply constraints caused by suppliers' inability to satisfy demand. Such postdisaster dynamics and industry interdependencies can cause large changes in output and gross product of the affected region, which at an individual level can result in a loss of employment and income.

Lastly, a new model that uses results from the previous three steps is used to determine well-being losses at the household level, considering its unique socioeconomic characteristics. The model builds on the approach used in the Philippines[20] by explicitly considering the impact of the disaster on employment and labour income and conducting the analysis at a high spatial resolution. This societal modelling step performs microsimulations of the household's change in consumption over a 10-yr recovery period, as shown in Fig. 1. Changes in consumption can result from the need to pay for housing reconstruction, loss of housing services and cost of temporary housing, and loss of labour income. Households can reduce their consumption losses by using their savings, which they will then need to replenish, or by receiving payments if they have insurance. Reconstruction and recovery of housing services depend on the severity of damages, repair time and the ability of a household to finance the repairs. Recovery of labour income depends on the recovery of the economic sector from which the household derives its income. Finally, well-being losses are calculated considering the utility of consumption losses corresponding to the household's wealth level. The final metric allows one to directly compare losses across households of differing socioeconomic status, as it considers losses in terms of utility and not absolute US$ amount. Model details and data sources are provided in the Methods.

## San Francisco Bay Area earthquake impacts

We consider the consequences of a large potential earthquake in the San Francisco Bay Area. The San Francisco Bay Area, also known as the Bay Area, is comprised of nine counties (see Fig. 2) in Northern California and is home to over 7.6 million people. The area has a complex governance structure, with 101 cities, 27 transit agencies, 67 water districts and four regional governance agencies. It has a 2017 gross domestic product (GDP) of US$748 billion and is growing rapidly[30]. The largest sectors by value added are finance, insurance, real estate, rental and leasing; professional and business services; and manufacturing. The largest employment sectors are educational services, health care and social assistance; professional and business services; and manufacturing. While the GDP of the Bay Area is high, large inequalities exist and upward economic mobility is limited[31]. Insufficient housing supply has caused the highest increase in housing prices in the country, further contributing to inequality[32].

The region is located in the middle of multiple fault zones capable of producing earthquakes of moment-magnitude ($M_w$) >6.7 (ref. [33]). The earthquake risk in the area is exacerbated by a vulnerable building stock, low residential earthquake insurance penetration and a large renters market raising concern over potential postdisaster out-migration. Here we analyse the impact of an $M_w$ 7.2 earthquake on the Hayward fault. We consider a baseline case with the current building stock, economic conditions and insurance penetration (assuming 13% of households are covered[34] with a 15% deductible). We then explore the impact of policy options on reducing losses.

## Results

A large earthquake in the Bay Area would be devastating. The average direct economic asset losses from the simulations are US$115 billion (15% of regional GDP). This is in line with previous studies[35]. Most losses (56%) occur in the housing sector, with only 7% of the housing losses covered by insurance. Only 56% of residents will be liable for paying for reconstruction because of the large renters market. Housing asset losses are concentrated around the fault rupture, where larger ground shaking is expected (Fig. 3). The most affected cities in terms of housing asset losses are Oakland, San Jose and San Francisco (Fig. 2). The three cities suffering the highest asset losses per capita are Piedmont, El Cerrito and Berkeley, which are located in Alameda and Contra Costa counties.

Damages in the productive private sector result in an average US$51 billion of direct asset losses. The destruction of productive capital ripples through the economy causing an additional US$35 billion of losses in value added (or flow losses, sometimes referred to as indirect economic losses) and it takes ~2.5 yr for the regional GDP to recover. The most affected sectors in absolute terms are professional and business services (35% of total losses in value added) and finance, insurance and real estate industry (32%). However, the sectors with the largest losses relative to their predisaster value added are service industries such as repair and maintenance services, personal and laundry services, and religious, grantmaking, civic, professional and similar organizations, collectively known as 'other services', whose total losses amount to 81% of the sector's annual value added. Information on economic sector losses and the associated uncertainty is provided in the Supplementary Information.

The decrease in production causes an initial drop in employment of 8.7% and an average of 36,200 employee-years are lost over the recovery period (around half of the employee-years lost in the fault zone of the 1994 Northridge earthquake[36]). Most of the lost employment is in service industries. Income losses over the recovery period are substantial—on average 23% of the housing asset losses. Figure 3 shows that income losses are distributed more broadly than asset losses, since employment income is related to the economic health of the entire region. The city of San Francisco is more affected in terms of employment losses than other major cities such as Oakland and San Jose, since it has a larger number of employees who work in highly affected sectors. In some areas, income losses can even exceed asset losses (Fig. 3). This shows the importance of looking beyond asset losses to understand disaster consequences.

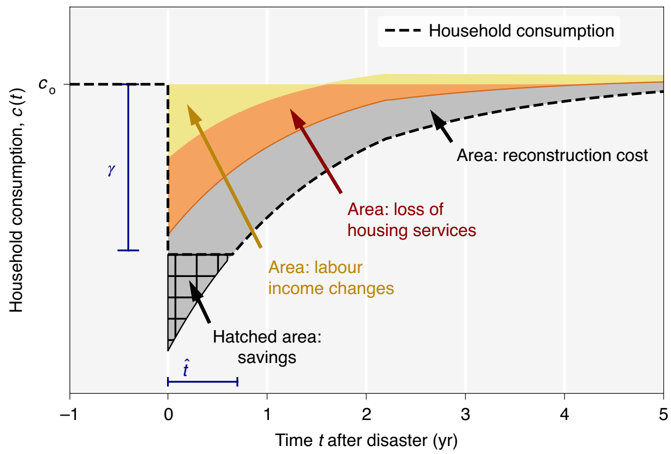


**Fig. 1 | Schematic of the household postdisaster consumption model.** The time interval $\hat{t}$ is the time during which savings are used to offset consumption losses and $\gamma$ is the consumption loss during that time.

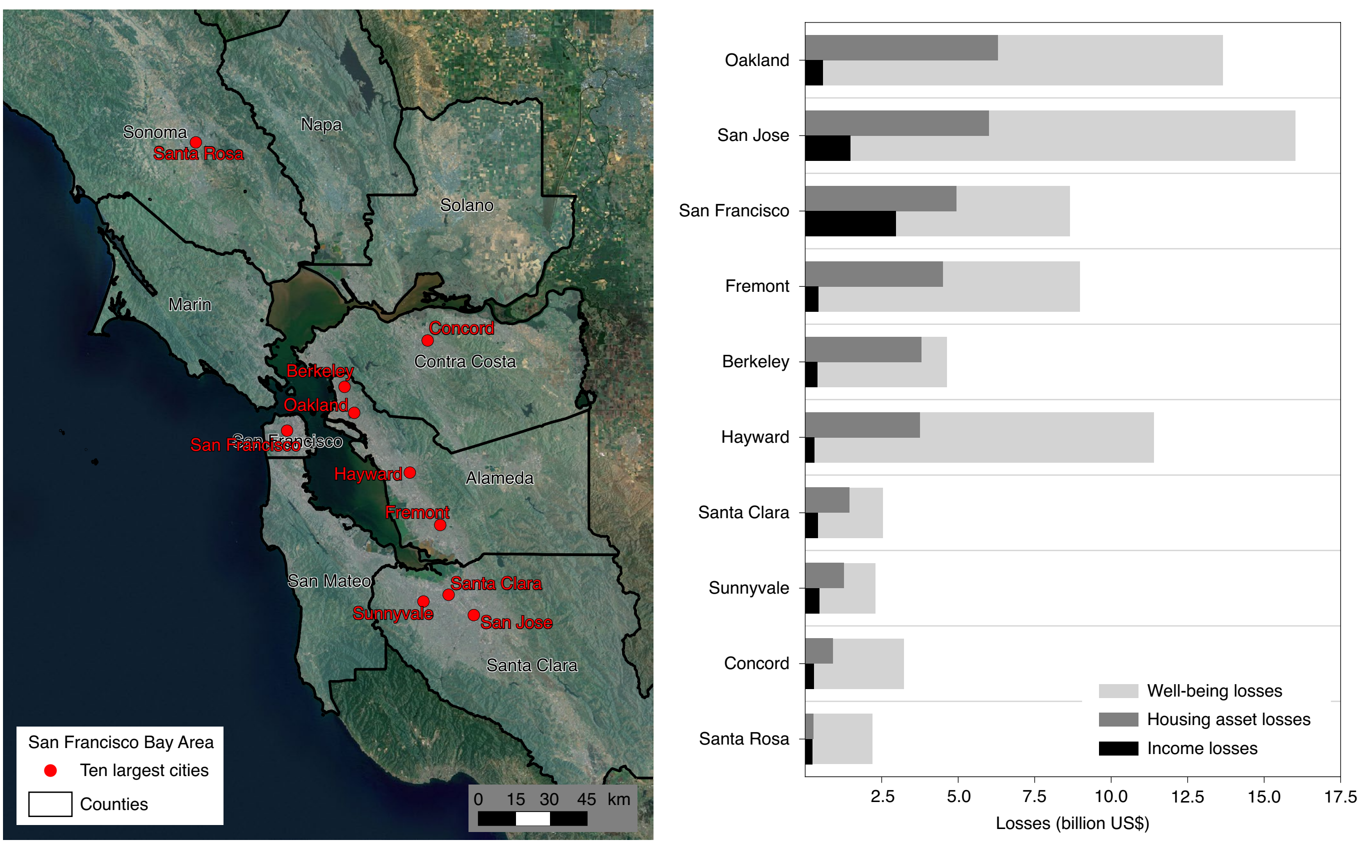


**Fig. 2 | The consequences of a potential earthquake in the San Francisco Bay Area on the largest cities.** Map of the Bay Area (left). Average total well-being losses, housing asset losses and income losses for the ten largest cities in the Bay Area, ranked by housing asset losses (right). Credit: ESRI, i-cubed, GeoEye (basemap); Metropolitan Transportation Commission and the Association of Bay Area Governments (counties shapefiles).

At the household level, housing asset losses tend to increase with predisaster income because wealthier households tend to be homeowners with higher valued assets (see Supplementary Fig. 4). The housing asset loss metric, however, does not indicate how the overall consumption and well-being of the household is impacted since it does not consider loss of labour income, availability of savings, the need to relocate during housing repair works and the household's predisaster socioeconomic status. Well-being losses, on the other hand, do consider such factors and the trend is the opposite to that of asset losses: well-being losses sharply decrease with increasing income (see Supplementary Fig. 4). The result reveals the disproportionate effect of disasters on lower income households (Fig. 4). While households in the poorest quartile suffer only 19% of the overall asset losses, they experience 41% of the well-being losses. On the other hand, the wealthiest quartile suffers 35% of the asset losses, while experiencing only 15% of the well-being losses.

At the regional scale, well-being losses are more than double the housing asset losses and extend beyond areas surrounding the

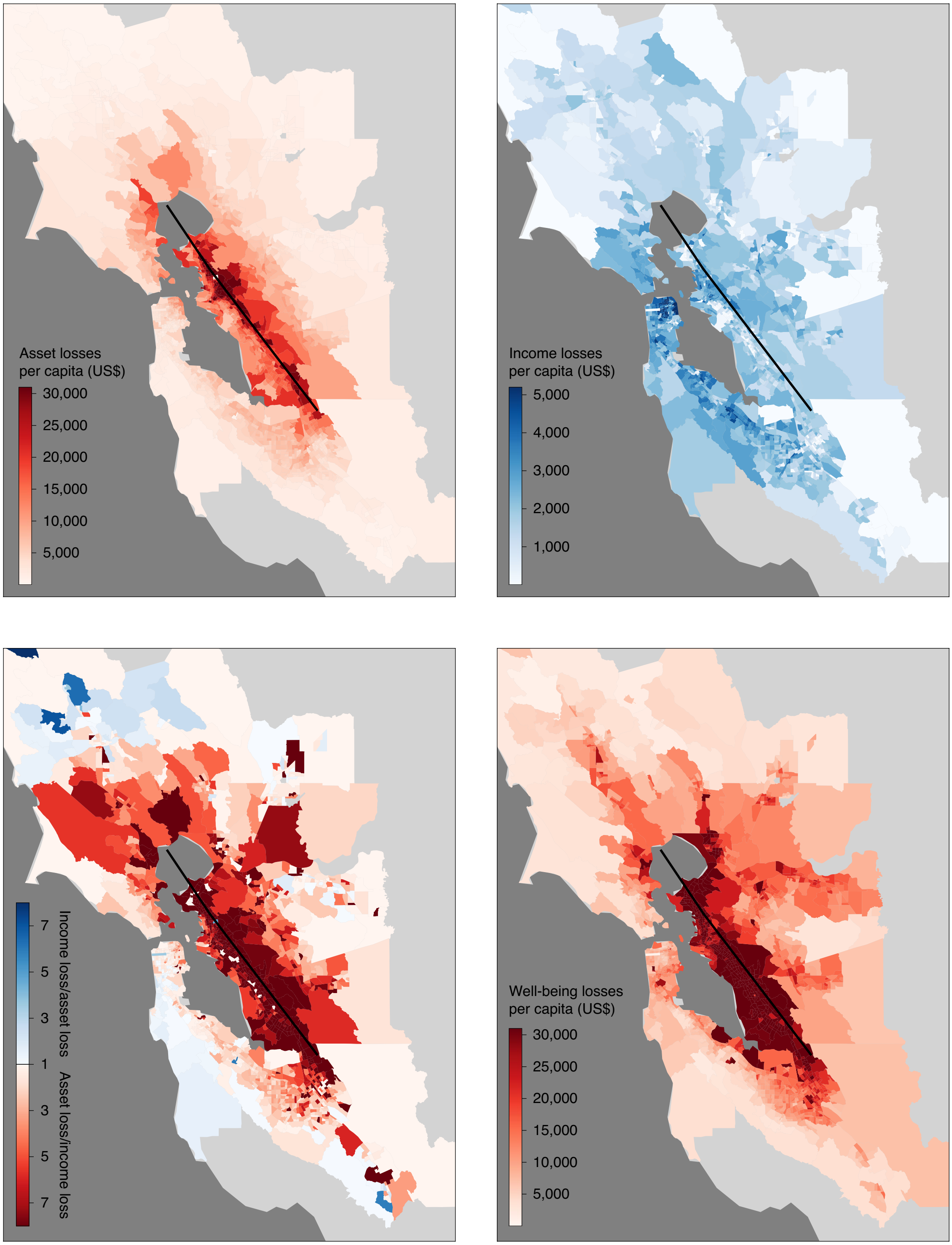


**Fig. 3 | Spatial distribution of average losses per capita.** Spatial distributions of average housing asset losses per capita (top left) and average income losses per capita considering a 10-year recovery period (top right). Relationship of average income losses and asset losses where in blue are areas where average income losses exceed asset losses and in red are areas where average asset losses exceed income losses (bottom left). Spatial distribution of well-being losses per capita (bottom right). Credit: US Department of Commerce, US Census Bureau, Geography Division/Cartographic Products Branch (census tract shapefiles).

earthquake fault rupture. Comparing asset and well-being losses in Fig. 3, this is particularly evident near Concord, San Francisco, and in the eastern San Mateo County. Considering the ten largest cities in the Bay Area (Fig. 2), well-being losses exceed housing asset losses by 1.2 to 8 times, depending on factors such as the city's proximity to the fault rupture, building stock composition, income level and predominant employment industries. The ranking of the most affected cities changes depending on the metric of choice. For instance, while Berkeley and Hayward suffer comparable asset and labour income losses, Hayward experiences two and a half times

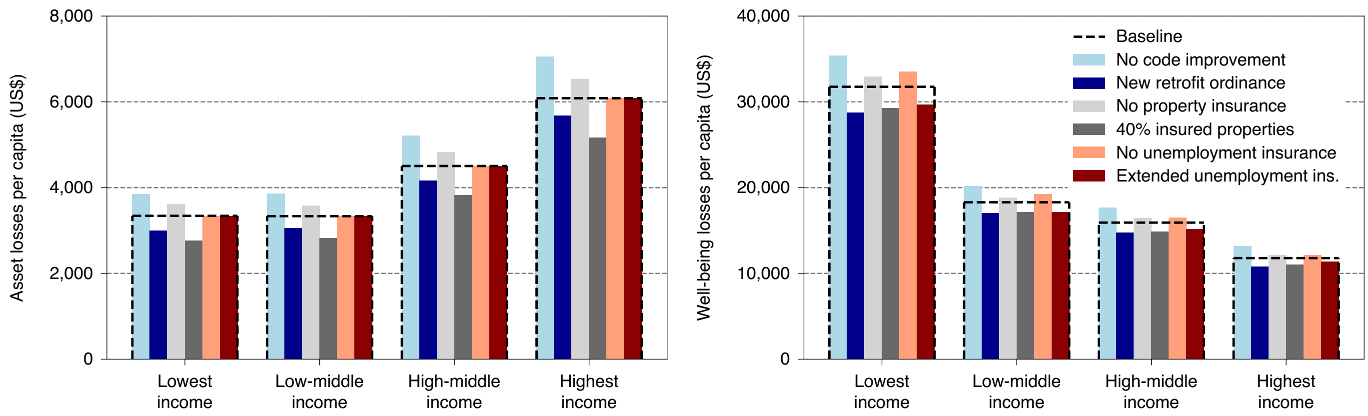


**Fig. 4 | Existing and potential future risk-reduction strategies.** Effect of existing and potential future risk-reduction strategies on the average non-insured per capita housing asset losses (left) and average per capita well-being losses (right) across different predisaster income categories. The income categories are defined according to income per capita ($i_{pc}$) 25th, 50th and 75th percentiles, with the following ranges: lowest income, $i_{pc} \leq$ US\$37,250; low-middle income, US\$37,250 $< i_{pc} \leq$ US\$48,340; high-middle income, US\$48,340 $< i_{pc} \leq$ US\$60,410; highest income, $i_{pc} >$ US\$60,410. ins., insurance.

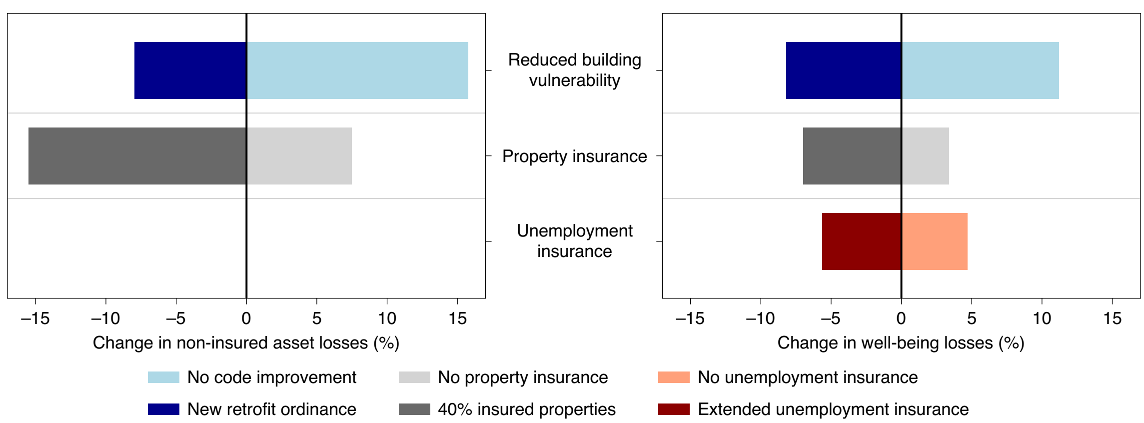


**Fig. 5 | Comparison of three risk-reduction strategies.** Effect of no policy and enhanced risk-reduction strategies as compared to the baseline in terms of percent change in average housing asset losses (left) and average well-being losses (right).

more well-being losses (Fig. 2). This stark difference can be partly explained by the difference in predisaster income levels (average income per capita: Berkeley US\$52,260 versus Hayward US\$34,720) and access to savings (average savings per capita: Berkeley US\$6,110 versus Hayward US\$4,410), which affects the households' ability to recover. The cities with the largest per capita well-being losses are Pinole, Richmond and San Leonardo, whose income per capita is 86% (or less) of Bay Area's average.

**The value of risk-reduction efforts.** Quantifying well-being losses allows one to evaluate both predisaster and postdisaster risk management efforts and compare their effects across socioeconomic groups. Here, three risk-reduction strategies are analysed and compared: reduced building vulnerability, property insurance and unemployment insurance. Because of the differing nature of these interventions, traditional direct asset loss assessments do not allow this type of comparison. For each of the strategies, we compare the baseline results presented in the previous section to a counterfactual evaluation with no policy (to assess the effectiveness of existing policies) and to an enhanced policy (to assess the potential for additional risk reduction). A summary of the results is shown in Fig. 5 and is also provided in Supplementary Table 2.

**Reduced building vulnerability:** Improving the building stock can reduce repair costs, shorten the loss of housing services and temporary relocation, and prevent loss of life in collapses (though this third benefit is not considered here). To evaluate the impact of an existing policy, we repeat the analysis assuming all post-1975 buildings were built only to 1975 building standards (corresponding to moderate-code in HAZUS[28]). In the absence of modern building standards, the average housing asset losses would increase by 16% and well-being losses by 11%. We also consider a potential future policy. This is a retrofit ordinance, where all pre-1975 apartment buildings (15% of residential asset value) would be brought up to modern building code standards (similar to the Mandatory Seismic Retrofit Program in San Francisco[37]). Such a policy would reduce both the housing asset losses and the well-being losses by 8%.

**Property insurance:** Our baseline scenario assumes 13% of homeowners have earthquake insurance (matching statewide adoption[34]) and that insurance penetration is uniform across income groups. If there was no property insurance, the homeowners' asset losses would increase by 8%, as compared to the baseline. If insurance penetration is increased to 40%, the average asset losses would decrease by 16%. This is double the reduction of non-insured asset losses as with a retrofit ordinance. The effect of insurance distribution among different wealth-level groups is discussed in the Supplementary Information. While residential earthquake insurance allows property owners to decrease out-of-pocket repair costs,

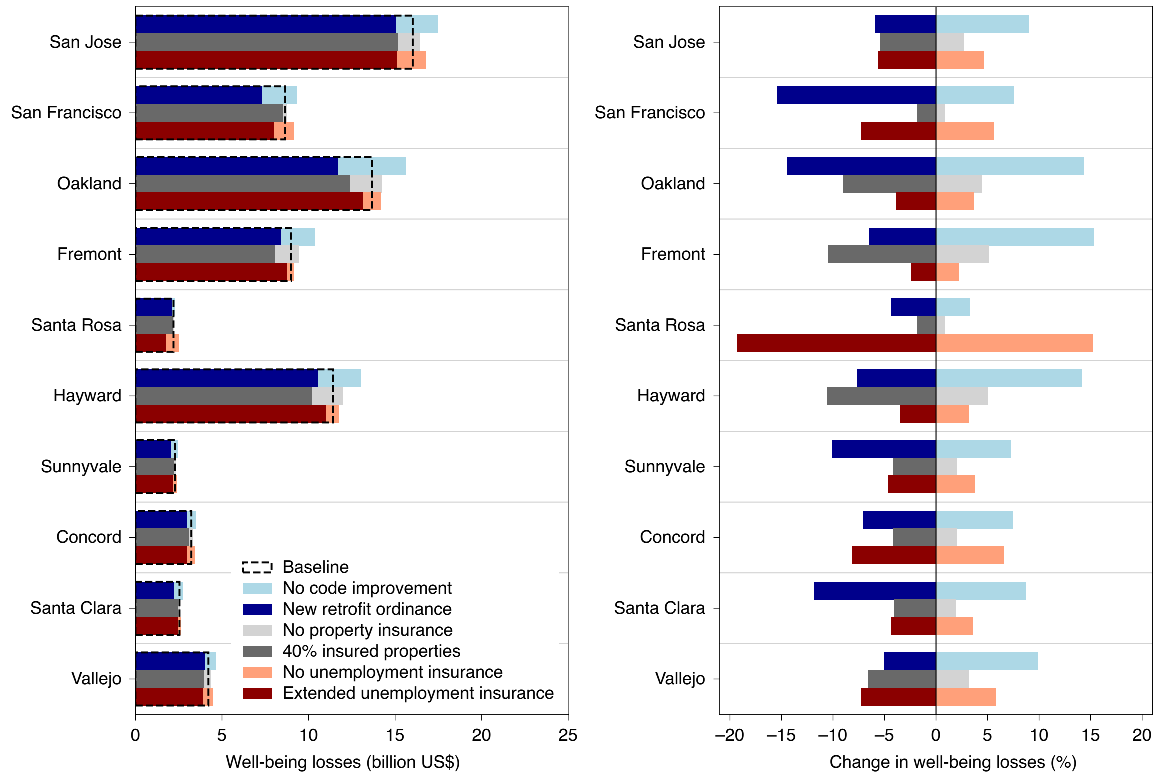


**Fig. 6 | Effect of risk-reduction strategies on the Bay Area's ten largest cities (ordered by population).** Effects of the various strategies are shown in terms of total average well-being losses (left) and percent change in average well-being losses (right).

it does not affect repair times or well-being of renters. This can be seen in the limited effect of insurance on well-being losses (Fig. 5). The absence of the current level of insurance penetration would increase well-being losses by only 3% and increasing insurance penetration to 40% would only decrease the baseline well-being losses by 7%. Relative to retrofitting, insurance is less effective for reducing well-being losses.

**Unemployment insurance:** California's Employment Development Department currently provides unemployment benefits that range from US$40 to US$450 per week for a period of up to 26 weeks for those who are eligible[38]. Unemployment insurance has no effect on asset losses but can reduce well-being losses after a disaster. If all employees whose jobs were affected by the earthquake did not receive unemployment insurance benefits, the well-being losses would on average increase by 5%. Extending the current insurance payment period to 1.5 yr would reduce the well-being losses by 6%, as compared to the baseline. Extending unemployment insurance for a longer time has a decreasing marginal benefit since more people are able to return to work at later stages of the recovery. Raising the benefit amount can be an alternative strategy to further reduce well-being losses.

**Comparison of risk-reduction efforts.** The results show the value of comparing the efficacy of different policies, although the cost of these remains to be assessed. The efficacy can also be evaluated for subsets of the population, offering further insights for policy makers. Figure 4 shows that the highest income quartile has the greatest reduction in non-insured housing asset loss under any risk-reduction policy. Conversely, the lowest income quartile has the greatest well-being benefits. Retrofitting multifamily apartment buildings in low-income areas is particularly effective, since a large portion of low-income households live in this type of housing (see Supplementary Fig. 1). However, seismic retrofit of apartment buildings is a substantial capital investment and costs may be passed on to renters[39]. Without an assistance program for lower income households that are unable to meet the added financial obligation, this can lead to unwanted relocation.

Increasing property insurance penetration can also be an effective mechanism for reducing well-being losses but only if insurance coverage is available to households at all income levels. Further analysis (see Supplementary Information) shows that insuring the lowest income households is twice as effective in terms of well-being loss reduction as insuring the highest income households. In reality, lower income households are less likely to be able to afford insurance premiums without government assistance. For unemployment insurance, well-being loss reduction is five times greater for lowest income group than for the highest income group, since they derive most of their income from wages or salaries.

**Risk mitigation at the city level.** Many recent seismic risk mitigation efforts have been enacted at the city level (for example refs. [37,40,41]). It is therefore important for city authorities to understand the local impact of potential risk mitigation strategies as their effectiveness can differ when looking at the city level versus the regional scale.

We see that the effectiveness of different risk-reduction strategies varies across the ten largest cities (Fig. 6). In San Jose, the enhanced retrofitting, insurance and unemployment policies yield comparable reductions in well-being losses. In San Francisco, a retrofit ordinance is much more effective than either type of insurance. This is due to San Francisco's relatively vulnerable residential building stock and the large number of renter-occupied households who benefit from reduced recovery times of strengthened homes but not from property insurance payouts. On the other hand, in Santa Rosa a large portion of well-being losses comes from loss of income, since the city is located further away from the rupture and therefore unemployment insurance is the most effective mitigation strategy.

While a particular mitigation strategy might have been effective in the past, further efforts of the same type may not be comparably effective. For example, while Fremont's residential building stock saw large benefits from previous building code improvements, retrofitting the remaining multifamily apartment buildings to modern code standards has relatively less impact and increasing insurance penetration has more impact.

Lastly, while the scale of well-being losses and the effectiveness of risk mitigation strategies largely depend on the built environment and demographics, they also depend on the earthquake location and resulting damage patterns, where Hayward fault rupture is only one of many possible earthquake scenarios in the San Francisco Bay Area.

## Discussion

Using well-being loss as opposed to asset loss as a metric to assess disaster impacts provides more insight into the consequences of a disaster throughout the recovery process. Here we measure well-being loss by integrating models at multiple spatial and temporal scales, including regional hazard simulation, building level damage and loss prediction, modelling of economic output variations, and simulation of resulting changes in household consumption.

The choice of metric to assess disaster impacts is extremely important. Standard asset loss metrics provide a biased representation of disaster consequences and emphasize impacts on the wealthy. However, if we consider well-being losses that take into account the utility of consumption changes throughout the recovery process, a completely different picture emerges in which the poorest quartile of the population is three times more affected than the wealthiest. This is also seen on a city level, where one city might be highly affected in terms of asset losses but substantially less affected when considering well-being losses. Ultimately, the metric should be chosen based on the objective of the stakeholder or decision-maker. Asset loss is an appropriate metric for an insurance company but well-being loss is more effective for considering policies that aim to 'focus on protecting the poor and people in vulnerable situations'[8].

The results presented here reflect real patterns and confirm our qualitative understanding of disasters. The distributions of asset losses are driven by the spatial distribution of the hazard event, and wealth and asset concentration. The housing sector is the most affected in terms of direct asset losses. Unemployment increases with the destruction of productive capital and produces ripple-effects in supply chains[42–44]. In contrast, employment increases in sectors that experience reconstruction-related demand, such as construction and manufacturing[45]. The impact on households extends beyond the immediate geographically affected area, where the poorer neighbourhoods are disproportionately affected over the recovery period and their recovery rate is lower than that of the wealthy.

When it comes to risk-reduction strategies, there is no one standard solution and each community needs to design approaches based on its drivers of vulnerability, whether it is aging building stock and infrastructure, low wealth levels or volatile income sources. The optimal approach is likely to involve a combination of predisaster interventions and preparedness action to help people cope and recover from unavoidable losses[46–48]. The methodology proposed in this research can support the design of such a package of interventions, combining the rigour of cost–benefit analyses with consideration of socioeconomic characteristics and vulnerabilities of the affected population.

## Methods

The results presented in this paper are derived by combining several probabilistic seismic, engineering and economic models. The four main models are summarized next.

**Earthquake rupture and ground motion simulation.** The earthquake rupture scenario is taken from the US Geological Survey's UCERF2 Earthquake Rupture Forecast[49]. The Abrahamson et al. ground motion prediction equation[26] is used to characterize ground motion shaking intensity throughout the Bay Area, considering factors such as distance from the rupture and local soil conditions. The uncertainty in the shaking is captured by simulating 500 ground motion maps that consider spatial correlation[27]. The ground motion uncertainty is the largest source of uncertainty (as compared to uncertainty in the building damage described in the next section) in the overall results of the well-being model.

**Physical damage and direct asset loss modelling.** For each of the analysed 1,577 census tracts, information on the number of buildings, their occupancy, structural type and building replacement cost is used to simulate damages for each of the 500 ground motions maps. In addition to residential buildings, the building inventory included industrial and commercial buildings that are linked to activities across different economic sectors. Fragility functions that specify the probability of various damage states (none, slight, moderate, extensive and complete) given a level of shaking are used to model building damage. Each damage state has an associated loss ratio (repair cost as a percentage of the building replacement value), which is used to assess direct asset losses to the region. The building inventory, fragility functions and loss ratios are taken from the US national standardized methodology, HAZUS[28], where building values and replacement costs are adjusted to 2016 US$.

**Postdisaster economic recovery modelling.** The disaster impacts on 15 economic sectors and their subsequent recovery are modelled using a modified version of the Adaptive Regional Input–Output (ARIO) macro-economic model[19,29]. The US Bureau of Economic Analysis's (BEA's) 15 aggregated sectors are used:

(1) agriculture, forestry, fishing, and hunting
(2) mining
(3) utilities
(4) construction
(5) manufacturing
(6) wholesale trade
(7) retail trade
(8) transportation and warehousing
(9) information
(10) finance, insurance, real estate, rental and leasing
(11) professional and business services
(12) educational services, health care and social assistance
(13) arts, entertainment, recreation, accommodation and food services
(14) other services, except government
(15) government

Direct asset losses are assumed to be associated with damages to factories, equipment, office space and other productive capital, which leads to a decrease in production until these damages are repaired. The decrease in each sector's productive capacity due to damages is proportional to the asset losses, using a unique average productivity of capital ratio for each sector. The average productivity of capital is derived by taking the ratio of sector's value added and fixed assets from the national BEA statistics. It is assumed that reconstruction efforts cause increased demand in construction (80% of the direct asset losses) and manufacturing (20% of direct asset losses) sectors. This is taken into account by adding demand from reconstruction to the local final demand, interindustry demand and export demand in the two sectors.

In addition to direct disaster impacts on a sector's production, the ARIO model captures several indirect effects from industry interdependencies. By using Bay Area's input–output matrix, the model captures output variations caused by changes in postdisaster interindustry consumption and reconstruction demand; input scarcity resulting from suppliers' inability to meet demand; exhaustion of input inventories; and overcapacity production, with production increasing above the predisaster level by engaging previously unused resources or increasing the use of available resources (for example, employees working overtime). Over the course of the recovery, the industries' productive capacity increases as physical repairs take place and productive capital is recovered. The physical reconstruction time is constrained by the construction and manufacturing sectors' ability to satisfy reconstruction demand and physical repair times defined in HAZUS[28]. The model also quantifies changes in employment and labour income for each of the industries, by assuming that they are proportional to industry output throughout the recovery process. The ARIO model has been previously validated using Hurricane Katrina economic losses[29], where changes in value added, employment, prices and profits across different industries were modelled. It has also been used to assess the impacts of the 2008 Wenchuan earthquake[50].

**Household well-being microsimulation.** The household model builds on Walsh and Hallegatte's socioeconomic resilience model[20] and adds to it by (1) explicitly including household labour income, rent and mortgage payments and (2) linking the household income to the impact of the disaster on jobs and labour income, as estimated by the ARIO model. In particular, the predisaster income level is decreased if the household is employed in the industry whose production is affected by the disaster.

The model performs microsimulations of households' consumption over a 10-yr postdisaster recovery period and determines the resulting changes in well-being. For each census tract, average per capita values for damages, savings, rental payments, mortgage and income sources are calculated and used to compute well-being losses. Below we describe the formulation of predisaster and postdisaster household models in terms of household's capital stock, income, consumption and well-being.

*Predisaster household capital stock.* Households derive income from three types of capital: (1) $k^{\mathrm{L}}$, capital that is associated with employment and is used in the process of earning a salary or wages. This includes buildings, machinery and equipment, where in some cases the capital is owned by the households earning the salary (for example, small shops) and in others it is owned by other investors (for example, owners of the factory where someone works); (2) $k^{\mathrm{oth}}$, other capital comprised of income-generating investments, such as financial investments; (3) $k^{\mathrm{h}}$, capital that provides housing services, regardless of whether this capital is owned or rented by the household. This capital (that is, the market value of the residence) is the sum of the land value ($k^{\mathrm{land}}$) and the value of the building structure ($k^{\mathrm{str}}$). The total predisaster capital stock ($k_{\mathrm{o}}$) used by the household is the following:

$$\begin{aligned} k_{\mathrm{o}} &= k_{\mathrm{o}}^{\mathrm{L}} + k_{\mathrm{o}}^{\mathrm{oth}} + k_{\mathrm{o}}^{\mathrm{h}} \\ &= \tfrac{i_{\mathrm{o}}^{\mathrm{L}}}{\pi} + k_{\mathrm{o}}^{\mathrm{oth}} + k_{\mathrm{o}}^{\mathrm{h}} \end{aligned} \qquad (1)$$

where $i_{\mathrm{o}}^{\mathrm{L}}$ is the labour income and $\pi$ is the US average productivity of capital. $\pi$ is derived using Penn World Tables[51].

*Predisaster household income.* The household's generalized income is comprised of labour income ($i^{\mathrm{L}}$), investment income ($i^{\mathrm{oth}}$) and non-monetary income associated with the receipt of housing services ($i^{\mathrm{h}}$). If the housing is rented, the rental payment ($p^{\mathrm{rent}}$) is removed from $i^{\mathrm{h}}$ to avoid double-counting the effective income derived from housing. The predisaster household income ($i_{\mathrm{o}}$) has the following formulation:

$$\begin{aligned} i_{\mathrm{o}} &= i_{\mathrm{o}}^{\mathrm{L}} + i_{\mathrm{o}}^{\mathrm{oth}} + i_{\mathrm{o}}^{\mathrm{h}} - p_{\mathrm{o}}^{\mathrm{rent}} \\ &= i_{\mathrm{o}}^{\mathrm{L}} + \pi k_{\mathrm{o}}^{\mathrm{oth}} + \pi k_{\mathrm{o}}^{\mathrm{h}} - p_{\mathrm{o}}^{\mathrm{rent}} \end{aligned} \qquad (2)$$

*Predisaster household consumption.* The predisaster consumption ($c_{\mathrm{o}}$) is equal to the predisaster income minus any mortgage payments ($p^{\mathrm{mort}}$), again to avoid double-counting housing services. We assume that the remaining income is consumed by the household in the same year and there are no financial savings, except for housing investments.

$$c_{\mathrm{o}} = i_{\mathrm{o}} - p^{\mathrm{mort}} \qquad (3)$$

*Household well-being.* At an instance in time, the utility derived from consumption is calculated using a constant relative risk aversion (CRRA) utility function, with $\eta$ the elasticity of the marginal utility of consumption (that is, the increase in utility when consumption is increased by US\$1 at one point in time), as per equation (4).

$$u(t) = \frac{c(t)^{1-\eta}}{1-\eta} \qquad (4)$$

For CRRA utility functions, the same parameter $\eta$ describes both risk aversion and the elasticity of the utility value of a marginal US\$1 increase in consumption. The utility function captures the fact that US\$1 in consumption is worth more to a poorer individual, which is one of the many reasons why poorer individuals are more vulnerable to natural disaster impacts. Well-being (or welfare in economics jargon) is then defined as the discounted sum of utility over time (see equation (10) for well-being loss formulation).

*Postdisaster household capital stock.* Capital changes occur as a result of physical damage to buildings and infrastructure. For households, this is represented by the repair costs associated with structural and non-structural damage to their residences. The labour capital is also affected by destruction of productive capital in industries by which the household is employed. To calculate changes in labour capital, we use labour income losses calculated using the ARIO model. It is assumed that the other capital ($k^{\mathrm{oth}}$) related to investments is outside of the affected area and is unaffected by the disaster. The postdisaster capital stock, $k(t)$, at time $t$ is shown in equation (5), where a positive $\Delta$ represents a loss, $\nu$ is the loss ratio which is repair cost divided by the total building value ($k^{\mathrm{str}}$) and $\lambda$ is the household's reconstruction rate determined by equation (12).

$$\begin{aligned} (t) &= k_{\mathrm{o}} - (\Delta k^{\mathrm{L}}(t) + \Delta k^{\mathrm{h}}(t)) \\ &= k_{\mathrm{o}} - \left(\tfrac{\Delta i^{\mathrm{L}}(t)}{\pi} + \nu k^{\mathrm{h}} \mathrm{e}^{-\lambda t}\right) \end{aligned} \qquad (5)$$

*Postdisaster household income.* Postdisaster income changes are derived from changes in labour income and changes in capital stock. The change in the housing capital leads to a loss in housing services (which approximates the expenses needed to pay for an alternative temporary accommodation). The labour income depends on the sector that the household is employed in, where we assume that change in household income is proportional to the change in sector's labour income from the ARIO model. In the case where a specific industry is over-producing to meet the increased reconstruction demand, labour income can actually increase, resulting in a negative $\Delta i^{\mathrm{L}}(t)$. The changes in labour income are adjusted to reflect unemployment insurance benefits in accordance with the Employment Development Department of the State of California[38]. If an individual in a given household becomes unemployed, they will receive weekly unemployment benefits ranging from US\$40 to US\$450 depending on their annual income. It is assumed that anyone who becomes unemployed as a result of the disaster is eligible to receive unemployment insurance benefits. With regards to rented households, it is assumed that renters will not have to keep paying the full rent for a damaged property and therefore in this model the rental payments decrease proportionally to the level of damage.

$$\begin{aligned} (t) &= i_{\mathrm{o}} - \Delta i(t) \\ &= i_{\mathrm{o}} - (\Delta i^{\mathrm{L}}(t) + \pi \Delta k^{\mathrm{h}}(t) - \Delta p^{\mathrm{rent}}(t)) \\ &= i_{\mathrm{o}} - (\Delta i^{\mathrm{L}}(t) + \pi \nu k_{\mathrm{o}}^{\mathrm{h}} \mathrm{e}^{-\lambda t} - \nu p_{\mathrm{o}}^{\mathrm{rent}} \mathrm{e}^{-\lambda t}) \end{aligned} \qquad (6)$$

*Postdisaster household consumption.* Postdisaster consumption is affected by changes in income and the need to pay for reconstruction of physical assets owned by the households.Therefore, the asset losses are explicitly accounted for in the form of homeowners paying for reconstruction. In addition, households can use their savings to make up for the decrease in consumption. Postdisaster consumption, $c(t)$, is illustrated in Fig. 1 and is expressed in equation (7):

$$c(t) = \max\{c_{\mathrm{o}} - \Delta c(t), \quad c_{\mathrm{o}} - \gamma\} \qquad (7)$$

where

$$\begin{aligned} \Delta c(t) &= \Delta i(t) + c_{\mathrm{reco}}(t) \\ &= (\Delta i^{\mathrm{L}}(t) + \pi \nu k_{\mathrm{o}}^{\mathrm{h}} \mathrm{e}^{-\lambda t} - \nu p_{\mathrm{o}}^{\mathrm{rent}} \mathrm{e}^{-\lambda t}) + \lambda \nu k^{\mathrm{str}} f^{\mathrm{o}} \mathrm{e}^{-\lambda t} \end{aligned} \qquad (8)$$

In equation (8), $c_{\mathrm{reco}}(t)$ is the repair cost at time $t$, $\gamma$ is the consumption loss considering the use of savings, which is found using equation (9), and $f^{\mathrm{o}}$ is the fraction of owner-occupied households. The postdisaster consumption remains constant at level $c_{\mathrm{o}} - \gamma$ until time $\hat{t}$ when savings are depleted. Both the asset and income losses are adjusted to consider payments from property and unemployment insurance. We also assume that reconstruction of rented residences is financed by investors (owners) who live outside of the disaster area. Therefore repair costs associated with rented residences do not affect household consumption in the affected area. Assuming that all owners of the rented residences are outside of the region is a simplification, which can lead to underestimation of impacts on households that own rental properties. However, more granular modelling is impossible at this stage due to the absence of data on the localization of rental property owners.

$$\{\gamma, \hat{t}\} \text{ s.t.} \begin{cases} \gamma = \Delta c(\hat{t}) \\ \gamma \hat{t} + \text{savings} = \int_0^{\hat{t}} \Delta c(t) \mathrm{d}t \end{cases} \qquad (9)$$

*Postdisaster household well-being losses.* We define well-being losses, $\Delta W$, as the present value of the change in utility from predisaster level over the recovery period, $T$, using continuous discounting and a utility discount rate $\rho$ (assumed to equal to 10%). The discount rate is calibrated such that the predisaster situation is optimal, with the marginal productivity of capital equal to the consumption discount rate. The marginal productivity of capital is classically estimated assuming a Cobb–Douglas production function, as the product of the average productivity of capital (the ratio of the output to capital stock) and the share of profit in total income (assumed equal to 30%). In addition, well-being losses include long-term effects associated with the decrease in household savings, with the assumption that that savings replenishment occurs far in the future, after the reconstruction is completed. Equation (10) shows the full well-being loss formulation.

$$\begin{aligned} \Delta W &= \int_0^T (u_{\mathrm{o}} - u(t)) \mathrm{e}^{-\rho t} \mathrm{d}t + \tfrac{\mathrm{d}u}{\mathrm{d}c}\big|_{c_{\mathrm{o}}} \Delta \text{savings} \\ &= \int_0^T \left(\tfrac{c_{\mathrm{o}}^{1-\eta}}{1-\eta} - \tfrac{c(t)^{1-\eta}}{1-\eta}\right) \mathrm{e}^{-\rho t} \mathrm{d}t + c_{\mathrm{o}}^{-\eta} \Delta \text{savings} \end{aligned} \qquad (10)$$

Finally, since the units in equation (10) are non-monetary and not easy to interpret, we convert $\Delta W$ into an equivalent consumption change, $\Delta C_{\mathrm{eq}}$ (see equation (11)).

$$\Delta C_{\mathrm{eq}} = \Delta W / \frac{\mathrm{d}u}{\mathrm{d}c}\Big|_{c_{\mathrm{mean}}} \qquad (11)$$

The equivalent consumption change represents the dollar amount by which a household earning the mean Bay Area income would have to decrease its consumption to experience the same well-being decrease as the considered household. The final change in equivalent consumption is what we refer to as well-being loss. This process is equivalent to scaling up losses affecting poor people and scaling down losses affecting rich people, such that a US$1 loss has the same impact on well-being regardless of the income of the affected household.

*Reconstruction rate optimization and constraints.* The household reconstruction rate, $\lambda$, is a minimum of three rates: the physical reconstruction rate, $\lambda_{hazus}$[28]; the reconstruction rate that maximizes the household well-being over 10 yr, $\lambda_{opt}$ taking into account that the household might prefer to defer reconstruction to maintain its consumption level; and the reconstruction rate at which the household is able to retain sufficient consumption to avoid extreme poverty, $\lambda_{pov}$. The mathematical formulation is shown in equation (12):

$$\lambda = \min\{\lambda_{\mathrm{hazus}}, \lambda_{\mathrm{opt}}, \lambda_{\mathrm{pov}}\} \tag{12}$$

where

$$\lambda_{\mathrm{opt}} = \underset{\lambda}{\mathrm{argmax}} \int_0^T \frac{1}{1-\eta}\left(c_{\mathrm{o}} - \left(\Delta i^{\mathrm{L}}(t) + \pi\nu k_{\mathrm{o}}^{\mathrm{h}}\mathrm{e}^{-\lambda t} - \nu p_{\mathrm{o}}^{\mathrm{rent}}\mathrm{e}^{-\lambda t}\right)\right.$$
$$\left. - \lambda\nu k^{\mathrm{str}} f^{\mathrm{o}} \mathrm{e}^{-\lambda t}\right)^{1-\eta}\mathrm{d}t$$

**Model limitations.** Several limitations should be highlighted for consideration in future research. In this model, damages to lifelines such as road, water, power and telecommunication networks are not explicitly modelled due to lack of data. Other studies predict that a similar size earthquake ($M_w$ 7.0) would cause damage to the water network, where 30–95% of service would be returned within 7 d, depending on the county, and full service within 30–210 d (ref. [35]). In addition, damage due to secondary hazards such as fire, liquefaction and landslides is not modelled. Post-earthquake fire can be a large source of loss, where the aforementioned study estimates a US$16 billion loss in terms of building replacement value. Considering these damages in our model would increase both asset and well-being losses.

The economic recovery model used in this study makes several simplifications. First, the assumption that each sector is homogeneous can lead to underestimating supply chain disruptions linked to specific products or services. It can also lead to underestimating the ability of firms to cope with the impact of the disaster[23,52]. Second, the assumption that the impact on jobs is proportional to the impact on value added can underestimate job losses (for instance, when a small firm loses half of its capacity and goes bankrupt) or overestimate job losses (for instance, when a large firm loses production capacity but keeps its workers during the recovery phase). Third, the model assumes that the economy is in a state of equilibrium before disaster and returns to this state during the recovery. In reality, post-reconstruction economies are sometimes notably different from predisaster ones[53]. In addition, postdisaster demand surge, which can increase the cost of repairs by 20% or more[54], has not been considered. Finally, the macro-economic impact of the disaster depends on the stage of the business cycle. Previous research suggests that if the economy is in the expansion stage the losses are amplified and if it is in the recession stage the losses are dampened through the mobilization of idle resources[55].

At the household level, the model makes several simplifications, largely forced by data availability. Informal support from friends and family after a disaster is not considered, and households are assumed to determine their reconstruction rate optimally. Permanent relocation of households within and outside of the affected area is also not considered. Previous studies show that disasters often lead to short-term migration and in some cases long-term migration patterns, which can affect labour supply and wages in both the affected area and in-migration regions[5]. Household decisions to relocate depend on factors such as the type of affected area (urban or rural) and socioeconomic status, where more educated and wealthier individuals in urban areas are more likely to relocate following a disaster. Renters can also relocate more easily given their mobility. This could be a concern in the Bay Area, given its wealth distribution and high percentage of renters, and should be investigated further.

Lastly, information on households is aggregated at the census tract level due to data availability limitations. A census tract is a geographic delineation that typically has between 1,200 and 8,000 people, with an average population of 4,000. While using census tract aggregation preserves the geographic distribution of damage, aggregation and averaging can distort household characteristics in highly heterogeneous areas. In particular, very low-income households whose consumption can go below poverty or subsistence levels after a disaster, might not be detected as a result of averaging within a census tract. A way to mitigate this is to either use a more suitable household survey where information on spatial and demographic distribution is preserved or generate synthetic population data through spatial microsimulation modelling[56].

**Data sources.** This research uses exposure data from US Federal Emergency Management Agency's HAZUS[57]; socioeconomic and demographic statistics from US Census and Consumer Expenditure through the Simply Analytics platform[58,59]; trade statistics from US Census Import and Export Merchandise; national and regional industry data from US Bureau of Economic Analysis and Regional Input–Output Modeling System (RIMS II); and labour statistics from US Bureau of Labour Statistics. Year 2016 is taken as the base year, where data from that year are used when available.

**Reporting Summary.** Further information on research design is available in the Nature Research Reporting Summary linked to this article.

## Data availability
The datasets generated and/or analysed during the current study are available from the corresponding author upon reasonable request. Several input datasets that support the findings of this study are available from different platforms and sources (as described in Data sources section) and restrictions may apply to the availability of such data. Input data can be obtained from the authors upon reasonable request and with permission from the relevant data owners.

## Code availability
All code used to conduct this analysis is freely available at https://github.com/mary-mark/well-being_model.

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## Author contributions
S.H. and B.W. conceived the well-being metric and the basic household model. M.M., S.H. and B.W. further developed the household model, including explicit representation of loss of labour income. M.M. and J.B. developed an integrated framework that includes regional seismic risk analysis and M.M. wrote the simulation scripts. S.H. provided further guidance on economic and well-being modelling. M.M. drafted the manuscript with contributions and editing from all the authors.

## Competing interests
The authors declare no competing interests.

## Additional information
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*Our web collection on statistics for biologists contains articles on many of the points above.*

## Software and code

Policy information about availability of computer code

| | |
|---|---|
| Data collection | Input data was collected from existing data platforms such as SimplyAnalytics, USGS OpenSHA platform, U.S. Bureau of Economic Analysis, U.S. Bureau of Labor Statistics, U.S. Census Import and Export Merchandise, and U.S. Federal Emergency Management Agency's HAZUS |
| Data analysis | Custom code in MATLAB and Python was used for all of the analysis and is available on https://github.com/mary-mark/well-being_model |

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The datasets generated and/or analyzed during the current study are available from the corresponding author upon reasonable request. Several input datasets that support the findings of this study are available from different platforms and sources (as described in Data sources section) and restrictions may apply to the availability of such data. Data are however available from the authors upon reasonable request and with permission from the relevant data owners.

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# Behavioural & social sciences study design

All studies must disclose on these points even when the disclosure is negative.

| | |
|---|---|
| Study description | The current study is entirely based on numerical computer simulations where no statistical analyses, experiments, or new data collection were performed. |
| Research sample | All input data was taken from existing datasets, via data platforms such as SimplyAnalytics, USGS OpenSHA platform, U.S. Bureau of Economic Analysis, U.S. Bureau of Labor Statistics, U.S. Census Import and Export Merchandise, and U.S. Federal Emergency Management Agency's HAZUS. |
| Sampling strategy | N/A |
| Data collection | N/A |
| Timing | N/A |
| Data exclusions | N/A |
| Non-participation | N/A |
| Randomization | N/A |

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| n/a | Involved in the study | |
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| ☒ | ☐ | Animals and other organisms |
| ☒ | ☐ | Human research participants |
| ☒ | ☐ | Clinical data |

## Methods

| n/a | Involved in the study | |
|---|---|---|
| ☒ | ☐ | ChIP-seq |
| ☒ | ☐ | Flow cytometry |
| ☒ | ☐ | MRI-based neuroimaging |