SIMULATING HOUSING RECOVERY CHALLENGES DUE TO POST-DISASTER REPAIR COST INCREASES

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Abstract*: Large scale disasters such as earthquakes can cause significant damage to the housing stock in a community. Insurance plays an important role in market-driven post-disaster housing recovery. However, insurance premiums are often defined based on costs defined before a disaster. Thus, reconstruction costs increase due to an imbalanced demand for services or due to a requirement of rebuilding to a higher standard can lead to the problem of underinsurance. This study presents an agent-based model for housing recovery simulation that can capture the influence of price surges and build-back-better requirements on housing reconstruction in an earthquake-struck community. This novel methodology is presented and applied to a case study of a hypothetical earthquake striking the city of Alameda, California. The model evaluates how cost increases and underinsurance affect the likelihood that homeowners will rebuild or sell their homes. Case study results show that up to 2,000 homeowners could find that selling their homes and leaving Alameda is a more economically viable alternative to repairing and staying. Moreover, most of these home sales is expected to happen among low-to-moderate income homeowners. This, the methodology can also provide insights into gentrification potential for an earthquake-struck community.*

1. Introduction

After a disaster, insurance claims are often the first source of coverage for losses. Insurance coverage varies by hazard. Homeowners exposed to perils perceived more frequently, e.g., floods, tend to have higher insurance coverage (Yang, 2020). In at-risk regions, disaster insurance is a requirement for a mortgage, e.g., wildland-urban interfaces exposed to wildfire hazards. Insurance covers the home's reconstruction cost minus a deductible, usually between 10 and 25 of the reconstruction cost. However, the insurer assesses the home reconstruction cost before a disaster, neglecting many factors that may increase reconstruction costs after a disaster (e.g., Kim (2022), Parker (2018)). Consequently, even insured households may rely on other sources of financing to repair their homes, an issue often called underinsurance. Underinsured homeowners may face challenges in rebuilding their homes, and in extreme cases, may be unable to do so. As such, it is important to understand how increase costs that are not covered by insurance can affect housing recovery for disaster-struck communities.

To mitigate post-disaster residual risk, communities have used post-disaster reconstruction as an opportunity to improve its built environment. For housing recovery, such initiatives include “build back better” practices for homes that did not meet certain criteria before the disaster and must be improved during reconstruction. For example, in 2015 and 2016, California adopted new building codes requiring resilience measures to mitigate risks from natural hazards, and in 2019, the California Build Energy Efficiency Standards for residential properties mandated solar power systems in all newly constructed residential housing. Consequently, a home destroyed by a natural hazard in California must abide by these new standards to have its rebuilding permit application approved. The California Department of Housing and Community Development estimates these costs to be 10% of the building replacement cost for a home (California Department of Housing and Community Development, 2019). Such costs are unlikely to be covered by insurance policies which are designed to replace the building to pre-disaster state.

Another issue that compounds to increased housing reconstruction costs and leads to underinsurance is demand surge after disasters due to an imbalance between supply and demand for construction materials and workforce (Olsen (2011), Hallegatte (2010), Chang (2010)). Estimates suggest that demand surges increased average repair costs between 10% and 40% after Hurricane Katrine (Guy Carpenter 2005), and 50% after Cyclone Larry (Australian Securities and Investments Commission (ASIC), 2007). This figure can be significantly higher for specific materials. For example, reports have documented price increases of 30% for oriented strand board following Hurricane Katrina (Grogan and Angelo 2005) to a 2,000% increase for securing a tarpaulin to a damaged roof after the 1999 Sydney hailstorm (Sweetman and Morris 1999).

The combination of price surges and new building requirements may make homeowners unable to rebuild their disaster-struck homes, forcing them to sell homes without repairing them. This may lead abrupt changes in population demographics, accelerating gentrification if the post-disaster area is reconstructed to higher standards (van Holm and Wyczalkowski, 2019), or concentrating socioeconomically disadvantaged persons if the disaster deteriorates local property values (Elliott and Pais, 2010). This study develops an agent-based simulation to capture some of the post-disaster recovery dynamics within a community and quantitatively evaluate the impacts of price surges and new building requirements on recovery. The simulation model consists of four groups agents: households who own destroyed buildings; financing institutions who provide recovery financing; (iii) contractors who charge for repair services; (iv) real-estate agencies who seek to purchase homes whose owners are unable to repair. The interplay between these agents simulates the dynamics of post-disaster recovery shedding on the influence of underinsurance on disaster-induced gentrification. The results in this study highlight that increases in construction costs may take away households' choice to stay in the community or move out due to an unfavorable balance between the costs of staying and leaving. Moreover, it is demonstrated that the majority of those expected to leave the community are in the low-to-moderate income range, highlighting a disasters' tendency to cause gentrification.

2. Regional disaster risk assessment framework

To investigate the relationship between price surges, increased construction costs, underinsurance, and gentrification, this paper builds upon a computational simulation developed by the third author and collaborators. For detail, see Costa *et al.* (2023), Costa and Baker (2023), Wang *et al.* (2022), Costa *et al*. (2021). The framework is expanded in this paper to include new agents. The framework can be interpreted as a combination of a regional risk assessment and an agent-based simulation, as schematically shown in Figure 1. The Regional Risk Assessment (on the left) includes a set of inputs and models. For applications to seismic risk, the first input comprises data regarding soil characteristics, and the rate of occurrence of earthquakes in the closest fault lines. These data are used to simulate potential futures in terms of seismic hazards using Monte Carlo sampling. The outputs of the hazard simulation are used in combination with exposure data (e.g., type and age of the buildings in the city) to simulate immediate earthquake impact. Exposure data is obtained by merging information from tax assessor data, Census surveys, and the Hazus Building Manual (Federal Emergency Management Agency, 2021). To simulate structural damage, fragility curves (Federal Emergency Management Agency, 2015) are associated with each building type. Fragility curves associate a level of shaking (e.g., estimated in the Hazard Simulation) to a probability that a building is damaged after an earthquake. In turn, building damage can be converted to repair costs using relationships called "damage ratios", which estimate the monetary cost to repair a building given the estimated damage.

The agent-based model (on the right in Figure 1) simulates the interplay between Household Agents who occupy homes which may be damaged, Funding Agents which provide financing for home repairs, Contractor Agents who conduct repairs, and a Real Estate Company Agent which seeks to purchase homes which they intend to repair and sell at a profit. Details about these agents are provided in the following. The interplay between agents allows us to estimate how many homes are expected to be sold and the pace of housing recovery in the community. It is assumed that the Real Estate Company Agent upgrades the homes it buys, with the goal of selling it to a more affluent buyer. Thus, the number of houses bought by the Real Estate Company Agent is used as a proxy for the gentrification of the community.

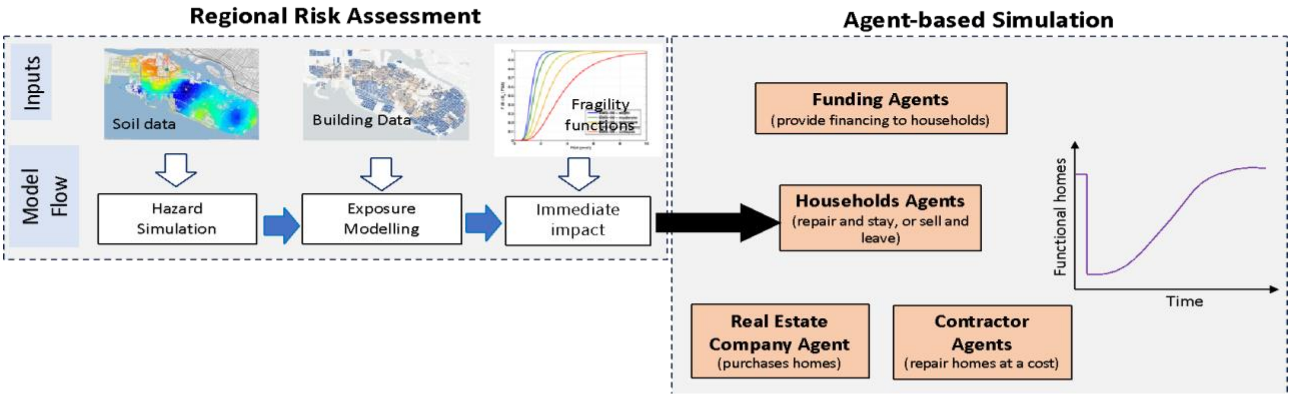

Figure 1. Computational workflow to simulate housing recovery.

3. Agent-based models

Figure 2 provides more detail regarding the agent-based models and their interactions. On each step of the simulation, the Household Agents face a decision-making process regarding whether to sell their property or remain in the area. To this end, the Household Agent engages with Funding Agents to assess the available funds for house repairs. The case study presented later focuses on a community in the US. Consequently, the Funding Agents are modeled according to agencies that provide funding for housing recovery in the US. If a Household Agent secures funding it interacts with agents that provide repair services (e.g., Engineering Firm and Contractor Firm Agents). On each step of the simulation, the Household Agents may also receive an offer from the Real Estate Company Agent. The Household Agents are assumed to possess perfect rationality; that is, their final decision is one that maximizes financial gain. This is a limitation of the current model as multiple other factors (e.g., place attachment, household structure, demographics) play an important role in this decision. Future iterations of the model will improve this aspect. If a Household Agent starts the repair process, it no longer considers offers from the Real Estate Agency. Conversely, if a favorable offer is received before repairs start, it is assumed that the Household Agent will sell its home. The number of homes sold is used the metric of interest in the following. This process is evaluated in time for several years. Moreover, multiple realizations of the entire process are employed to capture uncertainty in building damage, and interactions between agents. Details about the implementations of each agent are provided in the following.

3.1. Financing agents

There are multiple sources available for households to obtain funding for reconstruction of their damaged homes following an earthquake. Each financing source has a specific approval rate and criteria, maximum amount, and disbursement time. The expected process that households need to go through to obtain required funding may differ based on household income and resources availability. It is assumed that households will seek sources that are the most beneficial to them. The following are the primary sources for post disaster housing recovery financing in the United States. Nongovernmental organizations' (NGOs) aid is not considered in the financing model.

3.1.1 Earthquake Insurance

Earthquake insurance is often the first source to cover the disaster losses due to its relatively quick disbursement and comprehensive coverage. It covers the home's reconstruction cost minus a deductible, which is usually 10% to 25% of the home's reconstruction cost. However, it is not mandatory, and many households might not have earthquake insurance policy. Moreover, for earthquake insured homes, the insurer calculates the replacement cost based on pre-disaster conditions, neglecting factors such as surge in construction materials and contractor prices that might increase the reconstruction cost after the disaster (Kim (2022), Parker (2018)). Therefore, even insured homeowners might need other funding sources to complete the repairs, which is often referred to as underinsurance. In the model, financing from insurance F_{ins} is calculate as:

$$F_{ins} = \begin{cases} 0.85 \times replacement\ cost & if\ insured \\ 0 & otherwise \end{cases} \tag{1}$$

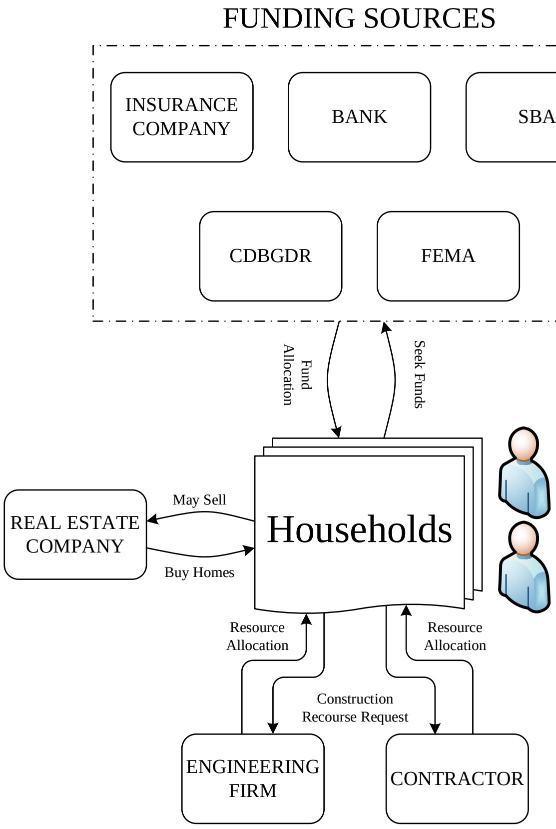

Figure 2. Interactions among agents.

3.1.2 Federal Emergency Management Agency Housing Assistance Grants

The Federal Emergency Management Agency Individuals and Households Program (FEMA IHP) provides financial assistance and direct services to disaster impacted homeowners with uninsured and underinsured needs (United States Government Accountability Office (GAO), 2020). FEMA IHP housing assistance (HA) program specifically provides funding for households with significantly damaged or destroyed homes. The HA grants are intended to repair the home to an occupiable state rather than to reconstruct it to the pre-disaster state and are capped at about $40,000, corrected by inflation annually. The probability of FEMA HA grants approval for a household is determined based on income and insurance status (Costa and Baker (2023), FEMA (2022)). FEMA HA grant received by household **X** is estimated as:

$$F_{FEMA}(X) = a_1(X) \cdot FVL^2 + a_2(X) \cdot FVL + a_3(X) \tag{2}$$

where **X** represents characteristics of the applicant households, i.e., insurance status and income; FLV is FEMA verified losses and it reflects the funds required to repair the home to an occupiable state which is determined by FEMA through inspection of disaster impacted homes (Costa and Baker, 2023); a_1, a_2, and a_3 are coefficients that depend on the household characteristics and are given in Table 1.

Table 1: Parameters used in Eq. 7 to estimate FEMA HA grant.

Insurance status	Income	Equation parameter		
		a_1	a_2	a_3
Insured	High	-7.72E-06	0.786	10,385
Insured	Non-high	-8.41E-06	0.877	8,335
Uninsured	All	-1.47E-05	1.223	6.201

3.1.3 Small Business Administration Loans

Small Business Administration (SBA) Household and Personal Property Loans (HPPL) Program provides low interest loans for disaster impacted households to account for losses that are not fully covered by FEMA and insurance (SBA, 2022a). Unlike FEMA HA grant, SBA loan is intended to restore the damaged property to pre-disaster condition. The SBA HPPL loan is capped at \$200,000 and it is designed to be more accessible than private loans. However, applicants still need to pass the eligibility criteria including sufficient income and ability to repay the loan, which is called providing collateral. Real estate is the preferred form of collateral (SBA, 2022b). The maximum potential SBA loan is estimated as:

$$F_{SBA} = \begin{cases} min\big(C(t), Loan_{cap}, SBA_{max}, RC(0) - F_{insurance} - F_{FEMA}\big) & if\ has\ collateral \\ min\big(Loan_{cap}, SBA_{min}, RC(0) - F_{insurance} - F_{FEMA}\big) & otherwise \end{cases} \quad (3)$$

where $C(t)$ is the household's available collateral at time t; $Loan_{cap}$ is the household's maximum loan limited by debt-to-income; SBA_{max} is \$200,000 and SBA_{min} is \$25,000 for large disasters. The conditions in Equation 3 imply that F_{SBA} is governed by the household's needs and ability to secure a loan. It is assumed that the household's collateral is equal to the home equity minus disaster loss. The home equity is the fraction of mortgage paid by time t. Therefore, $C(t)$ is estimated as:

$$C(t) = min\left(DP + 0.8 \cdot \frac{t - t_{bought}}{m_{mort}}\right) \cdot (HV - Loss) \quad (4)$$

where DP is the down payment as a fraction of the home value HV; t_{bought} is the time when home was bought; m_{mort} is the mortgage maturity; and Loss indicates the losses due to home repair cost. The SBA loan amount received by a household could also be limited by income. It is assumed that SBA utilize a maximum debt criterion which does not allow homeowners loan beyond a percentage of their income, called the gross-debt-to-income-ratio, $gdsr$. The $gdsr$ limits the maximum SBA loan that a household with income I can receive, which is called $Loan_{cap}$ and can be estimated as:

$$Loan_{cap} = I_m \ .\ gdsr \ .\ \frac{((1+r)^{m_{loan}} - 1)}{(r.(1+r)^{m_{loan}})} \quad (5)$$

where I_m is the household's monthly income: m_{loan} is the loan maturity in months and r is the loan monthly interest rate. SBA loans have a minimum annual interest rate of 4% and maximum maturity of 30 years.

3.1.4 Private Loans

Private loans (particularly bank loans) can assist households with losses not fully covered by other financing sources. Bank loans are modeled in the same way as SBA loans, but with higher interest rates. Therefore, households prefer to procure loans through SBA before applying for a bank loan. Bank loans have more strict approval criteria including sufficient income, high credit score, and ability to repay the loan through providing collateral. Hence, higher-income households have a better chance of securing a bank loan. The maximum potential bank loan can be estimated as:

$$F_{bank} = \begin{cases} min(C(t) - F_{SBA}, Loan_{cap}, RC(0) - F_{insurance} - F_{FEMA} - F_{SBA}) & if\ has\ collateral \\ 0 & otherwise \end{cases} \quad (6)$$

where $C(t) - F_{SBA}$ represents the household's residual collateral after applying for SBA loan. The loan amount that can be received by a household is bounded by the unmet needs for home repairs and maximum possible loan constrained by residual collateral and household income.

3.1.5 HUD CDBG-DR Grants

The Community Development Block Grant for Disaster Recovery (CDBG-DR) administered by the US Department of Housing and Urban Development (HUD) provides support for disaster-impacted households who were not able to obtain adequate funding for home repairs from aforementioned sources. The size of CDBG-DR is a fraction of disaster total losses, depending on the state and size of the disaster (United States Department of Housing and Urban Development (HUD), 2020). A PMDD is necessary but not adequate for allocation of CDBG-DR funds. The Congress authorizes and allocates the funding to the state authorities to support recovery of damaged homes while prioritizing lower-income households. However, this process can be slow, often taking more than a year for a household to receive the first payment (Costa and Baker (2023), Greer and Trainor (2021)). Therefore, CDBG-DR is assumed to be the last financing source for homeowners after seeking funds through all other possible sources. The maximum grant a household can receive from CDBG-DR program is estimated as:

$$F_{CDBGDR} = min\,(RC(0) - F_{insurance} - F_{FEMA} - F_{SBA}, CDBG_{max}) \tag{7}$$

where $CDBG_{max}$ is \$150,000 which sets the grant cap for each household.

3.2. Contractor agents

Contractor Agents provide home repair services requested by household agents. The contractor price to repair a damaged home at time t is determined based on the labor supply and demand. Labor demand is an indicator of the number of households who obtained adequate funding and requested home repair services. On the other hand, labor cost (C_{labor}) can be modelled as a function of the demand (D_{labor}) and supply (S_{labor}) of skilled workers if reliable data are available to supplement the model. The contractor price to repair a home at time t can be estimated as:

$$C_{labor}(t) = f\left(\frac{D_{labor}}{S_{labor}}\right) \tag{8}$$

where D_{labor} and S_{labor} are labor demand and supply, respectively; $f\left(\frac{D_{labor}}{S_{labor}}\right)$ is a function that calculates the contractor price at time t based on the labor supply and demand.

3.3. Real estate agent

The Real Estate Company Agent intends to buy damaged homes to repair and sell it at a profit. This agent is particularly willing to buy houses with lower prices compared to others in the neighborhood and houses located in neighborhoods with faster recovery rate. The number of houses bought by the Real Estate Company Agent is used as a proxy for the gentrification of the community. The amount offered by the Real Estate Company Agent for home i at time t is estimated as:

$$B_i(t) = \frac{HV_{med}}{HV_i} \cdot f\left(B_{rec}, B_{safe}, B_{total}\right) \tag{9}$$

where HV_{med} is the median of home values in the neighborhood; HV_i is the value of home i; $f\left(B_{rec}, B_{safe}, B_{total}\right)$ is a function that calculates the Real Estate Company Agent offer based on the recovery process in the neighborhood and extent of the damage to the home.

3.4. Household agents

Household Agents interact with other agents within the framework for different purposes, for example with financing agents to procure funding for home repairs, with contractor agents to obtain repair services, and with real estate company agents to sell their property. While households actively try to secure adequate funding for reconstruction of their damaged homes, at each time step they have the option of selling their property and leaving the community. Each of the two decisions either to sell and leave or to stay and reconstruct home has a set of advantages and drawbacks. The expenditure at time t associated with the decision to stay is estimated as:

$$E_{stay}(t) = RC(t) - F_{ins} - F_{FEMA} - F_{CDBGDR} + [HV_{bid}(t) - C_{new} - C_{fee}] \tag{10}$$

where $RC(t)$ is the repair cost at time t; F_{ins}, F_{FEMA}, and F_{CDBGDR} are the funding from non-loan sources, respectively insurance, FEMA, and CDBG-DR; $HV_{bid}(t)$ is the amount offered by the Real Estate Company Agent for the house at time t; C_{new} is the cost of a new home; and C_{fee} is the home selling fee, which is defined as 5% of the home value. The values in the squared brackets represent the opportunity cost of deciding to stay. That is, if the Real Estate Company makes a favourable offer that is denied by the Household Agent, we assume that the expenditure in staying increases.

The expenditure at time t associated with the decision to leave is calculated as:

$$E_{leave}(t) = -F_{ins} + C_{fee} + RC(0) - [HV_{bid}(t) - C_{new}] - F_{FEMA} - F_{CDBGDR} \tag{11}$$

where $RC(0)$ is the repair cost at time 0; F_{ins} is the funding from insurance; C_{fee} is the home selling fee; F_{FEMA}, and F_{CDBGDR} are the funding from FEMA, and CDBG-DR; and the values in the squared brackets together with F_{FEMA}, and F_{CDBGDR} stand for the opportunity cost of deciding to stay as explained above. The Utility of household's decision to stay or leave at time t is estimated as:

$$U_d(t) = a + b \cdot E_o(t) \tag{12}$$

where $E_o(t)$ is the expenditure associated with each decision at time t; a and b are the parameters of the utility equation and calculated as:

$$\begin{aligned} b &= 1/(-RC_{DS4}+RC_{DS3}-F_{ins}) \\ a &= -b \cdot (RC_{DS4}+C_{fee}) \end{aligned} \tag{13}$$

where RC_{DS3}, and RC_{DS4} are the repair costs associated with damage state 3 and 4, which are defined as 50% and 100% of the house replacement cost, respectively. Also, only homeowners with DS_3 and DS_4 will have to decide to stay or leave.

4. Case study

The proposed housing recovery model is applied in this section to a case study in the city of Alameda, CA. Alameda is located near the Hayward fault and is susceptible to earthquake shaking that could cause significant damage to housing. We simulate damages after a scenario earthquake, a M7.0 on the Hayward fault. We use earthquake simulations to obtain ground shaking intensities using the Chiou and Youngs (2014) ground motion model for peak ground acceleration. One thousand earthquake realizations are simulated using Monte Carlo Sampling, maintaining the magnitude fixed and epicenter locations uniformly distributed along the Hayward fault. Thus, for each building, the median impact (e.g., repair cost or debt) is the median from 1,000 Monte Carlo Samples.

This study focuses on single-family housing. As shown in Fig. 2, there are 10,464 single-family buildings in the city. Single-family buildings in Alameda are majority light-frame wood-frame structures. The Hazus earthquake methodology is used to simulate building damage ratios (i.e., Eq. 1) assuming buildings can be sufficiently well-described by the "W1-RES1" fragility curve (Federal Emergency Management Agency, 2015). Damage rations are multiplied by building values are obtained from the publicly available tax assessor database for the Alameda County to estimate repair costs.

Demographic data are collected from the American Housing Survey (United States Census Bureau, 2019). For this study, we focus on household income and housing tenure, since these directly affect access to post-disaster housing repair financing. It is assumed that 13% of the homeowners in the city have earthquake insurance which covers replacement costs that exceed a 15% deductible (Alisjahbana *et al.*, 2022). SBA loans and private loans have interest rates of 4% and 5%, respectively. Both loans are assumed to be second mortgages and have a 30-year maturity, based on historic mortgage maturity for Alameda from the Home Mortgage Disclosure Act.

Figure 3. Building portfolio in Alameda, CA. Blue dots are single-family buildings, the focus of this study (adapted from Mongold et. al., 2023).

4.1. Assessment scenarios

The proposed framework is employed across four scenarios: (i) baseline, (ii) price surge, (iii) building back better, and a (iv) combined scenario featuring both price surge and building back better. In the baseline scenario the housing recovery process in Alameda is modeled "as-is"; that is, price surges and building back better considerations are not accounted for. The second scenario addresses the demand surge following disasters, stemming from an imbalance between construction supply and demand, which subsequently elevates repair costs. Due to lack of reliable data to estimate the availability of skilled force in Alameda following the selected earthquake event, adjustments to building repair costs are determined by the following factor:

$$C_{ps}(r_d) = \begin{cases} 1.1 & r_d < 0.1 \\ 0.75\, r_d + 1.025 & 0.1 \leq r_d \leq 0.5 \\ 1.4 & r_d > 0.5 \end{cases} \tag{14}$$

where C_{ps} represents the factor that modifies building repair costs, and r_d signifies the proportion of buildings with damage states exceeding extensive. While the model in Eq. 14, it demonstrates how the proposed framework can incorporate the repair surge considerations. The building back better (BBB) concept serves as another significant factor influencing individuals' decisions regarding the sale of their homes. In this study, repair costs are adjusted according to the following factor, addressing this particular form of underinsurance.

$$C_{BBB}^{i}(y_b) = \begin{cases} 1.2 & y_b < 1900 \\ -\frac{1}{1180}(y_b - 3316) & 1900 \leq y_b < 2018 \\ 1 & y_b \geq 2018 \end{cases} \tag{15}$$

Where C^i_{BBB} represents the factor, and y_b signifies the year of construction for the i^{th} building. The final scenario combines the effects of the demand surge and the building back better concept.

5. Results

Using Monte Carlo Sampling, Figure 4 presents the exceedance probability curve for all the aforementioned scenarios. From the figure, it becomes evident that as repair costs increase due to the factors discussed earlier, homeowners are less inclined to sell their properties. For instance, when both the price surge and building back better factors impact repair costs, there is a reduced willingness to sell homes compared to the baseline scenario. This reduced willingness also holds true for the price surge and building back better factors when considered individually. The rationale behind this observation is quite intuitive: as repair costs rise, the likelihood of neighboring properties recovering diminishes. Furthermore, the offers from real estate companies, which are contingent on neighborhood recovery and the extent of damage experienced by the home, decrease. Consequently, the overall value of homes is considerably reduced. When an individual contemplates selling their home and relocating, they must account for the cost of acquiring a new property. Considering the further reduction in their home's value due to price surges and building back better initiatives, the expenses associated with selling their home and moving to a new location increase. Indeed, as the repair cost increases, the term [$HV_{bid}(t) - C_{new}$] in Eq 10 and Eq 11 will decrease, leading to a reduction in the expenses associated with staying and an increase in the costs of leaving. This ultimately leads more people choosing to stay in the area and undertake the reconstruction of their homes. Based on Figure 4, on average, out of the 7,739 households, 1,517 opt to sell their homes in the baseline scenario, 1,481 in the price surge scenario, 1,474 in the building back better scenario, and 1,435 in the combination scenario. The exceedance probability of the mean is similar across the four scenarios, standing at 62%, 61%, 62%, and 60% for the respective scenarios. Conversely, Baseline scenario is more likely to lead to a higher number of homes sold. For example, the probability of exceeding 1,700 homes sold is 50%, 39%, 39%, and 32% for abovementioned scenarios respectively, further emphasizing that people are less willing to sell their houses as an increase in repair costs.

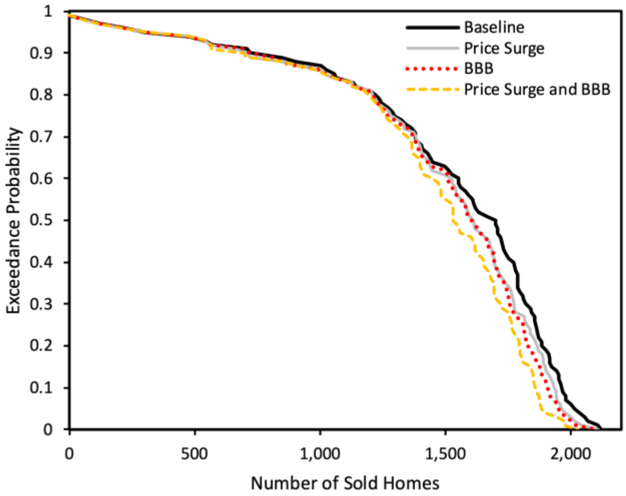

Figure 4. Exceedance probability of number of sold homes for different scenarios.

Figure 5 illustrates the mean number of homes sold by individuals based on their income levels across all scenarios. This figure highlights that individuals with higher incomes are less inclined to leave the area and are more motivated to rebuild and return to their homes. Conversely, lower-income individuals may face greater challenges in rebuilding their houses due to limited resources, making relocation a more financially sensible option, particularly when grants from various sources are delayed. To gain further insight into this matter, on average, only 0.29% of individuals with high incomes are willing to sell their homes in the baseline scenario, 0.31% in the price surge scenario, 0.3% in the building back better scenario, and 0.39% in the combination scenario. In contrast, 34.43% of individuals with low to moderate incomes express their desire to sell their homes in the baseline scenario, 33.60% in the price surge scenario, 33.44% in the building back better scenario, and 32.48% in the combination scenario. It is important to highlight that, although we consider that the decision to sell is an option for all households, this option becomes more attractive for households that are the least likely to be able to obtain the necessary financing to repair their homes. It is acknowledged that portraying results in this manner mask some of the socioeconomic inequalities in this process. From different lenses, the results in Figure 5 can be interpreted as a heightened risk of gentrification in the area following the earthquake.

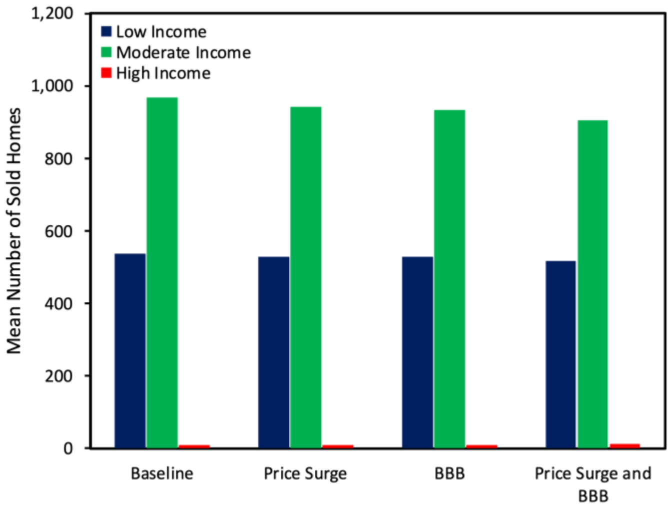

Figure 5. Mean number of sold homes based on income level.

6. Conclusions

This paper introduced a methodology to simulate post-disaster housing recovery for an earthquake-struck community. The methodology simulates damage and repair costs for individual buildings, as well as the capacity of individual homeowners to raise the necessary funding to repair their homes. Repair costs are estimated accounting for potential post-disaster increases in labor costs and additional costs related to building back better requirements. A case study is presented where the methodology is applied to simulate the impacts of a M7.0 earthquake near the city of Alameda, California. It is demonstrated that the earthquake can make it attractive for nearly 2,000 homeowners to sell their homes instead of rebuilding. However, arguably counter-intuitively, increases in costs due to price surge or build-back-better requirements increases the number of homeowners opting to stay. While naively this may be seen as a good outcome, this can also be interpreted as significant number of homeowners being forced to repair and stay. Among the building sold, the majority is expected to be occupied by low-to-moderate income homeowners. If these results are observed after a disaster, the community is expected to experience a fast gentrification process. The insights provided in this study highlight the importance of evaluating disaster impacts holistically to understand unforeseen consequences of these extreme events. Future research will be devoted to improving the model, particularly to improve the complexity of the household decisions with the goal including sociodemographic aspects that affect human decision. With these improvements, the proposed methodology will be able to better inform disaster recovery planning for communities.

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