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Modeling Rental and Multi-family Post-Disaster Housing Recovery

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Post-disaster housing recovery models increase our understanding of recovery dynamics, vulnerable populations, and how people are affected by the direct losses that disasters create. Past recovery models have focused on single-family owner-occupied housing, while empirical evidence shows that rental units and multi-family housing are disadvantaged in post-disaster recovery. To fill this gap, this paper presents an agent-based housing recovery model that includes the four common type-tenure combinations of single- and multi-family owner- and renter-occupied housing. The proposed model accounts for the different recovery processes, emphasizing funding sources available to each type-tenure. The outputs of our model include the timing of financing and recovery at building resolution across a community. We demonstrate the model with a case study of Alameda, California, recovering from a simulated M7.0 earthquake on the Hayward fault. The processes in the model replicate higher non-recovery of multi-family housing than single-family, as observed in past disasters, and a heavy reliance of single-family renter-occupied units on Small Business Administration funding, which is expected due to low earthquake insurance penetration. We find that multi-family housing relies more on Community Development Block Grants for Disaster Recovery (CDBG-DR), and has the highest total need and highest portion of unmet need remaining. However, many of these unmet cases have a large portion of their funding, and thus may practically be able to obtain the funds from personal sources.

INTRODUCTION

Post-disaster housing recovery is not uniform. Past disasters, including the Taiwan Chi-Chi earthquake, the Northridge earthquake in California, the Canterbury earthquake sequence in New Zealand, and Hurricane Charles in Florida, have shown that housing type (i.e., multi-

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family versus single-family) and tenure (i.e., owner-occupied versus renter-occupied) play a significant role in determining the recovery of a structure (e.g. Lu et al., 2007; Shao, 2002; Comerio, 2006). In this paper, we use the term type-tenure to refer to the combinations of these housing categories.

Rental housing tends to recover more slowly than owner-occupied properties (e.g. Henry, 2013; Tafti and Tomlinson, 2013; Zhang and Peacock, 2009). Scholars have demonstrated differences between the recovery of single-family structures due to tenancy, irrespective of damage (e.g. Lu et al., 2007; Nejat et al., 2016). The slower recovery of rental housing can be attributed to difficulties in decision-making and financing reconstruction (Zhang and Peacock, 2009). In the US, post-disaster financial assistance prioritizes homeowners, making it more difficult for owners of rental units to fund repairs (Comerio, 1997). These owners may also live in the same community as their rental unit and incur damage to both their home and rental property. Owners of multiple rental properties may not be able to repair all homes simultaneously (Tafti and Tomlinson, 2013). These factors negatively impact the recovery of rental housing after disasters.

The reconstruction of multi-family housing (e.g., apartments or condominiums) has been shown to be slower than single-family housing. Multi-family housing units are unique in their physical characteristics, ownership structures, and available financial resources after a disaster. Apartments are multi-unit buildings with one owner or multiple investors, but their residents are renters. Conversely, in a condominium, each unit is owned by an individual or household. Studies of past disasters have found that multi-family units, both owner- and renter-occupied, experience longer recovery times than single-family homes (e.g. Comerio, 1997; Wu and Lindell, 2004; Olshansky et al., 2006; Lu et al., 2007; Rathfon et al., 2013; Hamideh et al., 2021). Slow post-disaster condominium recovery has been associated with challenges for all owners to reach agreements and obtain funds for repairs (e.g. Wu et al., 2007; Shao, 2002; Finn and Toomey, 2017).

While studying past disasters provides valuable insights, lessons from these studies may not translate directly to future disaster scenarios. There are many different contexts included in their findings, being from different countries, different hazards, and different social contexts. This evidence illuminates trends that occur despite many differing factors between disasters.

Since empirical data are scarce and contextually specific to their source, risk modeling is an important tool to gauge possible future scenarios and their outcomes. Many existing models of post-disaster housing recovery seek to capture the recovery times of communities by accounting for various parts of the recovery process, such as financing, reconstruction, and impeding factors. Existing recovery models are often limited to single-family owner-occupied structures because post-disaster policies focus on this type of home and there are disproportionately more data available about their recovery in past disasters than about the recovery of other types of homes. Most recovery models at the community scale ignore rental units (e.g. Sutley and Hamideh, 2018; Moradi and Nejat, 2020; Miles, 2018) or account for slower renter recovery with a pre-determined addition to the time to seek resources (Costa et al., 2021). Similarly, the ResilUS model (Miles and Chang, 2011) is calibrated to the Northridge earthquake data such that 25% of renters relocate. These approaches predict slower rental unit recovery, but they do not capture the sources of that disparity and are thus unable to support exploring potential solutions. Landlord decision-making has been simulated in isolation, including future rent decisions but not recovery timing (Tafti and Tomlinson, 2021). DESaster simulates the decisions of renters and owners, accounting for financing processes of a landlord and a landlord having multiple rental properties, but not damage to the landlord's own home (Miles, 2017). Post-disaster repair financing has been modeled for single-family owner-occupied residences of various income levels after an earthquake (Alisjahbana et al., 2022), but neither for multi-unit buildings nor for rental properties. Many components of housing recovery have been modeled; however, no existing approach provides a full recovery model for rental and owner-occupied housing that includes landlord property damages and multi-family buildings.

This paper introduces a housing recovery model that includes four major housing types and tenures with their unique financing properties and paths to recovery. The model is applied to a case study of Alameda, California following a simulated magnitude 7.0 (M7.0) earthquake on the Hayward fault. The results demonstrate our ability to understand the timing of financing, sources of funds, and impacts on recovery between the four type-tenure categories.

MODELING POST-EARTHQUAKE RECOVERY OF COMMUNITIES

Two types of post-disaster recovery simulation models are proposed in the literature. Household recovery models focus on households and how they progress across four stages of post-disaster housing: emergency shelter, temporary shelter, temporary housing, and permanent housing (Quarantelli, 1982, 1995; Rodríguez et al., 2007). In these models, the buildings are simulated to the extent that physical damage triggers displacement (Sutley and Hamideh, 2018). From the perspective of the simulation, the damage state of the building is an attribute of the household.

Conversely, housing recovery models focus on the buildings, simulating how these are damaged at the time of the event and how they regain functionality over time (e.g. Nejat and Damnjanovic, 2012; Moradi and Nejat, 2020; Costa et al., 2021). In these models, the household that occupies or owns the building is simulated to the extent that its demographic profile affects recovery, e.g., lower-income owners may have more difficulty funding repairs. That is, the demographic profile of the household is an attribute of the building. The model proposed here falls in the latter category.

To simulate a community's post-disaster housing recovery process, we propose the agent-based model represented by the schematic in Figure 1. Agent-based models represent complex systems by simulating the interactions of simple, autonomous agents with attributes (i.e., characteristics) and behaviors (i.e., actions they take). A large number of interactions between these agents can capture the complexity and emergent behaviors of a system. For example, agent-based models are employed to study ecosystem equilibrium (e.g. Miyasaka et al., 2017; McLane et al., 2011), neighbourhood segregation (e.g. Crooks, 2010), and disease spread (e.g. Hoertel et al., 2020; Rockett et al., 2020). To simulate housing reconstruction within a community using an agent-based approach, we introduce three groups of agents: (i) building agents that represent the buildings and their owners; (ii) funding agents that represent entities that provide financial resources to building owners; and (iii) contractor agents that building owners hire to repair their buildings. Each group contains multiple agents represented by colored boxes in 1. These agents are described in detail in the following subsections.

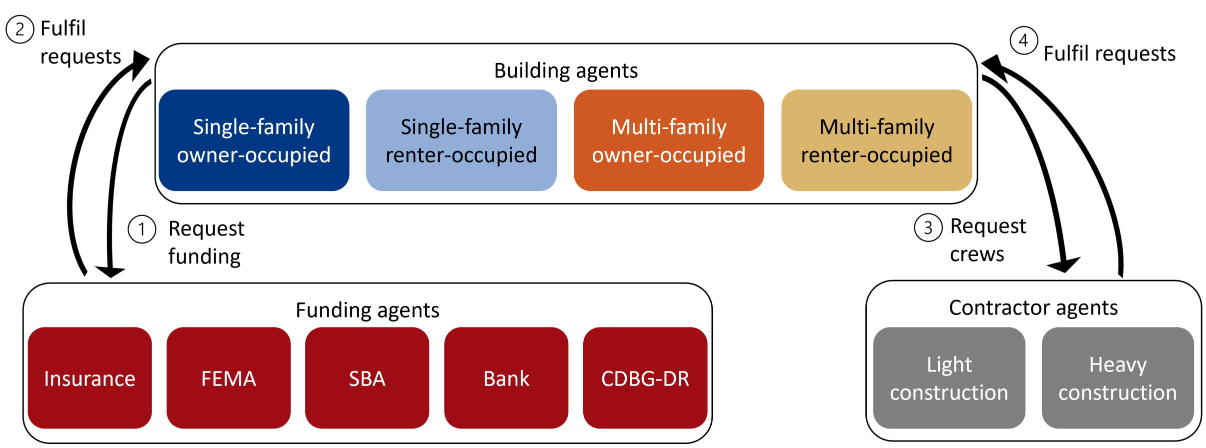

Figure 1. Schematic illustration of the recovery model, where recovery takes place through interactions between building agents, funding agents, and contractor agents.

The numbers by the arrows in Figure 1 highlight the order of agent interactions. If a building is damaged, it interacts first with the funding agents to obtain funding. Then, it seeks to hire a contractor agent to conduct repairs. The interaction between building and funding agents is influenced by both the physical properties of the building and the demographic profile of the building owner. The number of contractor agents may be limited to represent the number of contractor crews available in the community. Building agents compete for the available contractor agents. The goal is to capture interactions between physical vulnerability (i.e., building damage) and social vulnerability (e.g., hardship in obtaining funding leading to an extended housing recovery time). The proposed model provides a flexible architecture that can represent many behavioral, economic, and policy assumptions.

BUILDING AGENTS

Our literature review highlights significant differences in the recovery processes of residential buildings depending on their building type and tenure; here we refer to each combination as a type-tenure. These differences stem from the type and timing of available financing, the type of repairs needed, and the number of owners who must agree on repair decisions. Defining all type-tenure combinations is difficult due to the diversity in housing arrangements. Single-family housing may be either owner-occupied or renter-occupied. Multi-family housing may have mixed occupations, e.g., the same building may have both renter-occupied and owner-occupied units. The proposed model simplifies housing arrangements into four common type-tenure archetypes: (i) single-family owner-occupied buildings (SFOO), (ii) single-family renter-occupied buildings (SFRO), (iii) multi-family owner-occupied buildings (MFOO), and (iv) multi-family renter-occupied buildings (MFRO). These four type-tenure combinations have clear differences in available funding avenues and they represent the majority of residential buildings in the United States. As shown in Figure 2, each type-tenure is represented by one agent. In the following, we refer to these as SFOO, SFRO, MFOO, and MFRO agents.

There are many similarities between the implementation of the four building agents. We leverage these similarities through the concept of inheritance from object-oriented programming, as shown in Figure 2. The attributes and actions identical across agent types are assigned to a parent class of building agents. The specific type-tenure agents are implemented as four child classes derived from the building agent class and inherit all attributes and behaviors from the parent class. The unique characteristics of each type-tenure are defined under the corresponding child class.

Some rental housing may have an owner who also lives in the community. The proposed model accounts for this by assuming that if the owner experiences damage to their home and their rental property, they prioritize repairing their home over the rental home. This behavior assumes that renter protection policies exist and that owners cannot choose to occupy their rental property.

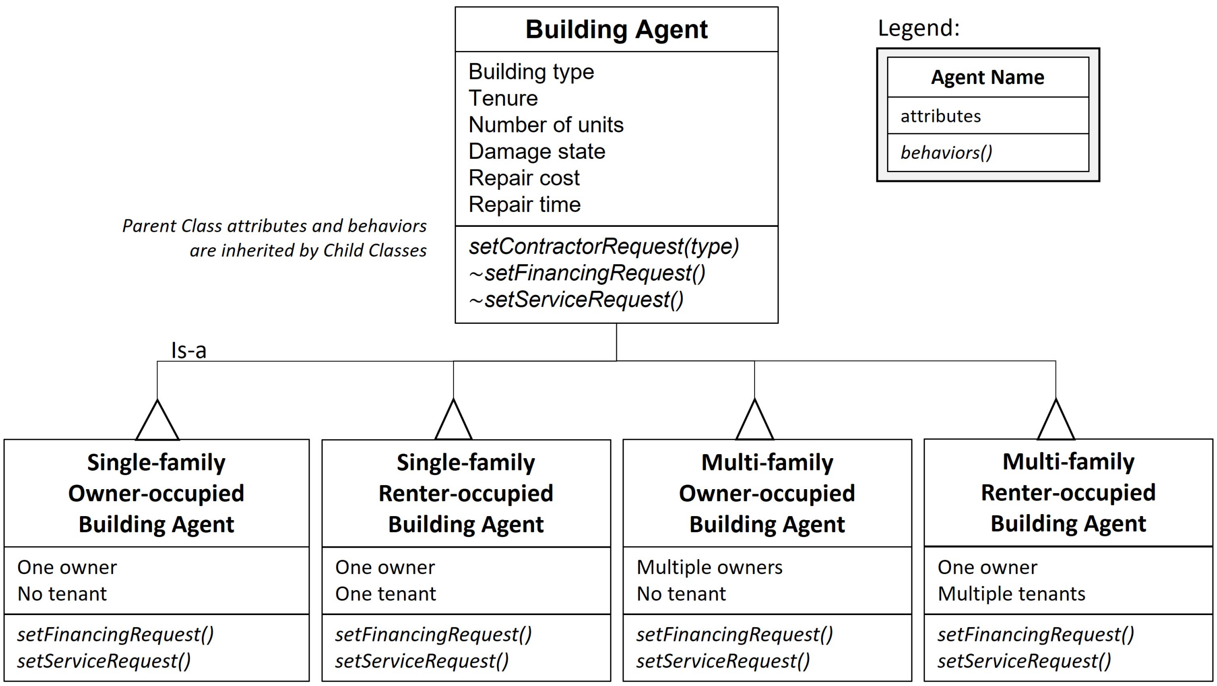

Figure 2. Building agent implementation with properties and associated attributes, behaviors, and data sets. Each type-tenure class has a specific function for financing and service requests. The associated data sets characterize the different owner and tenant structures.

The SFOO agents represent single-family owner-occupied buildings where the decision-maker occupies the building. SFOO agents prioritize their home repairs and quickly work to obtain financing. Their constraints are their ability to raise funds, based on the owner's income, and to compete for the limited number of contractors.

The SFRO agents have an owner and a tenant. Tenants occupy the building and are not the decision-makers for these agents. The building owner is responsible for financing repairs. This owner is assumed to be an individual instead of a corporation, and the rental home is treated as a business.

The MFOO agents represent multi-family owner-occupied buildings (i.e., condominiums). For these buildings, we assume that each household owns the unit it occupies. Thus, as shown in Figure 2, MFOO agents have multiple owners. In the proposed methodology, the value of each unit is the total building value divided by the number of units. The building repair cost is also evenly split between all units. We assume the owners prioritize repairs and all agree to rebuild. Thus, negotiation time is zero, and financing is sought immediately following the disaster. Since the owner of each unit must secure their funds, the recovery of MFOO agents is typically bottlenecked by the inability of a subset of unit owners to obtain funding.

The MFRO agents represent multi-family renter-occupied buildings (e.g., apartment complexes). These buildings are assumed to be owned by corporations, as opposed to individuals. Thus, as shown in Figure 2, MFRO agents have a single owner and multiple tenants. The key differences between MFRO and SFRO agents are the funding sources for which they are eligible. We assume that these buildings are treated as businesses by funding agencies.

FUNDING AGENTS

Buildings agents interact with the funding agents in Figure 1 that represent insurance companies, banks, the Federal Emergency Management Agency (FEMA), the Small Business Administration (SBA), and the Department of Housing and Urban Development (HUD). These agents provide funds through different grant and loan programs based on building type-tenure. Figure 3 shows the steps the building agents take to obtain funds. Owners are not assumed to use savings for repairs. The model is informed by empirical evidence and published policies. The agents seek the fastest and most favorable funding first. Thus, an insured building uses insurance before applying for a grant or loan. Similarly, SBA offers below-market interest rates (i.e., 4% (SBA, 2022d)), hence the SBA loans are sought before bank loans. Although the CDBG-DR is a grant, it becomes available several months to years after a disaster (Martín et al., 2022), so it is the last funding source buildings may obtain. Building agents that successfully obtain funding proceed with finding a contractor and repairing damages. Others are left with unmet needs and are unable to repair.

Funding agents may approve or deny requests for funding. If a building agent's request is not approved, or the provided funding is not sufficient, the building agent moves on to seek additional funding from the next funding agent. The funding needs of a building agent at a given time t, $F_{\text{needs}}(t)$ is

$$F_{\text{needs}}(t) = RC - F(t) \tag{1}$$

where RC is the building repair cost and $F(t)$ is the funding received by time t from all sources. Building agents progress along the flowchart in Figure 3 until $F_{\text{needs}} = 0$ or they reach the

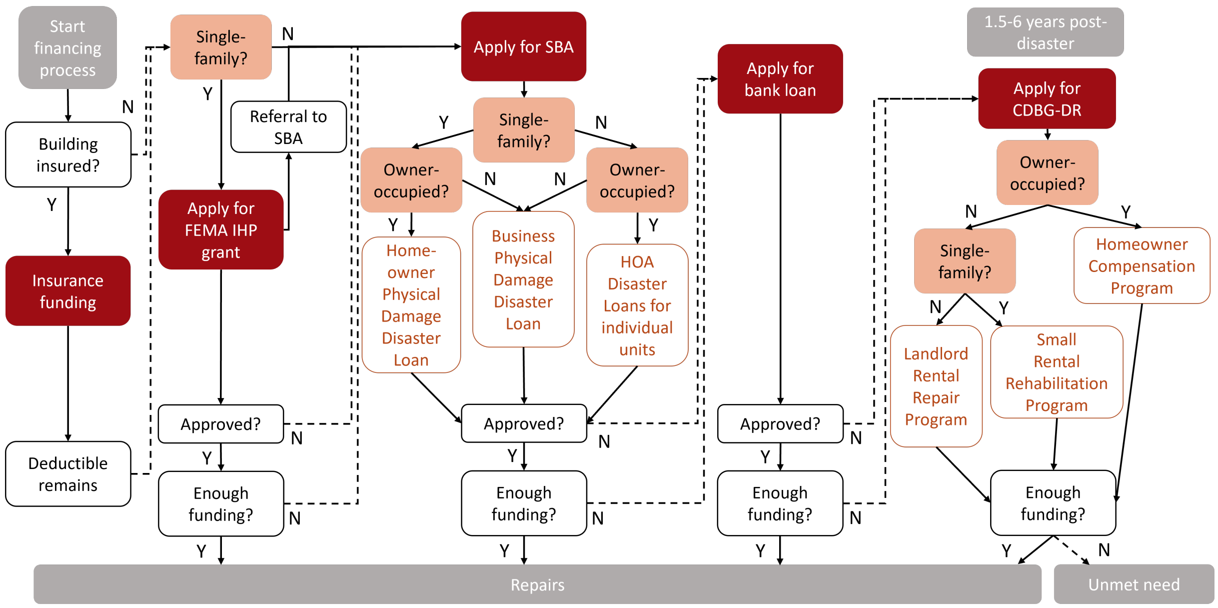

Figure 3. Process that building or unit owners follow after a disaster. Main funding sources are shown in red boxes, with specific programs in red outline with red font. Light red boxes show where paths differ based on building type-tenure.

end with unmet losses. Each building agent interacts with each funding agent once, at most. Approved or denied, requests incur a processing time. Using more funding agents lengthens the time to obtain funding. The five funding agents presented in Figure 1 are further detailed in the following.

Insurance agent

The insurance agent provides funding to insured building agents whose losses exceed a deductible that must be assumed based on the disaster and insurance type. Insurance is provided per building agent; thus, unit owners cannot have separate policies. We do not consider contents loss, which renters or unit owners may insure separately. This decision aligns with data on insured structures and reflects that homeowner associations may mandate insurance for the entire building.

Thus, the funding available from insurance, $F_{\text{insurance}}$, is

$$F_{\text{insurance}} = \begin{cases} RC - (I_d \cdot BV) & \text{if } RC > I_d \cdot BV \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

where I_d defines the deductible as a fraction of the building value, BV is the building value, and RC is the repair cost.

The disbursement time for insurance funds is modeled as a lognormal random variable with a median of 42 days and log-standard-deviation (dispersion) of 1.11 following the model developed by Almufti and Willford (2013).

FEMA IHP agent

The FEMA IHP agent simulates funding coming from the Individuals and Households Program (IHP) by the Federal Emergency Management Agency (FEMA). FEMA IHP funding is available to single-family and multi-family owner-occupied buildings (FEMA, 2016), and the amount received is affected by the repair costs (RC), insurance status (I_s), household income (H_{inc}), and the residence type, i.e., single-family or condominium (R). The cap for the FEMA IHP grant is \$36,000. The funding provided by the FEMA IHP agent, F_{FEMA}, is

$$F_{\text{FEMA}} = \begin{cases} f(RC, I_s, H_{\text{inc}}, R) & \text{if owner-occupied building} \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

where $f()$ indicates that F_{FEMA} is a function of the variables in parenthesis. Data from Major Disaster Declarations from 2001 to 2020 available through the OpenFEMA Portal (FEMA, 2022) informs $f(RC, I_s, H_{\text{inc}}, R)$. A predictive model developed from these data indicates that approval rates are close to 50% for uninsured households, compared to 25% for insured households. Insured households tend to receive more than \$7,500 while uninsured households tend to receive less than \$7,500. Income affects the amount received, with high-income households receiving more on average. Housing type-tenure affects approval rates, i.e., condominiums are less likely to be approved for FEMA funding (Costa and Baker, 2022).

SBA agent

The SBA agent provides loans following the Small Business Administration criteria. SBA loans are designed to support the repair of homes to their pre-disaster state. For single-family owner-occupied buildings, the cap is \$200,000 (SBA, 2022a). For multi-family owner-occupied buildings, the owners of each unit may apply individually for a loan (SBA, 2022c); however, the total amount that the entire building can obtain is limited to \$2 million (SBA, 2022b). Rental units are treated as businesses. As such, they can obtain loans of up to \$2,000,000. Caps are conditioned on the availability of collateral to back up the loan. When collateral is unavailable, loans are capped at \$25,000, per SBA criteria (SBA, 2022d). We model collateral as remaining property value, subtracting repair cost from the building value or equity. The equity reflects how much of the mortgage is paid at time t. Owners with outstanding mortgages use their estimated equity; those with paid mortgages use the total property value. We estimate the collateral C as

$$C = \begin{cases} P_0 + BV \cdot \Big((t - t_d)/M\Big) - RC & \text{if mortgage outstanding} \\ BV - RC & \text{otherwise} \end{cases} \tag{4}$$

where P_0 is the down payment on the building, t is the current time, t_d is the time of the most recent change of ownership, M is the mortgage maturity, and BV is the building value. In the US, data from the Home Mortgage Disclosure Act (Consumer Financial Protection Bureau, 2022) can be used to estimate P_0 and M. Tax assessor data contains t_d and BV. Eq. 4 assumes a linear relationship between time and home equity, which is optimistic. With this, the amount a building agent obtains from the SBA agent, F_{SBA} is estimated as

$$F_{\text{SBA}} = \begin{cases} min(max(C, 25000), 200000, F_{\text{needs}}(t)) & \text{for SFOO} \\ min(max(C, 25000), 200000, F_{\text{needs}}(t)) & \text{per MFOO unit, up to \$2,000,000 per building} \\ min(max(C, 25000), 2000000, F_{\text{needs}}(t)) & \text{for SFRO and MFRO units} \end{cases} \tag{5}$$

The SBA agent employs the Almufti and Willford (2013) model for the disbursal time: a lognormal variable with a median of 45 days and a dispersion of 0.57.

Bank agent

The bank agent represents private institutions that provide loans. The bank agent provides loans to applicants that can offer collateral, calculated as in Eq. 4. However, the bank may also provide loans to applicants with low debt-to-income ratios. Gross debt-to-income ratio is the relationship between one's income and monthly expenses. High gross debt-to-income ratios make it difficult for a household to obtain a loan due to the risk of insolvency (e.g., Cherry et al., 2021). We assume that households without a mortgage have a low debt-to-income ratio and could qualify for a private loan. The loan is calculated as a new mortgage, that is

$$P = G \cdot \Big(H_{\text{inc}}/12\Big) \cdot \Big((1+r)^M - 1\Big) / \Big(r \cdot (1+r)^M\Big) \tag{6}$$

where P is the maximum loan amount, G is the maximum gross debt-to-income ratio that the loaner would accept, H_{inc} is the annual loanee household income, r is the monthly interest rate, and M is the loan maturity in months. Our implementation uses $G = 0.3$ and $n = 360$ months to indicate a 30-year maturity. However, these values should be tailored to specific applications. Thus, the maximum loan provided by the bank agent is

$$F_{\text{bank}} = \begin{cases} min(C+P, F_{\text{needs}}(t)) & \text{if no mortgage} \\ min(C, F_{\text{needs}}(t)) & \text{otherwise} \end{cases} \tag{7}$$

The disbursal time for loans provided by the bank agent is modeled as a lognormal random variable with a median of 60 days and dispersion of 0.68 (Almufti and Willford, 2013).

CDBG-DR agent

Finally, the CDBG-DR agent represents the actions of the US Department of Housing and Urban Development that provide grants to low-to-moderate-income households impacted by disasters through its Community Development Block Grant for Disaster Recovery (CDBG-DR) program (HUD, 2022). After each disaster, a CDBG-DR program must be approved by Congress. HUD provides funds to state housing authorities that, in turn, assist households in need. For owner-occupied households, the CDBG-DR funds are disbursed through the Homeowner Compensation Program, which consistently provides grants with a \$150,000 cap (Martín et al., 2022). HUD assistance for rental units is inconsistent across disasters and designed by state authorities. Examples of well-documented rental assistance programs using HUD funds are the Landlord Rental Repairs Program (LRRP) and the Small Rental Rehabilitation Program (SRRP) implemented after Hurricane Sandy (Community Planning and Development, Disaster Recovery and Special Issues Division, 2013; Aurand et al., 2019). The LRRP provided owners up to \$150,000 to repair rental housing (Community Planning and Development, Disaster Recovery and Special Issues Division, 2013). The SRRP provided multi-family buildings with 25 units or fewer up to \$50,000 per unit (Aurand et al., 2019). However, the LRRP and SRRP were limited to rental buildings affordable to low-income families. Rent is considered affordable if it is less than 15% of the median household income. Thus, the funding provided by the CDBG-DR program to a household, $F_{\text{CDBG-DR}}$, is

$$F_{\text{CDBG-DR}} = \begin{cases} min(150,000, F_{\text{needs}}(t)) & \text{if low-to-moderate income SFOO or MFOO} \\ min(150,000, F_{\text{needs}}(t)) & \text{for affordable SFRO} \\ min(50,000, F_{\text{needs}}(t)) & \text{per unit, for affordable MFRO with} < 25 \text{ units} \end{cases} \tag{8}$$

Funding from the CDBG-DR program is disbursed slowly (Martín et al., 2022). The disbursal of CDBG-DR funds is broken down into multiple tasks. Funds are first appropriated by HUD ($\Delta T_{\text{appropriation}}$), then allocated by Congress ($\Delta T_{\text{allocation}}$), then awarded to state authorities (ΔT_{award}), and disbursed to households over time ($\Delta T_{\text{first}} + u(0,1) \cdot \Delta T_{90\%\text{ expenditure}}$). The disbursal time for the CDBG-DR agent is modeled as

$$T_{\text{CDBG-DR}} = \Delta T_{\text{appropriation}} + \Delta T_{\text{allocation}} + \Delta T_{\text{award}} + \Delta T_{\text{first}} + u(0,1) \cdot \Delta T_{90\%\text{ expenditure}} \tag{9}$$

where $u(0,1)$ is a uniformly distributed random variable and $\Delta T_{90\%\text{ expenditure}}$ is a proxy of the duration of the program.

To estimate $T_{\text{CDBG-DR}}$, we calculate the averages of data collected by Martín et al. (2022), where $T_{\text{appropriation}} = 0.6$ years, $\Delta T_{\text{allocation}} = 0.2$ years, and $T_{\text{award}} = 0.2$ years. The remaining components of $T_{\text{CDBG-DR}}$ differ between the Homeowner Compensation Program (HCP) and programs aimed at rental housing (i.e., LRRP and SRRP). We estimate $\Delta T_{\text{first,HCP}} = 0$ and $\Delta T_{\text{first,LRRP and SRRP}} = 1.75$ years (Martín et al., 2022, Fig. 5). That is, there is a 1.75-year gap between the first payment to owner- and renter-occupied housing. Finally, the duration of the program is estimated as $\Delta T_{90\%\text{ expenditure,HCP}} = 2.1$ years and $\Delta T_{90\%\text{ expenditure,LRRP and SRRP}} = 1.25$ years (Martín et al., 2022). Rental assistance comes later but is disbursed more quickly. On average, the CDBG-DR agent provides funding to owner-occupied housing in 2.05 years and renter-occupied housing in 3.8 years.

CONTRACTOR AGENTS

Contractor agents simulate the skilled workers in the community who can conduct repairs. Two types of agents are introduced to represent contractors: the light-construction and the heavy-construction agents. This distinction aims to capture the different skills needed to repair small and large buildings. Multi-family buildings with fewer than four units are assumed to be structurally similar to single-family homes and thus require light contractors. With four or more units, multi-family buildings require a heavy contractor. The number of construction crews may be a limiting factor in the speed of recovery. Once a contractor is allocated to a building, it is unavailable for the time needed to repair the building. The number of crews limits the number of buildings that can be under repair simultaneously, so even if every building has funding, they cannot all start repairs together. The model assumes that the number of crews available to work are the limiting factor in regional recovery speed once building owners have obtained funds instead of, for example, limited building materials or tools, transportation functionality, subcontractor availability, or other supply chain constraints.

DATA

The housing recovery simulation uses input data from a hazard and loss simulation, providing building damage from simulated ground motions. Table 1 outlines the data necessary for the housing recovery model that fall into three categories: housing stock, damage instances, and socioeconomic demographics.

Table 1. Input data necessary for each category and its use in the model.

Category	Data	Purpose
Housing	Housing type	Financing eligibility, contractor type, repair time
	Number of units	Division of repair cost, financing eligibility
	Replacement cost	Repair cost
	Owner location	Owner repair times, identify buildings with shared owner
Damage	Damage state	Repair cost, repair time
Socioeconomic	Building tenure	Financing eligibility, financing structure
	Owner income	Financing eligibility

The housing stock data should include the type of housing, number of units, and replacement cost. Housing type refers to whether the building is single-family or multi-family. Housing type determines the available funding avenues, what type of contractor the building needs, and how long the repairs take. The number of units in the multi-family structures informs the type of funding for which the building is eligible and how many instances of funding the building must obtain. The replacement cost of the building must also be included to determine how much monetary loss is associated with the damage experienced.

The damage state is obtained from a hazard and loss simulation. An analysis is needed to predict the cost and duration of repairs for the given ground shaking intensity, and whether the amount of damage is significant enough to trigger loss of occupancy. In the case of a Hazus analysis, each building has a fragility function assigned by structural type that is combined with simulated ground motions to sample the damage state (FEMA, 2020). This damage state is mapped to a loss ratio and repair time. The dollar loss amount is based on loss ratio and building value. For recovery modeling, we consider those with extensive or complete damage that require a contractor to perform repairs.

The necessary socioeconomic data are building tenure and building owner income. Tenure determines who finances repairs. In the case of single-family rental units, the owner's address is valuable to know. If the owner lives in the community, the model accounts for delays to the recovery of the rental units due to damage to an owner's home, i.e., the owner's recovery postpones the rental recovery. In cases where the owner's address is unavailable, the ownership of rental units can be assigned based on regional statistics to approximate the effects regionally. Lastly, the incomes of the building owner, or unit owners, in the case of condominiums, dictate for which funding they are eligible. It is important to note that most publicly available household income data include tenants' income instead of the building owner's, who finances the repairs.

CASE STUDY

The proposed housing recovery model is applied in this section to a case study in the city of Alameda, California. Alameda is located near the Hayward fault and is susceptible to earthquake shaking that could cause significant damage to housing. As shown in Figure 4, Alameda has a diverse housing stock with 10,464 single-family owner-occupied buildings and 6,979 buildings (with 21,830 housing units) that fall into the other three type-tenures. Thus, a model focusing only on single-family owner-occupied post-disaster recovery would capture less than half of the housing units in the community. This section presents the case study's input data, underlying assumptions, and illustrative results.

DATA AND ASSUMPTIONS

For the Alameda case study, we simulate damages after a scenario earthquake, a M7.0 on the Hayward fault. Building locations are obtained from the Alameda Tax Assessor database (Alameda County Assessor's Office, 2021). We use earthquake simulations to obtain ground shaking intensities using the Chiou and Youngs (2014) ground motion model for peak ground

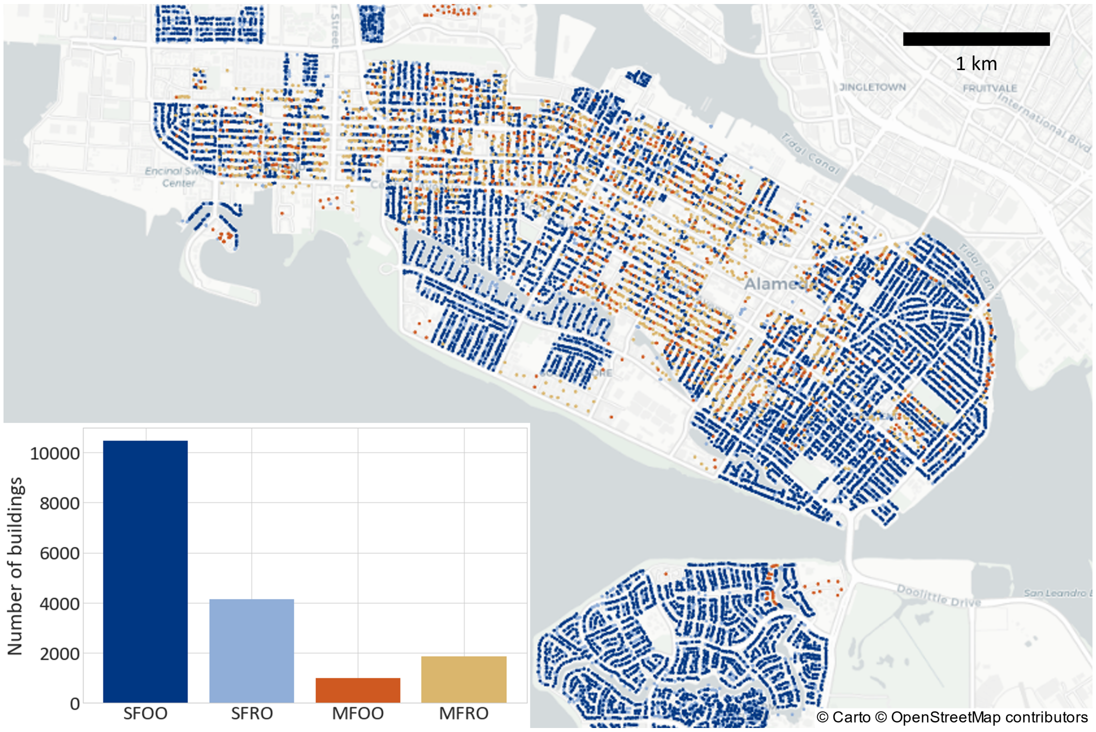

Figure 4. Residential housing in Alameda colored by housing type-tenure category, with a bar chart showing number of buildings in each category.

acceleration and use the Hazus earthquake methodology to simulate damage states for each building (FEMA, 2020). These damage states are discrete descriptions of structural damage based on the type of structure and the ground shaking at its location. The buildings in Alameda are majority wood construction. For multi-family housing, structure types are determined by the number of units using the Hazus methodology (FEMA, 2021). We use Hazus repair times for extensive and complete damage states of 90 and 180 days for single-family, and 120 and 240 days for multi-family houses, respectively (FEMA, 2020). This pre-analysis is performed using the SimCenter R2D Tool (McKenna et al., 2022).

Building values and tenure status data are taken from the Alameda Tax Assessor database (Alameda County Assessor's Office, 2021). Rent is determined based on data from the American Community Survey (Costa et al., 2022). Units that received a homeowner tax-exemption amount in the last assessment are assumed to be owner-occupied. A building i is owned by an owner-occupied building j, if the taxpayer mailing address of building i matches the site address of building j. To assign the owners' income, we estimate a household's minimum income to qualify for a mortgage on a building with value BV (Zhang et al., 2022). Based on data from the Homeowner Mortgage Disclosure Act (Consumer Financial Protection Bureau, 2022), the majority of homes in Alameda are purchased with a down payment of $P_0 = 20\%$ and loan maturity of $m = 360$ months (i.e., 30 years). Using these parameters, we estimate the minimum income a household would need to obtain a mortgage, I_p, as

$$I_p = \frac{12}{gdsr} \cdot \Big((BV - P_0) \cdot r \cdot (1+r)^m \Big) \Big/ \Big((1+r)^m - 1 \Big) \tag{10}$$

where $gdsr$ is the gross-debt-to-service-ratio, assumed to be 30%, and r is the interest rate for the year of purchase. The interest rate is assumed constant for the duration of the loan. Finally, since I_p is the income at the time of purchase, we estimate the current income I by multiplying I_p by the inflation rate between 2022 and the year of purchase.

The number of contractor crews is not limited for this study. This assumption removes construction crew availability as a barrier to recovery. We focus on the financing results in this study, which are unaffected by this assumption, instead of total recovery times, which are affected.

Approval or uptake rates for each funding source are summarized in Table 2. The model considers California earthquake insurance; we use a typical deductible of 15% (Roth, 1998). The earthquake insurance uptake rate for Alameda is 13% for homeowners and 7% for condos (California Department of Insurance, 2018). Since rental buildings with less than four units also have a lower uptake rate of 6%, this is adopted for both types of renter-occupied buildings (California Department of Insurance, 2018). Thus, insurance approval rates are applied as shown in Table 2, applied to whole structures, as explained in Section 2.2. Approval rates for public funding sources are based on statistics from past disasters (Alisjahbana et al., 2022). Bank loans are assured if SBA funding is accepted, and bank loan approval rates apply to the buildings that are denied SBA funding.

Table 2. Approval rates of various funding sources for the earthquake case study, separated by type-tenure. * denotes dependency on income, residence type, insurance status, and loss; ** denotes income-dependent approval rate.

	Funding Source				
Agent	**Insurance**	**FEMA**	**SBA**	**Bank**	**CDBG-DR**
SFOO	0.13	*	0.47	**	1.0
SFRO	0.06	–	0.47	0.91	1.0
MFOO	0.07	*	0.47	**	1.0
MFRO	0.06	–	0.47	0.91	1.0

RESULTS

Results are obtained from 100 simulations of housing recovery following the M7.0 case study event (where ground motion amplitudes and building damage states are sampled from model distributions for each simulation). Figure 5 shows the full recovery trajectories of the housing stock in each simulation. The initial drop on the left-hand side of the plot shows the immediate damage incurred by the event. These recovery curves show how many buildings are occupiable (i.e., either not severely damaged or repaired) at a given time after the earthquake. Thus, a steeper curve indicates a faster regional recovery. Recall that this is not limited by contractor crew availability, as mentioned in the data and assumptions subsection. There is variability due to initial differential damages and the inherent stochastic processes. The median, 10th, and 90th percentile realizations are identified based on the initial total community loss. At six years, the curves level out as few new buildings are recovering after that time. The recovery of each building is limited by financing, as discussed in the previous section.

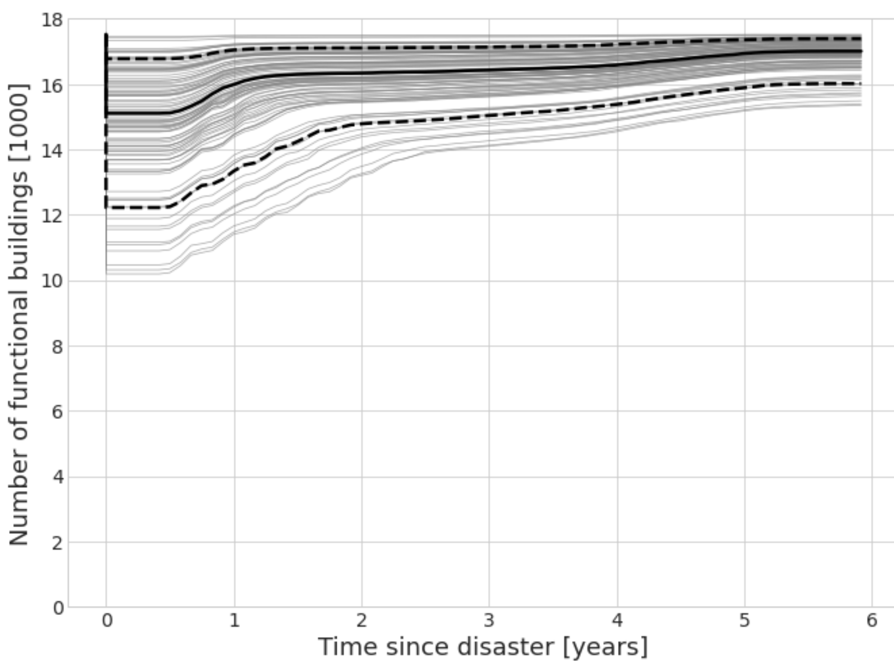

Figure 5. Recovery curves of functional units from 100 simulations with the median simulation in solid black and 10th and 90th percentile simulations in dashed black lines.

Figure 6 shows the breakdown of damage states (DS) for each type-tenure from the median scenario. Those in DS3 or DS4 (extensive or complete damage) require repairs in the model. This corresponds to the initial drop in the bolded curve in Figure 5.

Figure 7 shows the time to obtain full funding for each type-tenure, indicated by different

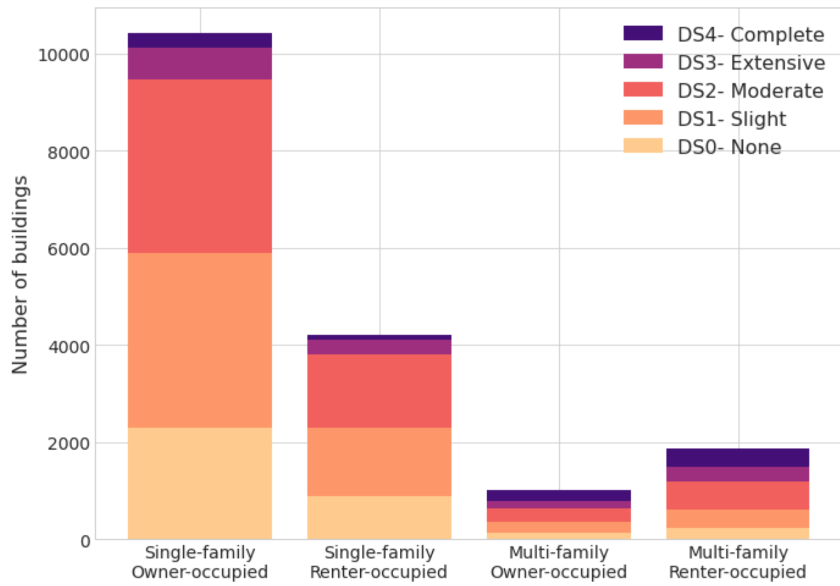

Figure 6. Histogram of damage states for each building of the four type-tenures in Alameda for the simulation with median initial total community loss.

colored lines. Here, we include the 10th, 50th, and 90th percentile simulations for each type-tenure, as highlighted in Figure 5. Immediately following the disaster, the housing type-tenure combinations are indistinguishable, but they separate within months of the disaster. Most single-family housing can obtain the funds needed within one year of the event. MFOO buildings receive financing more slowly and become saturated relatively early, i.e., few buildings receive any funding after the first year. MFRO housing has similar financing for the first three years. However, after about three years, they experience another surge in obtaining full funding. This is when CDBG-DR becomes available and highlights the importance of the CDBG-DR program for multi-family owner-occupied homes. These financing curves illustrate the model's ability to capture inequities in the ability to obtain funds for renters and multi-family housing. Despite optimistic assumptions, these trends show that the model captures some barriers to multi-family housing recovery.

In addition to modeling how many buildings have received funding over time, we can probe the resources available to those with only partial funding. Figure 8 shows more details about the portion of funding received over time for each type-tenure from the median simulation. The lightest shaded region represents fully funded buildings, corresponding to the complement of the solid lines in Figure 7. The darkest shade represents the buildings with unmet need in each category. Within six months, there is a sharp drop in buildings with unmet need. Where this levels off, few new buildings are getting financed. There is a second drop for MFRO agents,

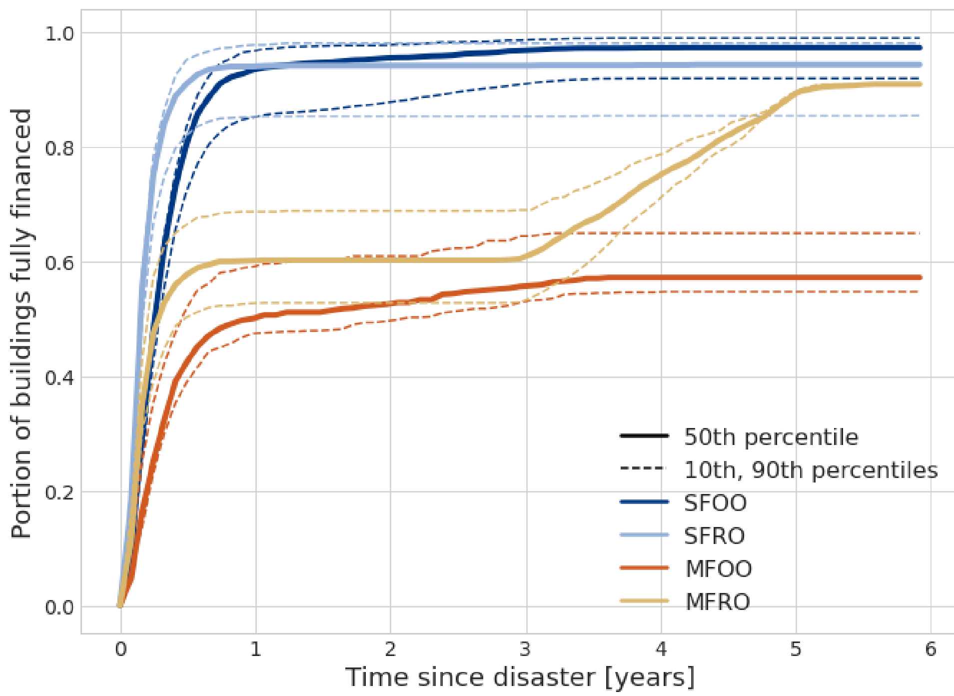

Figure 7. Portion of buildings initially seeking funding that receive full funding over the six years after a disaster, for the 10th, 50th, and 90th percentile initial loss runs, corresponding to the bolded lines in Figure 5.

signifying that they receive a second round of funding. Within six years, all modeled funding sources are distributed. The middle shade of each color represents buildings with over 80% of their funding received but without having obtained full funding. This distinction qualitatively separates the unmet cases that require large portions of funding from those with over 80% of their repair cost that may be able to supplement the cost, may repair to a lower quality, or may partially repair to a livable condition; further interpretation is provided in the discussion section. However, those with less than 80% of the losses financed may struggle more to fill the remaining need. Higher portions of multi-family buildings experience and remain in the 80% funding stage compared to the single-family buildings. Here we demonstrate how our model can be used to understand different experiences within non-recovery.

Figure 9 breaks down the total funds needed by each type-tenure in the median simulation. Multi-family buildings account for the majority of total need. While the largest number of buildings are SFOO, they account for about 30% of the need. The colors of the bars represent the funding received from each source. Renter-occupied and multi-family housing have the highest total portion of unmet needs. Owner-occupied buildings have the advantage of the additional FEMA funding, which covers more than 25% of the need for single-family buildings

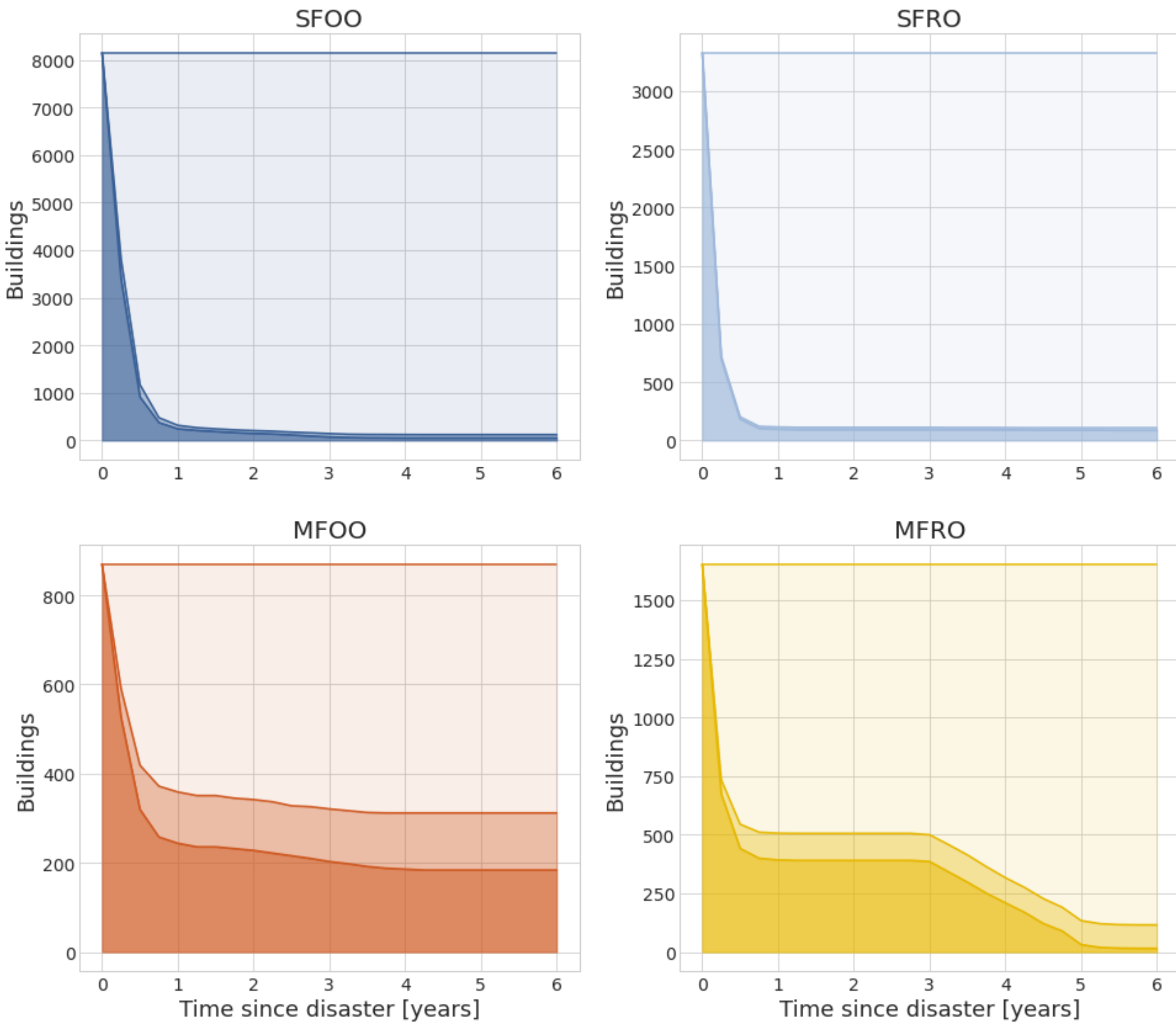

Figure 8. Number of buildings within each type-tenure with unmet need (darkest shade), 80% of their funding (middle shade), and fully funded (lightest shade) over time after the disaster.

and 5% for multi-family. SBA loans are pivotal in recovery financing, especially for single-family buildings. This aligns with empirical evidence, as after the 1994 Northridge earthquake, SBA loans were a large source of funding (20.7%), second only to insurance (65.3%) (Wu and Lindell, 2004). Current insurance uptake rates are smaller than pre-Northridge (Roth, 1998); thus, SBA is expected to have a central role in a future disaster, as indicated by model results. Since many SFRO buildings are not classified as affordable housing, they do not qualify for funding from CDBG-DR, explaining the negligible portion supported by that source. The model results can be interpreted to reflect how effective financing policies or strategies may be after a disaster and indicate what subset of the building stock may benefit from each funding source. Thus, the proposed model demonstrates how financing policy contributes to disparate recovery that has been evidenced in past disasters.

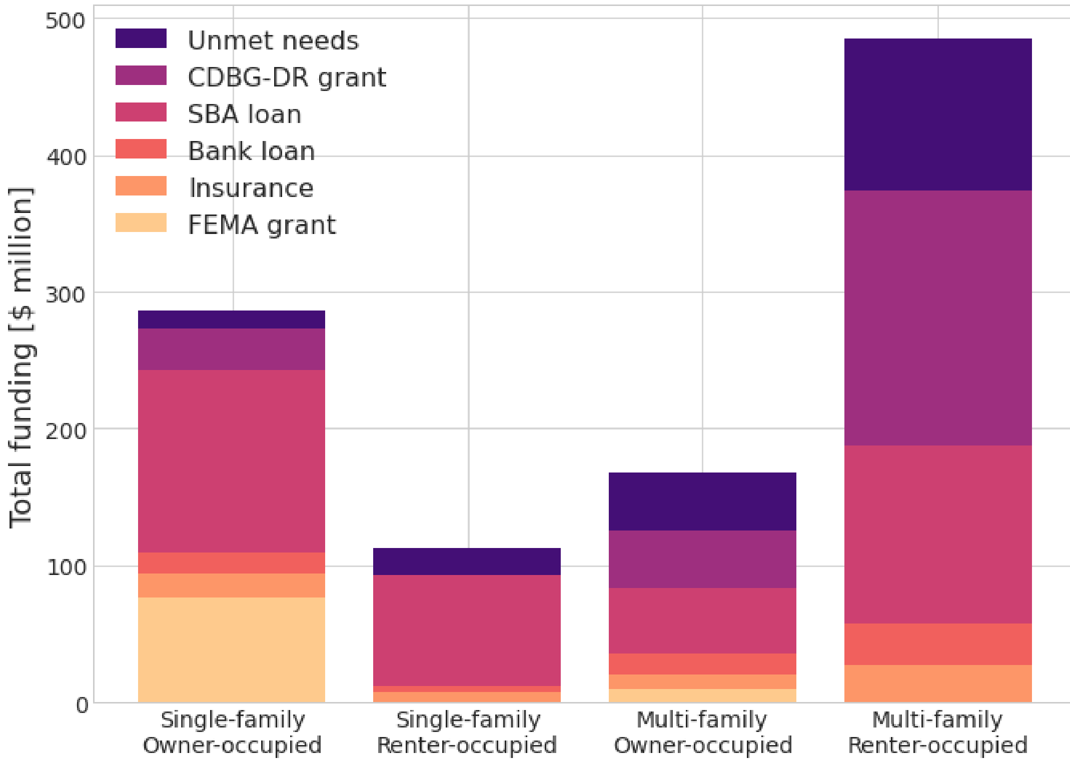

Figure 9. Total funding needed by each type-tenure group for the median scenario, and the sources from which the funds are obtained.

DISCUSSION

Post-disaster recovery is a complex problem hinging on human behavior and stochastic inputs that cannot be fully anticipated. Despite many associated challenges, housing recovery modeling is useful for understanding the processes that aid and impede recovery. This discussion touches on two important challenges, the first regarding the data and modeling process, which are variable in different regions and require simplifications and assumptions to be made. The second challenge is interpreting modeling results to real-world manifestations, which is useful to understand and qualitatively compare possible scenarios and mitigation actions.

DATA AND MODELING CHALLENGES

The model inputs require data on the housing in the region of interest. These data often come at various resolutions, from data for entire Census tracts to building-level data. Building-level data are unavailable in many communities, though most municipalities have a tax assessor with building values and use types. While more detailed data are generally preferred, they are not necessary to obtain outputs on a regional scale. Data that are unavailable at a high spatial resolution may be distributed based on regional data to produce outputs that describe the aggregate regional recovery. The same process works for information such as the locations of rental residence owners. Knowing only the zip codes or cities of these owners would contribute to an aggregate understanding of how likely it is that the owner is impacted and can generate reliable outputs at the same regional resolution.

Even with building-level data, assigning type and tenure to each building is non-trivial. For the case study, renter-occupied buildings can be identified by the lack of an owner-occupant tax refund or by having a different property tax mailing address from the residence address. These data are imperfect and do not always agree. Some misclassification is expected, such as when an owner of a multi-family rental building lives in one of the units, classifying the whole building as owner-occupied. These cases are believed to be relatively rare and are not expected to influence results on a regional scale.

With regard to modeling, one major challenge is the characterization of unknown future financing programs. Since CDBG-DR financing programs are created after disasters, they are not standardized and, in many cases, poorly documented. Thus, the programs included in the model use samples of past disasters; however, these examples may not be representative. Local governments may be able to draft policies before a disaster strikes; however, the allocation of funds is likely to depend on where damages and losses are concentrated in the community. In addition, since this program emphasizes disadvantaged populations with unfulfilled need after receiving other sources of funding, it is meant to be tailored to the remaining need in the community months or years after a disaster.

These data and modeling challenges highlight a need for partnerships between governments and researchers to understand the pre-disaster conditions of a community and anticipated recovery programs. Access to data, even at a block level, can improve modeling while maintaining residents' privacy. If other cities provided the city or zip code of owners, the model could be applied there, and the identification and understanding of damages and repair processes for connected units to renter-occupied housing would improve the performance of the model.

INTERPRETATION OF RESULTS

The financing and recovery time outputs are useful to compare subsets of the population and how interventions may improve their recovery. However, these interpretations should consider the assumptions embedded in the model. Decision-making is simplified, excluding the possibility of choosing not to repair. The assumption that all building owners want to recover quickly and know about each funding source likely overestimates the rates of obtaining financing. However, these results are useful in understanding how effective the funding sources would be in filling the needs of the population in an idealized case where they are all pursued when buildings are eligible.

While financing time results largely reflect empirical expectations, full recovery time is still affected by the assumption that all agents desire to rebuild quickly. Thus, the disparity in recovery times may not be fully captured, while the disparity in financing is more robust. Behavioral models are necessary to implement more complex decision-making and negotiation between owners.

In addition, much of the disparity in recovery is felt by the residents of the affected units; however, the model captures the trajectories of the building stock without making assertions about the residents' recovery, especially renters. In reality, a heavily damaged property may be redeveloped to a different configuration, or a rental home may be repaired with improvements and an increased rent, so the former tenants can no longer afford to live there. This post-disaster gentrification is damaging to the social fabric of a community and should be considered in policy and decision-making. Thus, this model provides insights into the financing and potential building stock recovery, but understanding the community of interest is integral to policy-making.

Another factor in recovery is the time that households and building owners are willing to wait to receive funds. If this is finite, funding an owner receives after their personal time limit is effectively 'unmet.' The time households are willing or able to wait may depend on whether they have work in the area, have family or friends living nearby, or have another place to stay while awaiting repairs. Needing to get to a job in the area may encourage a household to live in a damaged or partially functional building.

The interpretation of financing results must also be considered in cases of unmet need. Though we categorize the amount that is not filled by the five considered funding sources as 'unmet,' there are many ways this may manifest in reality. If most of the necessary funds are obtained, such as over 80% (Figure 8), the building owner may repair the building to lower than pre-disaster condition. Partial repairs could be performed, or occupants could reside in unsafe conditions long-term. Funds could also be borrowed from friends or family, or drawn from savings or liquid assets, depending on the finances and resources of the building owner. While the model focuses on financing from main funding sources, these unmet needs are interpreted as burdens on the building owners and possible causes of non-recovery. In reality, people are resilient and may employ alternate strategies to finance and repair their homes and buildings.

This model makes necessary assumptions to provide an architecture to include renter-occupied and multi-family housing in recovery modeling. Some of these assumptions overestimate recovery, while others underestimate recovery. Overall, we believe this model provides an optimistic outcome, holding constant some factors of human decision-making that may be difficult to affect through policy.

CONCLUSIONS

This paper presents a post-disaster housing recovery model to include four common type-tenures. The proposed model includes four classes of housing agents, funding agents that interact with each, two classes of contractor agents, and financing and repair processes for each housing type-tenure. We demonstrate the model on a case study to show how the financing processes and sources available based on type-tenure impact recovery trajectory and the ability of buildings to receive necessary funds to repair. This case study highlights challenges in financing despite an idealized pursuit of the funds through each program.

The financing model accounts for programs designed for specific type-tenure buildings. Building owner(s) are tasked with obtaining funds, allowing for unique financing processes depending on tenure. In the case of rental housing, we determine their owner and base repair funding on the building owner's income and the housing type, which determine eligibility for various funding sources.

We apply the recovery model to a case study to demonstrate the recovery trajectories and funding sources used between housing type-tenures. Multi-family housing obtains a lower overall portion of needed funds than single-family. The results show the breakdown of funding sources used by each type-tenure combination, demonstrating that large amounts of unmet need remain and public funding sources are insufficient to fill the needs with programs based on past disasters. It is also apparent that with the lack of earthquake insurance uptake in California, much funding is sought from the Small Business Administration after a large earthquake. The sources and distribution of funding, as well as remaining needs, capture many mechanisms that lead to disparate or non-recovery of many populations, specifically renters and those in multi-family buildings, after disasters.

Finally, we discuss data needs and remaining gaps in the model, emphasizing the need for a more quantitative understanding of post-disaster decision-making. We acknowledge the wide range of recovery possibilities and that resilient owners may fill or overcome unmet needs. In closing, this model includes a wider range of housing types than previous models, to explore recovery dynamics and provides a flexible architecture that can be expanded and refined as further data or future applications allow.

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