A Tale of Two Earthquakes: Dynamic Agent-Based Simulation of Urban Resilience

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1. Introduction

As cities increase in size and complexity they also become increasing vulnerable to unanticipated events, both natural and anthropogenic (Deppisch and Schaerffer, 2011; Godschalk, 2003). Large scale disasters such as the 1995 Kobe earthquake, hurricane Katrina, the Tohoku earthquake and tsunami and Superstorm Sandy have elicited research interest in the way cities cope with such shocks. This work tends to highlight either mitigation measures (Fleischauer, 2008; Godschalk, 2003) or 'bouncing back' strategies (Campanella, 2008; Chang, 2010; Chang & Rose, 2012; Olshansky, Hopkins & Johnson, 2012). It also tends to imply that urban recovery should be directly related to the magnitude of the disaster with larger shocks to the urban system requiring more drastic mediation or rejuvenation measures. However as this chapter shows, an exogenous shock does not have any predetermined outcome and multiple (unstable) equilibria may exist. The same shock may elicit wildly diverging urban responses in different environments. This has implications for the notion of urban resilience. It undermines much of the popular literature promoting a 'one size fits all' approach to both urban mitigation and rejuvenation and neutralizes the standard checklist approach to disaster management mechanisms, which while well-intentioned may be misleading (Prasand, Ranghieri, Shah, Tohanis, Kessler and Sinha 2009, UNISDR 2012).

As the urban environment is fashioned by the interaction of many agents such as residents, workers, local governments, developers and by sub-systems such as housing markets and transportation networks (Cruz, Costa, de Sousa, & Pinho, 2013), unraveling the key to urban resilience becomes extremely difficult (Müller, 2011). Local shocks may have global effects and innocuous, short-term perturbations may cause long term change. The result can be a shift of the entire system to one of a few possible unstable equilibria states. This situation plays havoc with attempts to formulate generic post-disaster urban resilience solutions without consideration of context (Kartez, 1984; Kartez and Lindel, 1987).

To illustrate this position, we use dynamic agent based (AB) simulation of a hypothetical earthquake in the downtown area of Israel's two largest cities, Jerusalem and Tel Aviv. The former is the national capital and seat of government. The latter is the business and economic center of the country. In the AB world, the complexities of the urban system are decomposed into the operation of 'agents'. These can be both individual entities such as citizens or aggregate institutions such as markets. Each of these operates according to certain (programmable) behavioral rules grounded in

classic behavioral foundations such as maximizing utility in terms of residence, minimizing risk and participating in activities such as work, leisure and commercial activities. In so doing, agents affect the behavior of other agents and in the aggregate, the operation of urban institutions such as land and housing markets and the planning system. We simulate the long run impacts on the urban system with a view to highlighting the complexity of restoring the urban equilibrium and rejuvenating city life. The rest of the chapter proceeds as follows. We first review current knowledge regarding urban resilience in the wake of a disaster, in light of the multiple possible equlibria states that can emerge. Then we present the AB simulation and the principles guiding its design. In the following section, the different urban contexts of Tel Aviv and Jerusalem are described. The simulation outcomes are then discussed. These are measured by time to recovery, land use rejuvenation and CBD shifting. Special attention is given to the effectiveness of urban policies aimed at restoring the urban equilibrium. These relate to land use regulation, public provision of shelter and the restoration of damaged urban services and run the gamut from status quo market-led initiatives to heavy handed regulation. Our results show very different outcomes from a similar shock and the implications of this with respect to urban resilience are discussed.

2.Literature Review

The concept of resilience emerged in the study of ecology in the early 1960's and the 1970's (Folke, 2006). One of the first definitions of the term sees resilience as a property of a system that has high probability of persistence in form and structure, embodied in an ability to absorb changes to its variables and parameters (Holling 1973). This definition has been further elaborated to include the self-organizing ability of a system, as well as the ability to adapt and learn (Folke, Carpenter, Elmqvist, Gunderson, Holling & Walker, 2002). This dynamic conceptualization of resilient systems extends the previous focus on the ability to restore equilibrium after a temporary disturbance (Holling 1973, 1996; Folke, 2006), The latter, sometimes referred to as 'engineering resilience', is criticized as static and deterministic, ignoring the possibility that the pre-shock state is only one of several states the system could present (Holling, 1973).

The notion of resilience has been imported by other fields of research including urban planning and disaster management. However, the ideal of a 'resilient city' is still a concept lacking universal definition and acceptance. Some authors follow Holling's definition and regard the resilience of a city as the degree to which it can sustain a shock before shifting to a new state (e.g. Alberti & Marzluff, 2004; Alberti, Marzluff, Shulenberger, Bradley, Rayn & Zumbrunnen, 2003). Others ascribe to the notion of to the city's ability to reorganize (e.g. Cruz et al., 2013). Others still adopt the 'engineering resilience' conception of rebounding, bouncing-back, and restoration (e.g. Campanella, 2008; Godschalk, 2003; Müller, 2011).

All views can be justified. On the one hand, as market mechanisms of supply and demand are involved in the behavior of many of the urban sub-systems (such as the housing and employment markets), the equilibrium-stability view seems to be valid. Yet, cities are complex systems whose state depends on many decisions by a wide assortment of agents and entities (Cruz et al., 2013; Godschalk, 2003; Müller, 2011). The stability approach is thus criticized for its reductionist and deterministic character (Davoudi, 2012; Martin, 2012). In this chapter we frame recovery and resilience within the concept of equilibrium. Yet, we accept that the pre-shock state is just one of many possible unstable equilbiria states. We therefore explore the feasibility of the bounce-back scenario and also the possibility of reorganization under a new state (i.e. 'bouncing-forward', see Grinberger and Felsenstein, 2014).

When operationalizing resilience and designing recovery strategies, both of these concepts present difficulties. The rigid policy options associated with rebounding and derived from the equilibrium view may paradoxically tilt the system away from stabilization by not allowing the freedom needed to achieve steady state (Folke et al., 2002). Viewing cities as complex systems, on the other hand leads to confusion regarding the processes and factors promoting urban resilience and to great difficulty in formulating absolute resilience strategies (Müller, 2011; Allan et al., 2013). As systems differ in terms of inputs, outputs, agents, and parameters, no two urban areas are alike and even the same urban space can change character over time.

The tendency of the discussion on resilient cities and urban recovery to "focus on process rather than place and form" (Allan et al., 2013, p. 244) only aggravates the situation. Portraying a picture of a general process, for example a shock leading to loss of lives, damage to property and infrastructure, diminishing accessibility and provision of services, may promote generic perceptions of the recovery process. These are expressed in the common conception that recovery is proportionate to the magnitude of the effect (Change and Rose, 2012) and in the typical knee-jerk reaction to disaster that involves time-compressing rebuilding and rejuvenation measures (Olshansky et al., 2012). These well-intentioned activities do not consider the existence of multiple and unstable equilibria resulting from different activities recovering at different rates. Neither do they consider the possibility of incongruence between the location of the event and the point of recovery.

3. Methodology

To deal with the complexities of the urban system, an AB model requires the specification of three elements: the agents and their characteristics, simple behavioral rules driving their actions, and their situation within an environment (Macal & North, 2005). These are discussed in turn below. Uniquely, we move beyond the traditional demand-oriented representations of the environment by including a dynamic element in the form of dynamic house pricing. This system mediates between agents' behavior and the land-use system and reflects supply side dynamics. It is based on the conceptualization of buildings as semi-autonomous, quasi-agents which lack mobility and initiative but still react to changes in their environment. In this manner, the response of the urban system to an earthquake becomes a consequence of the way a shock alters the behavior of city inhabitants as depicted in Figure 1. Policy interventions are also considered within this model and are treated as exogenous inputs that impact the behavior of citizen agents and the functionality of buildings (quasi-agents). While the specification of such a model is complex and requires various assumptions as summarized in Table 1, these are generally simple and intuitive. Model development is done using Repast Simphony 2.0 (North, Collier, Ozik, Tatara, Macal, Bragen & Sydelko, 2013), a popular agent-based development environment, programmed in Java.

<Insert Figure 1>

<Insert Table 1>

3.1. The Urban Environment

The environment of the city reflects the fixed results of previous round of investment, in the form of infrastructure, buildings and the land-use system. All of these elements exert powers of attraction and repulsion within the decision process of the individual agent, as detailed in section 3.2. Therefore we move beyond the grid representation common to agent-based modeling (Brown, Riolo, Robinson, North, & Rand, 2005), which relates one specific value to a unit of space, to a more detailed representation which characterizes individual buildings and the road network connecting them. This is achieved by importing three GIS-based data layers into the model. These are first, a statistical areas (SA) layer. SA's are small, homogenous areas defined by the Israeli Central Bureau of Statistics (CBS) that include data on population size, income and migration trends. Second, we utilize a GIS buildings layer, provided by the Israel Land Survey which includes data on buildings by height, number of floors, land-use and floor-space. Finally, we use a streets layer from the Hebrew University GIS database.

While these layers contain some information at a sufficiently disaggregated spatial resolution (e.g. use and floor-space for buildings), much of the data is available only at the coarser level of the SA. Therefore we generate building-level data by using data fusion and population gridding as described in Lichter and Felsenstein (2012).

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This disaggregates coarse area-level data to individual buildings according to their share of the area or city floor-space, as follows:

a. Initial resident population in a building:

$$\operatorname{Re} s_i = Pop_{SA_i} * \frac{FS_i}{\sum_{j \in SA_i} FS_j} \quad (1)$$

where $\operatorname{Re} s_i$ is the number of residents of building i, Pop_{SA_i} is the population size of the statistical area SA in which building i is located, and FS is floor-space volume (area times number of floors).

b. Initial residential building value:

$$V_i = \frac{HP_{SA_i} * FS_i * \frac{SL_i}{SL_{SA_i}}}{HHS} \quad (2)$$

where V_i is the value of a residential building i, HP_{SA_i} is the average housing price per meter (in New Israeli Shekels – NIS) in statistical area SA in which building i is located, FS is floor-space volume, SL is the service level – non-residential buildings to residential buildings ratio (i indicating within a vicinity of 100 meters from building i), and HHS indicates citywide average of household size.

c. Initial non-residential building value:

$$V_i = CS * \frac{FS_i}{\sum_{j=1}^{J} FS_j} \quad (3)$$

where V_i is the value of non-residential building i, CS is the citywide capital stock value, FS is floor-space volume, J is the global number of non-residential buildings.

3.2. Citizen Agents

Agents are generated according to initial population size. Each agent has only two characteristics: place of residence, and level of income (in NIS). While residence is determined in accordance with the results of Eq (1), income is randomly drawn for each agent from a normal distribution, the average of which is the average income per month in the building's SA, and the standard deviation is 0.1 of this value.

The goals of each agent are simple – attaining an adequate place of residence, and participating in daily activities (see Figure 1). In each iteration (representing one day), the agent first makes a decision regarding current place of residence, depending on the citywide probability of out-migration and the probability of intra-urban migration in its' SA of residence.. These probabilities are calculated based on the assumptions in Table 1, as follows:

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$$OutP_t = \frac{OC_{t-1}/Pop_{t-1}}{365} \quad (4)$$

$$IUoutP_{SA_t} = \begin{cases} OC_{SA_{t-1}} > 0 & \dfrac{OC_{SA_{t-1}}/Pop_{SA_{t-1}}}{365} \\ \\ OC_{SA_{t-1}} \leq 0 & 0.00001 \end{cases} \quad (5)$$

where $OutP_t$ is the global out-migration probability at time t, $IUoutP_{SA_t}$ is intra-urban out-migration probability from SA at time t, $OC_{t-1}/OC_{SA_{t-1}}$ is the number of citizens leaving the city/SA at time $t-1$, $Pop_{t-1}/Pop_{SA_{t-1}}$ is population size at time $t-1$. Values of $t-1$ elements stay constant during the simulation.

A random number is drawn out of the range [0,1]. If the number fails to exceed $OutP_t$, the agent will leave the city and be deleted from the simulation. Otherwise, if the number fails to exceed $IUoutP_{SA_t}$, the agent will enter a new process of residential choice. The criteria for this process are based solely on the potential residential location price and agents income and are defined according to three assumptions (Table 1). These are first, that the agent will not spend more than 1/3 of monthly income on housing (see section 3.3 for derivation of house prices). Second, similar people earn similar wages and third, agents strive to live among agents of similar social class or higher, i.e. earning similar or higher wages. According to this, a potential location will be within a monthly cost range of 1/6 to 1/3 of an agent's income. The agent searches randomly chosen locations until these conditions are satisfied or until more than 100 locations are searched. In the latter case, the search process fails and the agent leaves the city and is deleted from the simulation.

When the relocation process succeeds, the agent turns to its second goal of daily activities. These are expressed by the agent visiting locations within the simulation area. In each iteration, the agent visits three locations at least one of which is non-residential. The other two have an equal probability of being either residential or non residential. The location visited is determined according to simple behavioral principles (Figure 1, Table 1). Each building is given an attractiveness score. This is based on the nature of its surroundings. The share of empty buildings nearby is taken to represent risk evasiveness, distance from current location is considered a push factor and in the case of non-residential uses, the amount of floor-space represents a pull factor:

$$Attract_{in} = \frac{1 - Empty_i/Buildings_i + D_{in}/\max D_n + 1\{LU_i = non\mathrm{Re}s\}FS_i/\max FS}{2 + 1\{LU_i = non\mathrm{Re}s\}} \quad (6)$$

where $Attract_{in}$ is the attractiveness score of building i for agent n, $Empty_i$ is the number of unoccupied buildings in the vicinity of (100 meters from) building i, $Buildings_i$ is the number of buildings in the vicinity of (100 meters from) building i, D_{in} is the distance of building i from the current position of agent n, $\max D_n$ is the distance of the building farthest away from the current position of agent n, $1\{LU_i = non\operatorname{Re}s\}$ is an indicator function receiving the value of 1 is building i is of non-residential land-use and 0 otherwise, FS_i is floor-space volume of building i, $\max FS$ is floor-space volume of the largest building in the city.

The agent does not search for the building showing the optimal score, but instead looks for the first building whose score exceeds a utility level, randomly drawn from the range [0,1]. When failing to find a building which satisfies this condition (after considering 20 buildings), the agent updates its preferences by drawing a new utility level.

After completing participation in these 3 activities, the agent returns home. The paths chosen are based on the principle of satisficing behavior (Simon, 1952). The agent moves from current position to the next junction which is closest to the destination measured in aerial distance and chooses the first path that leads to the destination. While this assumption can be questioned it is needed for decreasing computational load, as the model needs to simultaneously generate paths for thousands of agents.

To balance out-migration trends, the model also generates immigrants in the form of new citizen agents. The number of new citizens is proportional to the volume of current out-migration and is dependent on previous trends of inter-urban migration:

$$InMig_t = outMig_t * P \quad (7)$$

where $InMig_t$ is the volume of in-migration at time t, $outMig_t$ is the volume of out-migration at time t, P is a random number drawn from a normal distribution whose mean is the ratio between in-migration volume to out-migration volume at time t-1 (this ratio stays constant during the simulation), and whose standard deviation is the absolute value of 1-migration ratio.

Each agent is assigned an income value based on a random draw from a normal distribution whose mean is the global average income, and whose standard deviation is 0.25 of that value. The agent attempts to find a residential location suitable to its preferences, in the same manner detailed above. In the case of failure, it does not move to the city and is deleted from the simulation.

3.3. Land-use and Housing Prices Dynamics

The residence and activity choices of agents impact the land-use system. This impact is straightforward: residential buildings can become unoccupied and unoccupied buildings can become residences when populated and subject to land-use regulation

policy. However a full articulation of the supply side needs to consider the dynamics of non-residential property and house prices. We consider buildings as quasi-agents, i.e. semi autonomous entities that are immobile and unable to initiate action on the one hand but are sensitive to their environment and respond to changes within it, on the other hand. This implies that direct actions of agents such as residence or visits are not necessarily required for a change in land-use or land price. This change may occur indirectly through changes in buildings' environment.

This quasi-agent nature of buildings is embodied in the sensitivity of the non-residential stock to traffic loads. This sensitivity induces land-use change. We assume that the number of visits to a building is proportional to traffic load on the nearest road thus making traffic load a proxy for revenue and floor-space a proxy for operating costs. Two conditions for land-use change can now be formulated: from non-residential to unoccupied (Eq.8) and from residential/unoccupied to non-residential (Eq. 9):

$$\frac{a * e^{b * \frac{t_i}{\max T}}}{1 + e^{b * \frac{t_i}{\max T}}} > \frac{\left(\frac{FS_i}{\max FS}\right)^q}{p + \left(\frac{FS_i}{\max FS}\right)^q} \quad (8)$$

$$c * \frac{a * e^{b * \frac{t_i}{\max T}}}{1 + e^{b * \frac{t_i}{\max T}}} \leq \frac{\left(\frac{FS_i}{\max FS}\right)^q}{p + \left(\frac{FS_i}{\max FS}\right)^q} \quad (9)$$

where a,b,c,p,q are constants, t_i is the traffic volume on the road nearest to building i, $\max T$ is the maximal traffic volume, FS_i is the floor-space volume for building i, $\max FS$ is the floor-space volume for the largest building in the city.

The logic underlying these functions is that the scores on each side of the equations reflect a location in a distribution so that the volume of traffic needed to sustain non-residential use will be proportional to the distribution of both traffic load and floor-space. The constants are used to create proportions between the distributions of the two variables so that the simulation achieves an acceptable rate of land-use change. The logit-like function is chosen to increase the probabilities that large scale land-use will be difficult to sustain as they demand greatest revenue while decreasing the probability that very small scale land-use will become non-residential.

The second feature of the agent-like nature of buildings is reflected in the dynamic housing-price system. This presents a spatial trickle-down process that is sensitive to local supply of housing and amenities. As seen above (Eq. 2) the value of a residential building is a function of the average housing price in its SA and of the level of services in the immediate vicinity. Here we add change in house prices at the SA level. The actions of agents affect the demand, supply and service level within

each SA which in turn affects house prices. They rise when demand or service level increases and decrease it when supply increases:

$$HP_{SA,t} = HP_{SA,t-1} * \left[1 + \log \left(\frac{ \left(\dfrac{Pop_{SA,t}}{Pop_{sa,t-1}} + \dfrac{\mathrm{Re}\,s_{t-1}}{\mathrm{Re}\,s_t} + \dfrac{Comm_t}{Comm_{t-1}} \right)}{3} \right) \right] \quad (10)$$

where HP is average housing price per meter in NIS, Pop is population size, $\mathrm{Re}\,s$ is the number of residential buildings, $Comm$ is the number of commercial buildings, t is the current simulation iteration, $t-1$ is the previous simulation iteration.

This effect of overall change induced by the behavior of agents also affects the values of individual buildings. This is achieved by making Eq. 2 time-dependent. This effect can further trickle down to the level of the individual apartment, by assuming a constant dwelling unit size (Eq.11) from which the monthly cost of housing can be derived (Eq.12):

$$V_{du} = \frac{V_b}{FS_b/90} \quad (11)$$

$$P_{du} = \bar{Y} * \left[1 + \frac{V_{du} - \sigma_{V_{du}}}{\bar{V}_{du}} \right] \quad (12)$$

where V_{du} is the value of dwelling unit du, V_b is the value of building b, FS_b is floor-space volume for building b, P_{du} is the monthly cost of living in dwelling unit du, $\bar{Y}$ is citywide average income, $\sigma_{V_{du}}$ is the citywide standard deviation of dwelling unit values, $\bar{V}_{du}$ is the citywide average of dwelling unit values.

These prices and the changing market affect the behavior of agents and are carried over to the next iteration, as detailed above (section 3.2)

The changes to residential and non-residential stocks may also change urban morphology (Figure 1). This is reflected in change in the location of the central business district (CBD). While not of a direct importance to the behavior of agents, a shift in CBD location can indicate the level of disruption wrought by an earthquake. The center of the CBD is identified as the location of the single building with the highest average non-residential floor-space of all the buildings in its vicinity (within 250 meters).

3.5. Exogenous Interventions

In sections 3.1-3.4 all actions within the urban system are determined endogenously based on pre-determined initial values for variables. We simulate the earthquake as an exogenous shock whose epicenter is located randomly in space and with an impact

that decays exponentially with distance. This impact makes no attempt to capture the seismic details of such an event but rather focuses on the probability of a building suffering damage and collapse. This probability, along with distance decay, is proportional to building height:

$$I_b = \frac{a * 10^p}{D_b * |\log(D_b)| * F_b} \quad (1)$$

where I_b is the impact building b suffers, a is a constant, p is the earthquake magnitude (similar to Richter scale), D_b is building b's distance from the earthquake epicenter, F_b is building b's number of floors.

Whether or not a building collapses is determined by drawing a random number from the range [0,1]. If the impact exceeds this number, the building is demolished by the earthquake. In such a case, all the streets within a 50 meter radius from the structure become unusable until the building is restored. The duration of restoration is proportional to building floor-space. In the case of collapse all residents have an equal probability of leaving the city or relocating. Relocation will be to a new home via the search process detailed in section 3.2 (above) or to shelter in accordance with policy intervention.(see below).

We specify three stylized policy options, which do not correspond to actual planned responses but span the continuum ranging from passive-liberal through to regulative-rigid scenarios:

a. Land-use regulation – this aims at containing impacts by preventing any change to the land-use system. Unoccupied or demolished buildings can only recover to their initial use. When this policy is not exercised, structures can switch uses freely, in accordance with market forces.

b. Sheltering – this option outlines the way agents affected by the earthquake are treated. In order to prevent population depletion, agents whose residence has collapsed are clustered into one randomly, pre-selected residential building where they are sheltered until their home is restored. Otherwise, the agents are left to find a new home or move away, according to their ability. This could be thought of as giving the affected citizens an income level-based housing voucher.

c. Service substitution – many public structures that offer services to citizens may become unavailable after the earthquake. This policy option "nationalizes" buildings of commercial use and similar size to the damaged structures and uses them for the provision of public services until the original building structure is restored. When not activated, the service will remain unavailable until restoration. Since public uses are stable and do not depend on market dynamics, this policy creates more stability in the non-residential stock, thus indirectly affecting housing prices.

Activating all three of these binary policy states represents the stability-equilibrium view. Policy attempts to direct the city towards the pre-shock state by minimizing the effect on population, non-residential stock, and the land use system. The opposite no policy scenario, leaves the city entirely subject to market forces.

4. Case Studies: One Earthquake - Two Cities

We choose Jerusalem and Tel Aviv as case study locations in order to compare the long term impacts of a similar event in different urban contexts. An earthquake is a probable hazard in both places due to their proximity to the Dead Sea Fault, a geologically active fissure that has activated a number of earthquakes in the past (Salamon, Katz, & Crouvi, 2010). Jerusalem is located on top of the Judean ridge, 30 kilometers southwest of the fault and Tel Aviv is located further northwest on the shores of the Mediterranean Sea and is 90 kilometers from the fault.

To limit computing overload, we define the case study area in both cities as the vicinity of the CBD (Figure 2). Both locations are roughly similar in population size, both contain mixed land uses with residential properties alongside commercial and public sector buildings. Both encompass major traffic arteries (the Ayalon Freeway and Dizengoff St. in Tel Aviv and the triangle of King George, Jaffa and Agripas Streets in Jerusalem) and both have focal commercial concentrations that compete with the CBD, such as the Mahane Yehuda Market in Jerusalem and the Dizengoff Center in Tel-Aviv. The cost of housing in Tel-Aviv is almost twice as high as the cost in Jerusalem but Tel-Aviv's population is characterized by higher incomes and smaller households.

<Insert Figure 2>

<Insert Table 2>

An important distinction between the two locations is that while Tel-Aviv's CBD is larger in area than that of Jerusalem, the area of Governmental-public buildings is greater in the latter. Moreover, in Jerusalem, public buildings exceed commercial buildings. By contrast, in Tel Aviv commercial density is higher and commercial buildings have more floors (average=3.9) than their counterparts in Jerusalem (2.6). These features indicate Tel-Aviv as a business-led CBD with a smaller public sector presence than in Jerusalem. This correlates with the public perception of Jerusalem as a national center heavily regulated by administrative functions in contrast to the image of Tel Aviv as a business center with global aspirations (Alfasi and Fenster, 2005).

Despite some similarities, these two cases represent very different urban contexts. A similar shock may evoke very different responses in each case study location and their ability to cope with disaster is not pre-ordained or symmetrical. To test this discord empirically, we simulate two polar scenarios for each city. In the first, none of the three policy interventions are activated (no-policy scenario) while in the other all are initiated (policy scenario). Each scenario is simulated 35 times in each

city (140 simulations in total) and while the epicenter of the earthquake is located randomly, in order to avoid possible location bias, the timing of the event is set to the 5th iteration (day). This allows a 'run-in' period for the urban system. Each simulation comprises 1000 iterations (days). This somewhat arbitrary number is chosen as it allows for a reasonable level of convergence while still being computationally manageable. The results that follow relate to the average (homogenized) values from the simulations by city and policy scenario.

5. Results

As outlined in section 3, the simulation model generates initial values for variables at a high level of spatial resolution, such as the individual building or agent. The mechanics detailed above allow these values to vary over time in response to changes in the environment. While these changes can be re-aggregated at various spatial scales, the results below present averages for the case study areas in order to present an aggregate picture of overall trends. This allows for comparing across policies in both urban areas.

Figure 3 presents population dynamics over time for all scenarios. As expected, the earthquake causes an immediate loss of population. This is due to either lack of supply of physical stock due to damage to structures or due to the indirect effect of rising prices as demand increases with no commensurate reaction on the supply side. The size of this impact varies over scenarios. In both cities, policy is effective for the short term when the shock is mitigated. However in the long run, even if population recovers it is below former levels. In Tel-Aviv the picture is even more severe, as policy intervention leads to a sharp decrease with almost no recovery to begin with. This is surprising, since the sheltering policy option strives to contain the initial shock and retain as much population as possible within the city, facilitating faster recovery to pre-shock state. This result could be due to insufficient recovery of the housing market, a time delay in response, rising prices or a combination of all these factors.

<Insert Figure 3>

Figures 4a through 4d visualize the frequency of land-use change by building in the study areas. The policy scenario enforces strict land-use regulation resulting in vacant buildings at the end of the simulation. All of the figures tell a similar story with those buildings that change land-use most frequently characterized by commercial use and large floor space. When no policy is exercised, the residential stock seems unstable as many residential structures with limited floor-space change use creating an outward dispersal (sprawl) of commercial activity. Since conversion from residential to commercial use is a function of traffic volume, this trend can be attributed to agents changing movement patterns as they face the damage caused to the traffic network. Over the long run this sprawl can become self-reinforcing as agglomeration effects start to lock-in. The cluster of buildings changing their character close to the boundaries of the Tel-Aviv study area may serve as an example.

<Insert Figures 4a-4d>

Figures 5a-5b, describe changes to the amount and value of non-residential stock over time. Under the no-policy scenario the number of non-residential buildings steadily increases over time, in relation to the policy scenario. In the aftermath of the shock, average values of the non residential stock decreases. This indicates the conversion of small residential buildings into commercial uses ("less malls, more convenience stores") since non-residential value is closely related to amount of floor-space. While this trend is generally true in both CBD's, Jerusalem displays sharper reactions in the no-policy scenario. Tel-Aviv's values rebound to a much lower equilibrium when policy is exercised, suggesting that the urban system is more entrenched.

<Insert Figures 5a,5b>

The dissimilarities between the two cities become heightened when comparing change in residential stock over time. In this respect the cities are almost mirror images. Figures 6a and 6b show that while policy intervention promotes a sharp increase in average residential values in Tel Aviv in relation to the stable values achieved when no policy is exercised, such an increase is caused in Jerusalem by the absence of intervention. Under the no-policy scenario in Jerusalem demand decreases, while housing supply rebounds and service supply only rises slightly. This increase cannot be attributed just to the growing number of commercial venues. As building values are closely related to amount of floor-space, the change can be explained as previously commercial buildings with much floor space becoming residential thereby increasing average values. In the Tel Aviv policy scenario, on the other hand, such explanation is not applicable, since policy prevents such flexibility of land-use. The increase can only be attributed to a short-fall in supply of housing. This cancels out any reduction in property values through decrease in demand and service supply. These two explanations, grounded in opposing scenarios (Jerusalem policy, Tel Aviv no policy) suggest that in the aftermath of an earthquake the Jerusalem CBD could potentially change its nature whereas in Tel Aviv, the CBD is likely to maintain its current function.

<Insert Figures 6a,6b>

Given the potential for the development of new clusters on non-residential activity in the wake of a disaster, we test for a change in urban morphology reflected in a shift in CBD location. Table 3 shows that such a change rarely happens. The strength of the Tel-Aviv's CBD as an emerging global center is reflected in the relative stability of the CBD location and in the volume of non-residential floor-space which decrease only marginally. In Jerusalem, where the CBD serves a more limited market, change in location is registered a number of times, mostly under the no-policy scenario. This suggests the dispersal of agent movement in the aftermath of a

catastrophe is rarely strong enough to generate a change in urban morphology even in second tier CBD's such as that in Jerusalem.

<Insert Table 3>

The results of the no policy scenario in Tel Aviv and the policy-on scenario in Jerusalem show evidence of bouncing back and could be construed as interventions promoting resilience. As noted, the Jerusalem - no policy scenario presents a conflicting picture while the Tel-Aviv policy scenario results in a weaker outcome in terms of activity and population. However, the results so far do not present any evidence regarding the stability of these outcomes. In fact, a period of less than 3 years post-earthquake is probably not long enough for the city to recover entirely. The outcomes presented so far may therefore have captured the city in temporary disequilibrium. To address this issue, we test for convergence of different indicators over time at the end of each simulation. An index is said to be stable if the values of its moving average over the last 50 iterations (or more) show insignificant changes. The results of this analysis are presented in Table 4. The two bouncing-back scenarios, which indeed reach pre-shock values, do not stabilize around these values, and therefore do not represent resilience, as defined here. The only scenario to show stabilization is the Jerusalem no-policy scenario, in which the city experiences large scale transformation. This new stable state, while not reflecting the traditional bounce-back concept of resilience, suggests a reorganization of the system embodied in bouncing-forward to a new equilibrium state.

<Insert Table 4>

6. Conclusions

This chapter has presented an agent-based model of urban resilience. Resilience is conceived here as the ability of a system to regain pre-shock equilibrium, in the wake of an unanticipated event. The results of the simulation for Jerusalem and Tel Aviv suggest that policy directed at rebounding to pre-shock state does not do well and may even inhibit stability. Elsewhere, we have suggested that cities contain a self-organizing mechanism that facilitates recovery when equilibrium is disrupted and that needs to be considered when policy is formulated (Grinberger and Felsenstein, in press). The results here reinforce this conclusion, showing how policy interventions lead to unexpected results. The mechanism leading to the formation of such variations can be described in terms of centripetal and centrifugal morphological forces (Fujita and Krugman, 2004). The urban system is the result of previous rounds of investments that generate agglomeration advantages (centripetal forces) in the formation of consumption centers. An unanticipated shock galvanizes centrifugal forces into action by making some places less accessible and dispersing movement and consumption. Progressive rounds of investment are characterized by the tension between centripetal and centrifugal forces. This process may result in rejuvenation of existing urban structures (bouncing back) if agglomerations are

strong enough or in the formation of new morphological equilibria ('bouncing forward').This can result in the emergence of newly formed competitive centers or in the dispersal of activity such as in the case of the Jerusalem-no policy scenario.

Interpreting the results of the scenarios this way we can suggest that the Jerusalem CBD characterized by a large public sector presence and substantial government intervention, has not managed to develop the critical mass for agglomeration economies to develop. Consequently, when liberal intervention is used to jump- start development in the aftermath of a disaster this is insufficient to counter the influence of centrifugal forces pushing for dispersal. Due to similar weakness, intervention directed at restoring the previous state fails to display any real recovery, as the city does not reach a stable state. Tel-Aviv, on the other hand, displays an almost exact mirror image. While none of the scenarios reach equilibrium, the policy scenario converges towards bounce-back by inhibiting the work of centrifugal forces, while the no-policy scenario results in a low functioning unstable equilibrium. The role of Tel-Aviv as the economic enter of the country shaped by centripetal market forces, correlates with these results. Due to the magnitude of its agglomeration, a large scale shock is insufficient to push it off its pre-shock development trajectory.

The fact that the same basic process have led to almost mirror images between the two cities and that none of the results may resemble the 'desired' outcome, implies that a procedural check-list approach to urban recovery is insufficient. Our findings show that the rejuvenation goal of having a city 'bounce back' is hard to attain. None of our four simulated scenarios stabilized on pre-shock conditions. This is not surprising since, as suggested earlier this view of resilience neglects the possibility of a set of unstable equilibria. In fact, over the test period of less than 3 years the only stable state witnessed (the Jerusalem – no policy scenario) reflects an 'extended' understanding of resilience that stresses the ability to reorganize when a large enough shock appears (Folke et al., 2002). These results would seem to cast a shadow over the feasibility of the stability view of resilience. The take-away message for urban recovery praxis would seem to be that resilience is not just about the absorption and containment of a change. It is equally about the ability to direct change and exploit the opportunities it presents.

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Figures and Tables
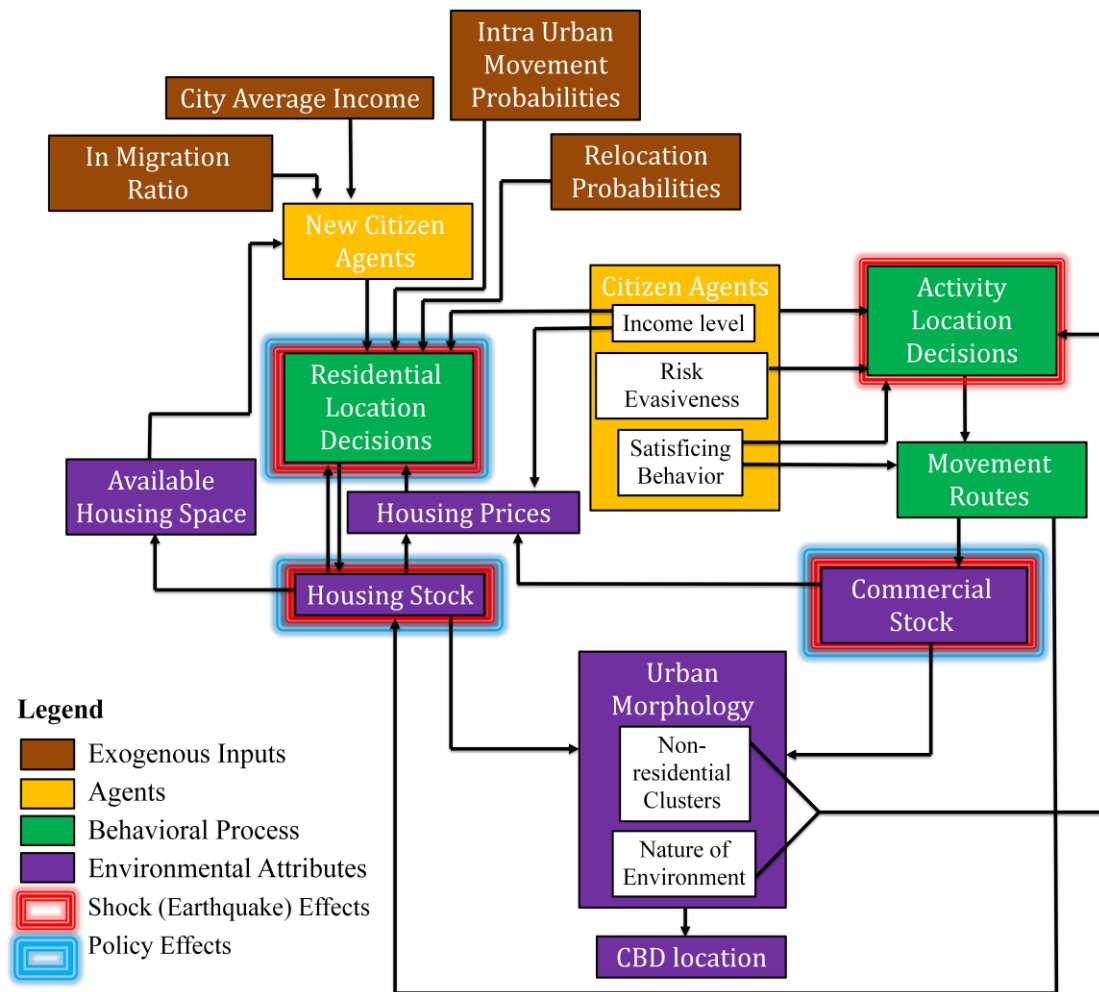
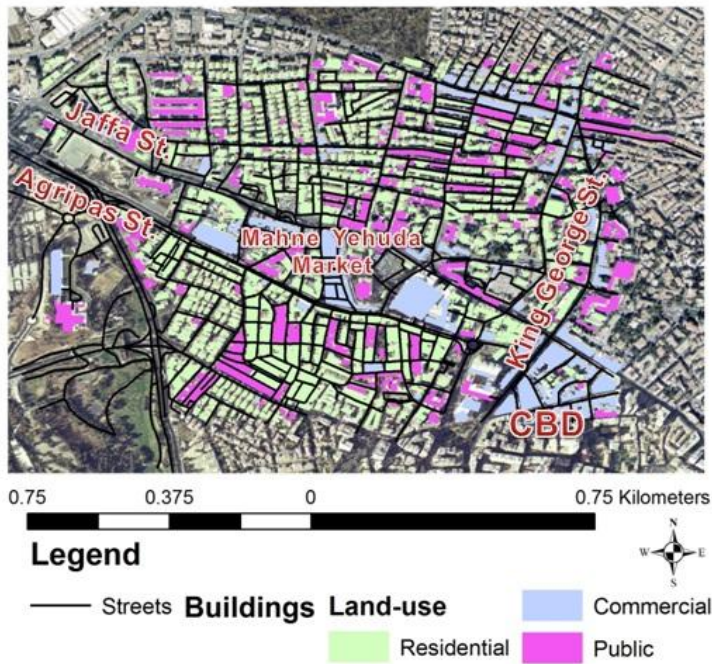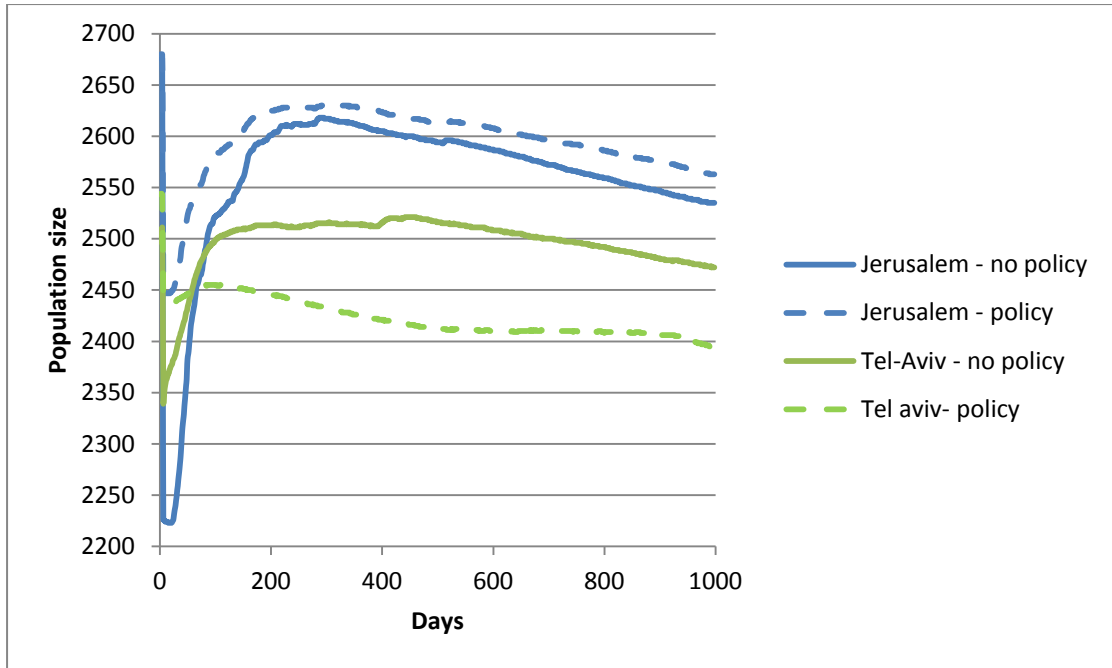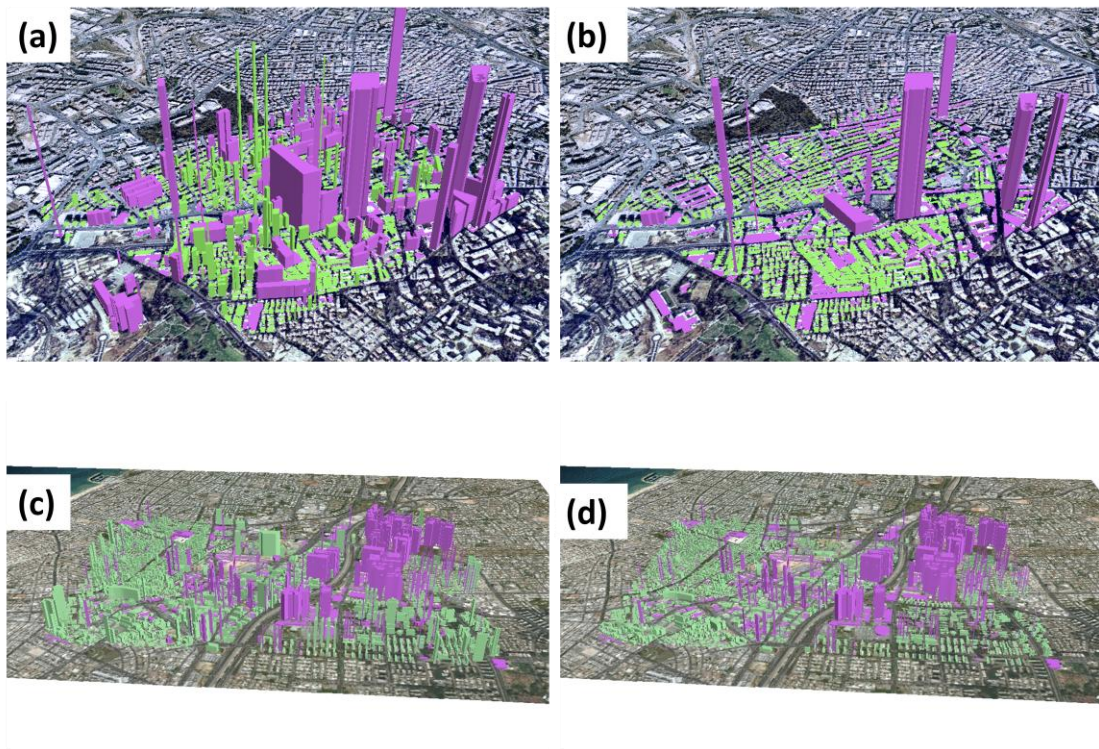**Figure 1** – a conceptual representation of ABM of an earthquake in a city
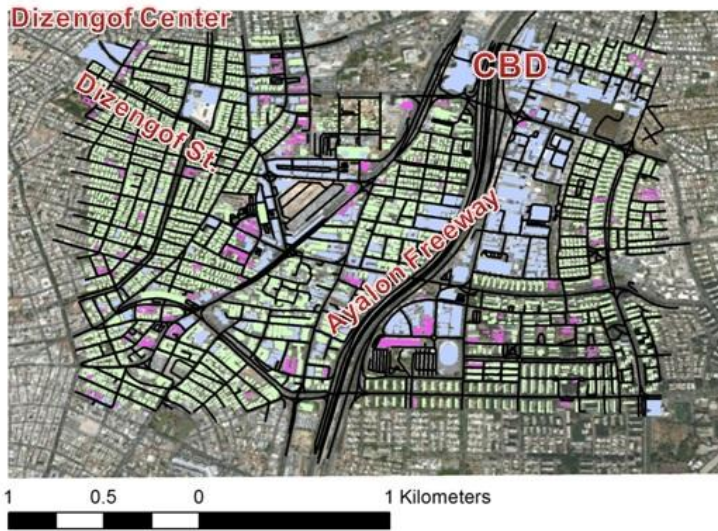
Figure 2 – study areas

Figure 3 – population dynamics over time

Figure 4 – frequency of land-use change for (a) Jerusalem - no policy, (b) Jerusalem – policy, (c) Tel Aviv - no policy, (d) Tel Aviv - policy. Color represents initial land use (green – residential, purple – non-residential), height represents frequency of different land-use at the end of a simulation.
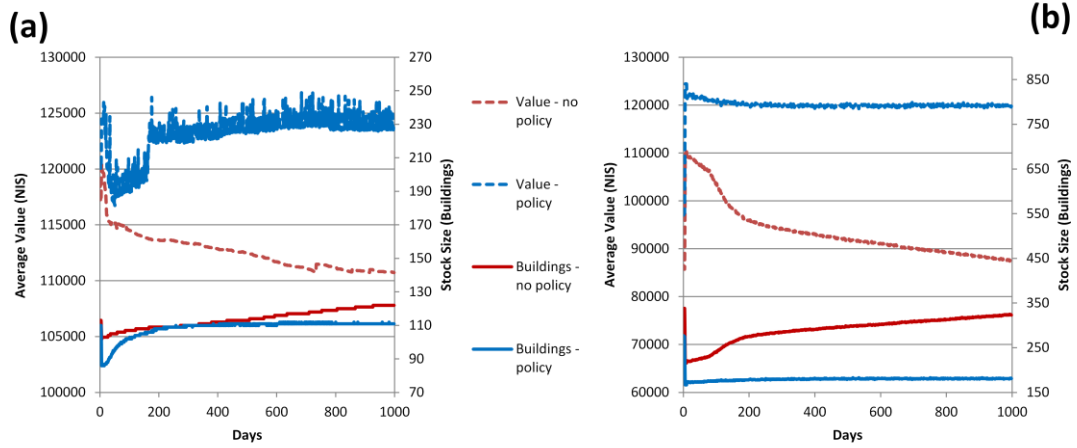
Figure 5 – changes to non-residential stock over time, for (a) Jerusalem and (b) Tel-Aviv
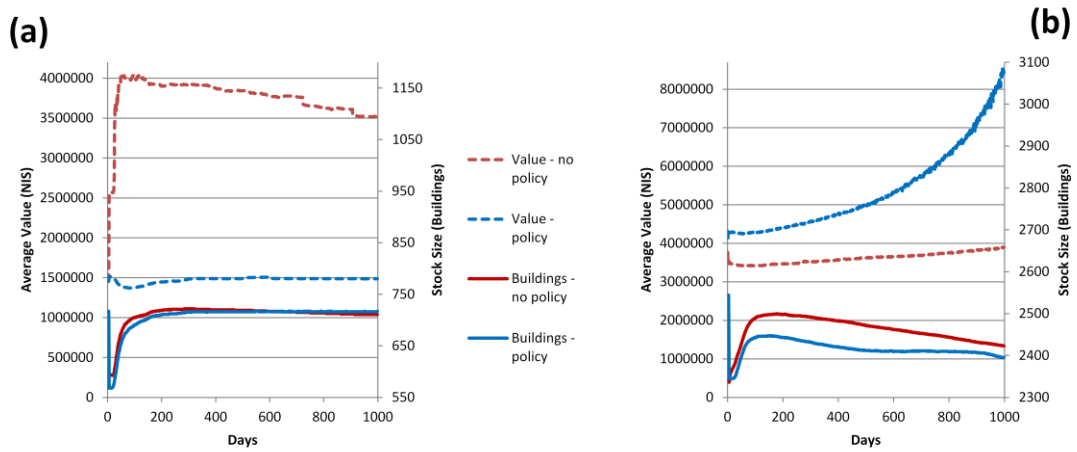
Figure 6 – changes to residential stock over time, for (a) Jerusalem and (b) Tel-Aviv

Entity	Behavior	Assumption
Citizen agent	Migration	Migration probabilities, both inter and intra-urban, are dependent on previous trends of migration.
	Choice of place of residence	Willingness to pay for housing up to 1/3 of monthly income. Wages reflect social class. Aspiration for residence amongst equal or better.
	Choice of activity location	Push and pull factors. Satisficing behavior Risk evasiveness.
	Movement path	Satisficing behavior.
Building quasi-agent	Land-use change	Traffic load as a proxy for revenue. Floor-space size as a proxy for operating costs.
	Housing prices	Spatial trickle down effect of housing prices. Sensitivity of prices to competition and amenities.

Table 1 – Model Assumptions

Variable	Tel Aviv	Jerusalem
Area (square meters)	5,574,110	1,433,277
Population	2,550	2,681
Average income (NIS per month)	8,378	6,003
Average household size	2.6	3.4
Residential buildings	2,550	717
Residential floor-space (square meters)	852,060	243,075
Commercial buildings	482	119
Commercial floor-space (square meters)	2,496,457	504,347
Governmental (public use) buildings	139	179
Governmental floor-space (square meters)	481,527	419,932
Average housing price by SA range (NIS per meter)	18,400-34,500	10,052-20,024

Table 2 – Case Studies Characteristics

Region	Scenario	State	N	Average Non Residential Floor Space around CBD	Total Non Residential Floor Space	CBD movement (Meters)
Jerusalem	**No Policy**	**Initial State**	35	4,575.97	924,279.59	0
		Average Final State – all	35	3,217.63	722,116.30	20.38
		Average Final State – CBD movement	4	3,421.54	726,528.41	178.33
		Average Final State – no CBD movement	31	3,191.32	721,547.00	0
	Policy	**Average Final State – all**	35	3,940.65	804,589.79	5.1
		Average Final State – CBD movement	1	3,301.20	779,024.24	178.33
		Average Final State – no CBD movement	34	3,959.45	805,341.72	0
Tel Aviv	**No Policy**	**Initial State**	35	50,298.71	2,977,984.40	0
		Average Final State – all	35	49,856.00	2,922,949.19	0
		Average Final State – CBD movement	0			
	Policy	**Average Final State – all**	35	49,860.01	2,826,227.80	0
		Average Final State – CBD movement	0			

Table 3 – changes to CBD

| Scenario | | No policy | | | | Policy | | | |
| Region | Measure | Achievement of pre-shock values | | Stabilization | | Achievement of pre-shock values | | Stabilization | |
		frequency	average duration	frequency	average duration	frequency	average duration	frequency	average duration
Jerusalem	**Population Total**	0/35		35/35	858	0/35		35/35	860
	Residential Value	0/35		20/35	835	33/35	246	8/35	916
	Average Residential Value	0/35		22/35	843	33/35	54	9/35	918
	Total Non-Residential Value	1/35	12	35/35	324	31/35	122	2/35	937
	Average Non-Residential Value	22/35	145	32/35	819	24/35	40	1/35	940
Tel-Aviv	**Population Total**	16/35	54	33/35	806	1/35	206	26/35	879
	Residential Value	32/35	168	2/35	930	35/35	95	0/35	
	Average Residential Value	27/35	65	1/35	904	11/35	43	0/35	
	Total Non-Residential Value	0/35		34/35	515	0/35		35/35	281
	Average Non-Residential Value	24/35	459	0/35		0/35		0/35	

Table 4 – Rebounding and stabilization of scenarios