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Dynamic agent based simulation of welfare effects of urban disasters

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ABSTRACT

An agent based model for assessing the welfare impacts of urban disasters is presented. This couples a population allocation algorithm with a simulation platform. The fully articulated model fuses both bottom-up (locational choice for workplace, residence and daily activities) and top-down (land use and housing price) protocols. This study moves beyond current research by addressing economic welfare consequences of urban disasters. The resilience capabilities of different income groups are identified. This is illustrated for the Jerusalem central business district. Empirical results at the micro-scale suggest that physical destruction leads to a zero-sum game within the housing market in which wealthier residents hold an advantage over the poor. This results in the transformation of neighborhoods and displacement of poor and vulnerable populations. Low income groups lose both physical ground and the social support systems that go with location. Policy implications of these findings are discussed.

1. Introduction

The ability of cities to cope with unanticipated disasters is an issue high on the urban agenda (UNISDR, 2012; Masterson et al., 2014). Shocks to the urban system are mediated through the aggregate behavior of agents operating in urban space. These shocks can be both natural such as eathquakes, flooding and forest fires or anthropogenic, such as terror attacks or industrial accidents. In coping with these shocks, households, workers, land developers, firms, city authorities and intervention agencies act as agents creating complex network patterns of change. The patterns are not predictable through simply aggregating individual agent behavior. This is because agents affect the behavior of other agents and in aggregate, impact on the operation of urban institutions such as land and housing markets and the planning system. Agent Based (AB) models allow the analyst to simulate system- wide urban change from a bottom-up (agent) perspective and test previously untestable hypotheses relating to urban resilience and rejuvenation in the wake of a disaster.

One aspect of urban resilience addresses the city's ability to mitigate these disturbances, absorb their impacts and return to an equilibrium growth path. These macro-scale patterns emerge from many micro-scale interactions between individual agents. The latter can be modeled within a computable system grounded in the basic tenets of micro-economic behavior. This gives a rich set of opportunities for understanding the reactions of affected populations under varying conditions, times frames, levels of aggregation and spatial scales.

Given this analytic potential, unanticipated disasters have attracted considerable agent based modeling attention. Numerous studies exist; for example see Dawson, Peppe, and Wang (2011) on flooding, Chen and Zhan (2008) on fires, Crooks and Wise (2013) on earthquakes, Park, Tsang, Sun, and Glasser (2012) on terrorism and Salze et al. (2014) on industrial accidents. Much of this interest is in the short-term, evacuation and recovery aspects of the disaster with an emphasis on route optimization and emergency management (Chen, Kwan, Qiang, & Chen, 2012; Zimmerman et al., 2010).

The studies that take a longer-term view of urban recovery often approach this issue from a more fully articulated theoretical base. Recent efforts have seen agent based models fuse the rich detail embodied in agents with more sophisticated micro economic behavior protocols. These can be exploited to understand broad urban processes such as suburban sprawl, leapfrog development, economic deconcentration, localized competition in product markets such as gasoline stations and gentrification. This has given rise to AB models that try to represent the full working of markets with supply and demand schedules, price emergence and market clearing effects (Ettema, 2011; Filatova, 2014; Hepenstall, Evans, & Birkin, 2005; Magliocca, McConnell, & Walls, 2015; Magliocca, Safirova, McConnell, & Walls, 2011; Olner, Evans, & Heppenstall, 2015). Agents are represented with increasing sophistication. They are governed by behavior rules that account for preferences, competitive bidding, resource and budget constraints, utility and profit maximization and search behavior. In some models, supply and demand schedules and price emergence are fully endogenous processes (Ettema,

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2011). Invariably, these AB initiatives are more about urban growth and expansion than urban recovery and rejuvenation (Huang, Parker, Filatova, & Sun, 2014). While studies exist that account for change within the city such as gentrification (Jackson, Forest, & Sengupta, 2008; Torrens & Nara, 2007), most of the emphasis is on land use change and its feedback effect on agent activity at the urban fringe.

This paper extends current research in three respects. First, it offers a fully articulated modeling framework for addressing the longer term outcomes of urban disasters emphasizing the rejuvenation rather than the expansion, of the urban area. This issue has hitherto received scant attention in the urban AB simulation literature. Unanticipated shocks differentially affect the urban population. The coping capacity of individuals and communities is far from uniform. 'Weathering the storm' is not just an issue of short-term survival, adequate physical protection and insurance coverage. The dislocation involved in searching and relocating to a new place of residence and/or work has long-term effects on land use, mobility patterns and property values. These are modeled in a framework that accounts for the various form of demand generated by forced relocation and the supply response from the housing and non-residential property market.

This paper also breaks new ground by simulating the economic welfare consequences of disaster recovery. Aggregate change in the value of residential and non-residential capital stock is distributed across income groups. In this way the differential coping capabilities (resilience) of social classes is identified. Finally, this is conducted in the context of a realistic (rather than a stylized) urban landscape. Welfare outcomes are simulated with respect to a hypothetical earthquake in central Jerusalem. Within this context, we emphasize the process by which distributional inequalities are generated. The AB model is therefore used as a tool for theoretically-driven discovery rather than for explaining empirical regularities. Accordingly, the model relies on broad behavioral assumptions rather than context-specific parameters and its validity lies in the stability of simulated patterns rather than the replication of reality.

The paper proceeds as follows. A conceptual framework for analyzing the welfare impacts of resilience and the simulation design are described in the next section. Thereafter, the operationalization of the agent-based model is detailed in Section 3. This involves outlining three locational choice sub-models (for workplace, residence and activity location) on the demand side and two sub models (land use and dynamic house pricing) on the supply side. The earthquake case study is presented in Section 4 while simulation results and parameter sensitivity are discussed in Section 5. The paper concludes with some policy implications.

2. Methodology

2.1. Welfare impacts and resilience: a framework for analysis

Disaster recovery theory is surprisingly silent on the issue of welfare impacts (Chang & Rose, 2012). We conceptualize urban resilience as more than just recovering or bouncing back to a previous state. It refers to the differential coping capacities of various population sub-groups in the city (Grinberger & Felsenstein, 2014). We propose tacking the hitherto unaddressed issue of the differential welfare outcomes of recovery across these groups in the city. This involves engaging questions such as: which income classes are most likely to cope with unanticipated disasters? who loses most from these shocks? which social groups are likely to be displaced or dispersed in the aftermath of an extreme event and to where? These are all notions of resilience that lend themselves to dynamic, spatially-explicit analysis.

We hypothesize two main factors as characterizing urban resilience in the aftermath of a disaster: the magnitude of the disturbance to the urban attribute (W) and the effect of time(t). The former can be expressed as a shock to both urban stock variables such as capital investment, population, infrastructure capacity etc. and to disturbances

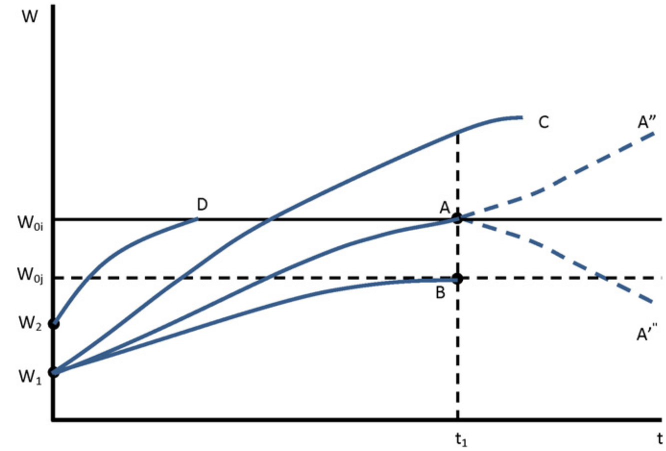

Fig. 1. Urban Resilience for Different Population Groups by Magnitude of Shock to Urban Wealth (W) and Time (t). Note: Growth paths A–D: A = initial equilibrium growth path; A′, A″ = divergence from initial path; B = failure to recover path; C = accelerated recovery path; D = new growth path.

to urban flows such as traffic and productivity. Shocks to the former are supply-side shocks while shocks to the latter generally operate on the demand side. Time measures the speed of recovery and adds dynamics. These are expressed in endogenously-driven baseline values that change from one period to the next. For example, a shock to urban stock variables such as building function or land use in period t means that the relations between this stock variable and other variables such as density or productivity have to change in time $t + 1$. Differing recovery rates of both stock variables such as housing and flow variables such as productivity over time highlight the importance of dynamics.

To fix ideas, assume for simplicity that position on the W axis represents level of urban wealth (acknowledging that 'urban resilience' captures much more than this single measure, see MacAskill & Guthrie, 2014). A shock at t_1 can reduce a steady state growth pattern in urban wealth W_{0i} experienced by a high income population i, to a lower level, W_1 (Fig. 1). Over time, the urban area will strive to restore the old equilibrium (path A) or diverge from it (paths A′ and A″) if the initial equilibrium is unstable. Shock W_1 can also cause city income to never fully recover (path B) or can be an accelerator for attaining new levels of wealth (path C). A smaller shock (W_2) may elicit a very different response and a more rapid recovery (path D).

Two caveats need to be considered further. First, given two different populations and the same shock (for example a shock of magnitude W_1) - a rich population[1] (i) with a pre-shock level of W_{0i} and a poor population (j) with a pre-disaster state of W_{0j} - we hypothesize that the rich tend to recover more fully even if the absolute magnitude of their monetary loss is greater in the first place. This loss, (L_i), is proportional to their initial state W_{0i} and their ability to bear the burden over time, i.e. $L_i = \theta(t) W_{0i}$ where $\theta(t)$ is the time-dependent rate of loss. For the rich, $\frac{\partial\theta(t)}{\partial t} \rangle 0$, while for the poor, the adjusted marginal impact of time will be zero or negative. At timet_1, the ability of the poor to bear the burden of W_1 results in a new lower equilibrium at B. The absolute value of their monetary loss may be smaller than that of the rich (cheaper housing, less valuable possessions etc.) but its relative weight in their overall wealth may be higher. In addition, the coping capability of the urban area (C) which includes recovery, is also contingent on type of population. The coping capacity of the rich (C_i) will be the product of initial state of wealthW_{0i}, a coping rate λ_i and L_i, such that $C_i = \lambda_i W_{0i} L_i$ where

[1] The terms 'rich' and 'poor' are used here generically. In the simulation that follows they are operationalized as one standard deviation above and below the area average (Section 5.1).