Integrating Labor Market Dynamics into the DIM2SEA Agent-Based Model: A Framework for Analysis

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Increasing Urban Resilience to Large Scale Disasters: The Development of a Dynamic Integrated Model for Disaster Management and Socio-Economic Analysis (DIM2SEA)

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1. Introduction

The labor market comprises an essential element of the urban system. The way in which this market functions affects the characteristics of the entire system. By setting income levels and rents as well as attracting or repelling populations and firms, it serves as a spatially- and functionally-organizing element of the system (Lowry, 1964; Scott, 1988). Following established economic thought, a significant shock to local capital will catalyse a decline in worker productivity (Bascarino et al., 2006). The result of such a decline is the subject of intense debate (Loayza et al., 2009), but there is little doubt that the subsequent recovery of productivity is inherently linked to reconstruction, and thus to both land use and population size. Hence, in order to articulate the consequences of a large-scale urban disaster, due consideration must be given to the disruption caused to the labor market. In particular, any discussion of urban resilience must acknowledge the sensitivity of the urban labor market to capital shocks.

In the literature, urban disasters are often referred to in the context of a singular event, whose consequences are mostly measured by the extent of physical damage and casualties, promoting a conceptual framework dominated by tangible dimensions such as reconstruction (Haas et al., 1977; Chang & Nojima, 2001; Chang, 2010). However, 'urban resilience', despite its fuzzy nature, is widely accepted to be much more than just physical recovery. This is true even if the ‘engineering resilience’ (Holling, 1973) view is adopted. This relates to the ability of a system to bounce-back to the pre-shock equilibrium (Godschalk, 2003; Campanella, 2008; Müller, 2011), where equilibria are defined by much more than the state of physical stock. But 'bouncing back' is not the only route to resilience. An urban system can also 'bounce forward' and reorganize (Cruz et al., 2013; Grinberger & Felsenstein, 2014), or endure repeated events (Holling, 1973; Alberti et al., 2003; Alberti & Mrarzluff, 2004). Given the above, it is not surprising that the literaure offers only limited therorectical and empirical insights on the behavior of labor markets in the aftermath of disasters (for some exceptions see Groen & Polivka, 2008; McIntosh, 2008; Fabling et al., 2016; Groen et al., 2016).

Agent-Based Modeling (ABM) is a simulation framework that accounts for this behavioral nature of change. An ABM defines decision rules for system’s ‘atomic’ units (i.e. agents). These guide agent behavior and fashion the environment in which agents act (Macal & North, 2005). The ABM framework can contribute towards understanding observed patterns (e.g. Schelling, 1971), gaining conceptual insights regarding possible outcomes (e.g. Grinberger & Felsenstein, 2014) or creating empirical predictions (e.g. Devillers et al., 2008).

Labor market changes are highly behavioral: changes in employment/unemployment, participation, etc. have only an indirect effect on the tangible fabric of the city (commuting patterns, demand for residential and non-residential land). While the behavior of labor markets has been addressed within the ABM literature (Chaturvedi et al., 2005; Nugeart & Richiardi, 2012), spatially-explicit models are still rare (for exceptions, see Deissenberg et al., 2008; Dawid et al., 2008, 2009). This framework is also extensively applied in urban and spatial contexts (Batty, 2007; Matthews et al., 2007; Filatova et al., 2013). Recently it has been utilized to study processes of urban change during and after disasters (Chen & Zhang, 2008; Dawson et al., 2011; Crooks & Wise, 2013; Grinberger & Felsenstein, 2014, 2016; Grinberger et al., 2015, 2017). These studies tend to stress change in physical/tangible outcomes such as change in land use, morphology, the center of gravity, density, traffic and mobility patterns, etc. A rare exception which focuses on behavioral outcomes is Grinberger and Felsenstein's (2016) agent-based analysis of income distribution effects of a disaster.

In this paper, we seek to highlight the importance of human dynamics as the main driving force behind the urban restoration/reorganization process. We develop a conceptual model of the behavior of the urban labor market following a large scale shock to the supply of capital. Using an ABM, we illustrate how this can dominate the behavior of the urban system as well as catalyze shifts in the long-term urban equilibrium. Labor markets present a complex array of interdependencies between the behaviors of individuals and institutions. Consequently, simulating labor market dynamics requires a comprehensive framework that accounts for other dynamics in the system affecting workers and businesses. For example, changes in residential decisions and land-use patterns are clearly related to the location decisions of the workers living and employed in the city. These dynamics create the required inputs for simulating supply and demand in labor markets.

The framework developed here builds on a previously developed simulation model of urban resilience that simulates the behavior of households and individuals as well as environmental changes (Grinberger et al., 2015, 2017). The current development adds two sub-models that account for supply and demand side dynamics in labor markets. These sub-models rely on the existing components of the wider framework and also inform its subsequent rounds of activation.

We continue as follows: first, we present a brief description of the larger simulation framework into which we integrate the new procedure. This is followed with two sections presenting the formal background for our procedure and the procedure itself. Finally, the paper concludes with some observations regarding further elaboration.

2 Simulation Framework

As noted above, labor market dynamics account for only a part of the behavior of the urban system. They are also interrelated with other sub-systems such as the housing and land-use markets system, using them as inputs but also affecting their dynamics. Accordingly, the procedure used here is integrated into a more comprehensive simulation framework which consists of a number of sub-models (Figure 1). This framework relies on disaggregating the behavior of the urban system into the behavior of its smallest units – individuals and households. Additionally, in order to represent effects that are not directly related to the behavior of these individuals, the model also simulates the sensitivity of quasi-agent entities within the environment (e.g. dwelling units, non-residential buildings).

Initially, the model comprises four sub-models, two relating to the behavior of the agents (residential location model, activities location model) and two relating to environmental changes (house pricing model, land-use model). We add two further sub-models which relate to labor market dynamics, workforce participation and workforce location model (for individuals) and labor demand and wages model (for environmental entities). These models are integrated into the framework through changes to the land-use system and the distribution of population produced by the existing sub-models (inputs) and through the creation of outputs that inform residence and activity location models animated by agents. A disaster (shock) is conceptualized as directly affecting building stock and agents, thereby indirectly affecting dynamics.

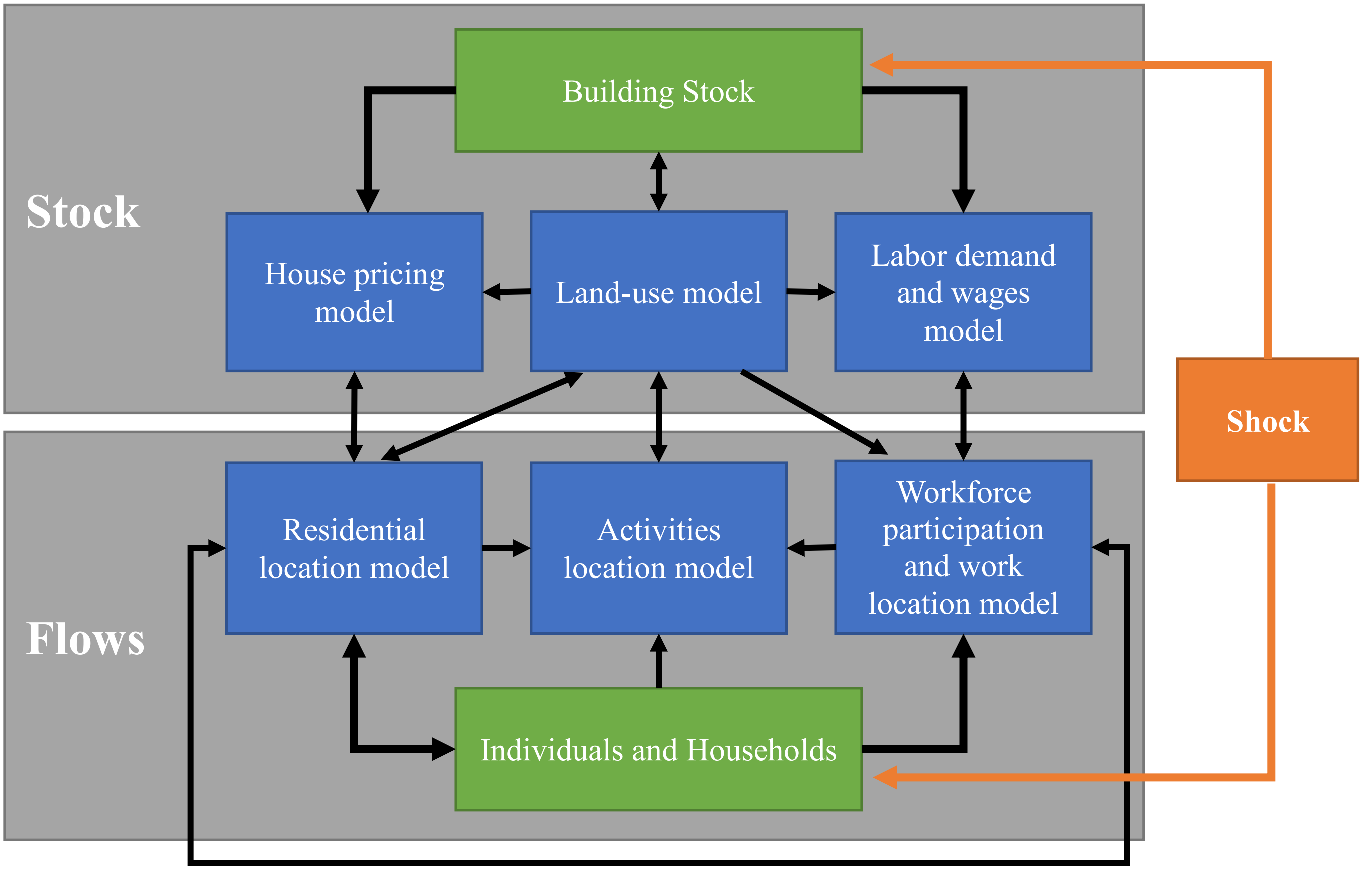

Figure 1. Schema of an agent-based model of urban dynamics following a shock.

3 Formal Background

3.1 Demand Side

The formalization of demand rests on a few assumptions. Firms act as profit-maximizers and production follows the Cobb-Douglas function. Denote total local output:

(1) $x = f(A, K, L) = A \cdot K^{\alpha} \cdot L^{\beta}$

where:
x is the amount of goods produced,
A is worker productivity level,
K is capital stock,
L is the amount of labor employed,
α, β are parameters, signifying the relative share of labor and capital.

Accordingly, firms' production decisions are the outcome of prices, production levels, wage levels, the amount of labor and capital stock, and capital rent (assumed to be fixed over the immediate time frame):

(2) $\pi = f\left(P_y, x_y, L, W, K, r\right) = P_y \cdot x_y - L \cdot W - K \cdot r$

where:
π is profit,
P_x is the unit price of product x
W is wage,
r is rent.

Combining eq (1) and (2) yields:

Eq. 3 $\pi = P_x \cdot A \cdot K^{\alpha} \cdot L^{\beta} - W \cdot L - r \cdot K^{\alpha}$

Over the short term, firms will adjust the amount of labor so as to maximize profits. This is given by the first order condition, i.e. that the amount of labor invested would be the one for which the first derivative of the profit function is zero:

(4) $\frac{\partial \pi}{\partial L} = 0 \rightarrow P_x \cdot A \cdot K^{\alpha} \cdot \beta \cdot L^{1-\beta} - W = 0$

When re-arranged, (4) can be used to estimate the demand for labor (Eq. 5) and the wage levels offered (Eq. 6):

(5) $L = \sqrt[1-\beta]{P_x \cdot \beta \cdot A \cdot K^{\alpha} / W}$

(6) $W = P_x \cdot A \cdot K^{\alpha} \cdot \beta \cdot L^{1-\beta}$

Using these equations, it is now possible to estimate how wages and demand Would react to immediate changes in capital or other variables. Under the unlikely conditions of full equilibrium and no price friction, it follows that unemployment will be zero and wages readjust to the new marginal productivity of labor. In order to relax this assumption, we introduce a matching friction coefficient δ (ranging from 0-1) which regulates the rate at which the demand for labor is met. Consider the immediate drop in labor, assuming no wage changes, and no inhibitors on employee termination

(7) $\frac{L_t}{L_{t-1}} = \delta \frac{\sqrt[1-\beta]{P_x \cdot \beta \cdot A \cdot K_t^{\ \alpha} / W_t}}{\sqrt[1-\beta]{P_x \cdot \beta \cdot A \cdot K_{t-1}^{\ \alpha} / W_{t-1}}} \Rightarrow \frac{W_t}{W_{t-1}} = \delta^{1-\beta} \frac{K_t^{\ \alpha}}{K_{t-1}^{\ \alpha} \cdot \left(L_t / L_{t-1} \right)^{1-\beta}}$

Eq. 7 assumes that prices and productivity do not change over time.

3.2 Supply Side

The following assumptions are made with respect to the behavior of workers: every worker has a threshold wage ω_i beneath which they refrain from participating in the work force; threshold wages are distributed normally within the population, such that $\omega_i \sim Norm(\overline{\omega}, {\sigma_\omega}^2)$; the supply of labor is dependent upon the difference between average wage and average threshold wage:

(8) $L_s = Pop \cdot \phi\left(\dfrac{\overline{W} - \omega_i}{\sigma_\omega}\right)$

where:
Pop is the number of individuals participating in the workforce from the population,
ϕ is the normal probability density function.

Such a labor supply function satisfies the following intuitive conditions:

- $\frac{\vartheta \dot{L}(\omega_i,\omega_j)}{\vartheta \omega_j} > 0$, Positive marginal labor supply
- $\frac{\vartheta \dot{L}(\omega_i,\omega_j)}{\vartheta^2 \omega_j} < 0$, Decreasing marginal labor supply

We further assume that in choosing a workplace, each individual assesses alternatives based on a personal utility function. Within this function, both the wage offered (in relation to the threshold wage) and other considerations (such as commuting distance) are weighted to produce a utility level (Eq. 9). Our final assumption is that individuals use a satisficing (rather than optimizing) decision criteria in which the selected position is the first one that meets the requirements of the individual's utility threshold.

(9) $U_i = \lambda_i (W - \omega_i) + (1 - \lambda_i) v_i$

where:

U is utility level, λ is weight, v is a vector of variables.

Equilibrium is the wage level at which employers want to hire exactly as many workers as the population is willing to supply.

Eq. 10 $L_S(W,P) = L_D(W,K) \rightarrow \ Pop \cdot \phi\left(\frac{W-\overline{\omega}}{\sigma_\omega}\right) = \delta \cdot \sqrt[1-\beta]{\frac{P_x \cdot A \cdot \beta \cdot K^\alpha}{W}}$

While this expression cannot be derived analytically, it is possible to calculate such a wage level for every set of parameters. Figure 2 represents a closed urban market with such a point:

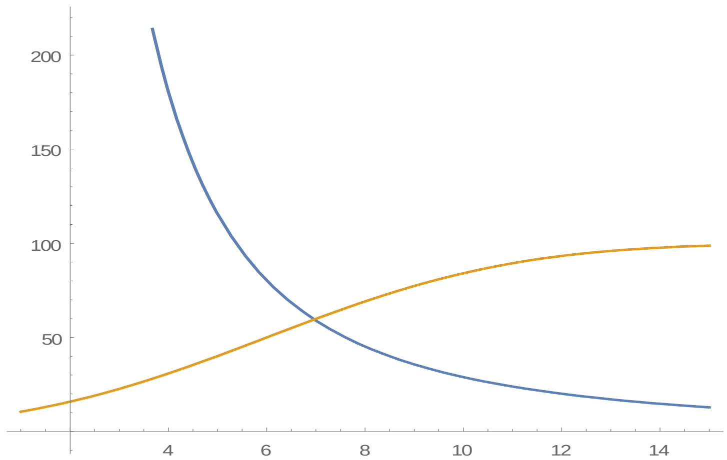

Figure 2. The estimation of wage levels ($\sigma_{\omega} = 4, \overline{\omega} = 6, P = 100, K = 10, \alpha = 0.5, \beta = 0.5, A = 8.5, \delta = 1$).

It is worth noting that equation 10 does not depict true equilibrium, unless $\delta = 1$. This pseudo-equilibrium facilitates flexibility in the model, as it allows for modeling various rigidities simply as a parameter. However, it is not unreasonable to argue that such a friction ratio is by nature a product of capital, or at least that it is effected by large scale shocks to capital.

4 Simulation Procedure

4.1 Operationalization

Operationalizing the above formalization requires many variables. Data on some of these variables is close-to-impossible to collect. Our application, therefore, relies on a number of simplifying assumptions which make the procedure less data-intensive. First, we do not attempt to simulate changes to price levels or to workers' productivity. These are assumed to remain constant throughout the simulation. Second, as data regarding the location of firms is difficult to collect, we assume every commercial or industrial building represents one firm. Accordingly, the floor-space volume of each building is chosen to represent capital stock.

The values of other required variables are derived from the attributes of the individual agents. When the model is initialized, each agent is assigned two characteristics – participation in the workforce and employment status. Each of these is binary in nature; the first must be true if the latter is. The initial condition for the model is that of full employment, and this makes the demand for employees equal to the number of employed agents. The supply of labor is represented by the number of individuals participating in the workforce. The matching (friction) coefficient δ is computed as the ratio between the number of employed agents and the number of agents participating in the workforce. Agents are assumed to consider commuting distance, along with wage levels, in deciding between workplaces.

The remaining variables - $\overline{\omega}_i, \sigma_{\omega_i}, \alpha, \beta, \lambda$ (see Eqs. 1,8,9) - are treated as parameters estimated or imported into the system. As we do not have data regarding the specific activities conducted within each building, we assume that four employment sectors exist, each related to a specific land-use: commercial, industrial, public, and residential.

4.2 Procedure

The procedure is activated separately for each employment sector. It considers that the study area is not a closed system, allocating some positions to individuals residing outside of the area of interest and flagging some agents as not employed within it. The procedure first relies on the activation of the residential location and land-use models (which themselves rely on the housing pricing and activities location sub-models; see Fig. 1 and Box 1). The first of these, by generating in- and out-migration within the study area, affects the supply of labor. The latter, which is translated into the elimination of existing workplaces and the generation of new vacancies, affects the demand for labor. The outputs of these sub-models set the stage for the activation of the wage setting and labor supply models. First, wage-levels are derived by sector (Box 2). The supply sub-model then comes into action by computing the willingness of individuals to participate in the work force and activating a vacancy-agent matching procedure based on utility levels derived from wage levels and commuting distances (Box 3). The outputs of this model inform the next round of agents' behavior, by formulating new levels of income disposable for housing and by revising agents' activity patterns (Box 1).

It is within this procedure that the effects of a shock to the system can be evaluated. The shock has a multi-dimensional effect on the labor market: it affects directly by destroying workplaces and homes, thus leading to the migration of business and population. This directly affects wage levels presenting a second round of indirect disaster effects. Finally, these changes alter the behavior of individuals in terms of both residential location and activity location decisions, thus inducing further land-use changes (which again affect supply, demand and wage levels).

In accordance with the formalization of the procedure, the result of the initial shock is dependent upon the relative effect on both demand and supply. This determines the magnitude of the change in wages and activates a new process of market-level adjustment which is highly dependent upon recovery rates and durations. Thus, the simulation procedure considers the long-term effects of a shock as a non-deterministic process in which both the pre-shock state and the immediate post-shock state individually cannot account for the final outcome.

Store $L_{s,t}$:= set of unemployed individuals participating in the work force.

For each employment sector *sect*:

Store $L_{d,sect,t-1}$:= number of vacancies in sector *sect* at t-1.

Store $W_{sect,t-1}$:= wage levels in sector *sect* at t-1.

Store $K_{sect,t-1}$:= total capital stock for sector *sect* at t-1.

End For.

Activate residential location model.

Update $L_{s,t}$:= add in-migrating agents participating in the work force.

Update $L_{s,t}$:= remove out-migrating unemployed agents which are part of the work force.

For each employment sector *sect*:

Store $Vac_{sect.t}$:= the set of vacancies (including location and wage) for sector *sect*.

End For.

Activate land-use model.

For each employment sector *sect*:

Update $Vac_{sect,t}$:= remove all existing positions unavailable due to land-use change.

Update $Vac_{sect,t}$:= add all new positions generated due to land-use change (wage level = Null).

Store $L_{d,sect,t}$:= size of $Vac_{sect,t}$.

Store $K_{sect,t}$:= total capital stock for sector *sect* at t.

Store $L_{d,sect,t}$, $W_{sect,t}$, $Vac_{sect,t}$:= wages_model ($L_{d,sect,t}$, $L_{d,sect,t-1}$, $W_{sect,t-1}$, $Vac_{sect,t}$, $K_{sect,t-1}$, $K_{sect,t}$).

End For.

Store Vac_t := a set of all vacancies (regardless of sector).

Store Vac_t, $L_{s,t}$:= labor_supply_model ($L_{s,t}$, Vac_t).

Box 1. General procedure.

Function wages_model ($L_{d,sect,t}$, $L_{d,sect,t-1}$, $W_{sect,t-1}$, $Vac_{sect,t}$, $K_{sect,t-1}$, $K_{sect,t}$):

Update $Vac_{sect,t}$:= remove *inLabor* portion of new vacancies (*inLabor* being a pre-defined model parameter indicating the portion of positions held by employees residing outside of the study area).

Update $L_{d,sect,t}$:= size of $Vac_{sect,t}$

Store $W_{sect,t}$:= $\delta^{1-\beta} \dfrac{{K_{sect,t}}^{\alpha}}{{K_{sect,t-1}}^{\alpha} * \left(L_{sect,t} / L_{sect,t-1} \right)^{1-\beta}}$

Update $Vac_{sect,t}$:= allocate wage levels for new vacancies and update wages for existing vacancies based on $W_{sect,t}$.

Return $L_{d,sect,t}$,$W_{sect,t}$,$Vac_{sect,t}$.

Box 2. Labor demand and wages model.

Function labor_supply_model ($L_{s,t}$, Vac_t):

Update $L_{s,t}$:= remove *outLabor* portion of agents (*outLabor* being a pre-defined model parameter indicating the portion of residents employed outside the study area).

For each agent *i* in $L_{s,t}$:

Store ω_i := minimum wage threshold for *i* (draw a value if not allocated).

If all wages in Vac_t < ω_i:

Update $L_{s,t}$:= remove *i*.

Else:

Store U_i := randomly draw minimum utility level for *i*.

Store p_i := Null.

Store j := 0

While p_i is Null and j<length of Vac_t:

Store V := Vac_t[j]

Store $d_{i,v}$:= distance of i's home location from v.

Store $U_{i,v}$:= $\lambda_1(W_v - \omega_i) + \lambda_2 d_{i,v}$

If $U_{i,v}$ >= U_i:

p_i := V

Update Vac_t := remove V.

End If.

End While.

End Else.

End For.

If size of Vac_t > 0:

Update $L_{s,t}$:= randomly add agents to the workforce in accordance with the size of Vac_t.

Return Vac_t, $L_{s,t}$

Box 3. Workforce participation and workplace location model.

5 Conclusions

This paper presents the integration of a labor market component into the ABM developed as part of the DIM2SEA project. Labor markets are identified as an important element within the urban system, affecting residential location decisions and daily mobility patterns. An theoretical framework for the development of supply and demand schedules for the labor market is developed and then translated into a procedure compatible with an ABM application. This procedure presents the labor market‘s complex reaction to the direct and indirect effects of a large scale disaster on the urban system. The long-term reaction of the labor market to such a shock is understood to be complex.

The addition of this component to the model is expected to enrich the outputs produced as part of the research, promoting a wider understanding of urban vulnerability and resilience to disasters. These outputs include changes in unemployment and wage levels, the mixture of opportunities within the job market, the spatial distribution of employment clusters by employment sector, and related welfare effects. As research within the DIM2SEA project progresses, this framework will be applied to the effects of disasters in both abstract and real-world environments while considering various policy interventions. As such, the model is expected to produce guidelines for disaster management tools in the context of the behavior of labor markets in the aftermath of a disaster.

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